Macrofinancial Imbalances in Historical Perspective: a Global Crisis Index

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Abstract

Global crisis episodes are "rare events" that can be properly studied by adopting the long run view of macroeconomic history. In this study we explore the strength of the relationship between current account imbalances, credit growth and equity returns at global level and document new evidence of a recurring sequencing pattern ahead of global crisis periods where credit booms are preceded by growing external imbalances, and crisis episodes occur at the low end of the contraction phase of equity returns. We use this information to construct a single aggregate measure with the aim of signaling periods of increasing risk of macroeconomic and financial instability at global level. Three major crisis episodes are identified with our global crisis index: the 1929 crisis, the breakdown of the Bretton-Woods system and the recent financial crisis. Since past global crisis episodes at international level culminated with the collapse of existing international monetary systems, the ongoing debate on the reforms needed to enhance the stability of international financial markets indicates the recent global financial crisis as a major turning point in the evolution of the international financial and monetary system.

Key words: Macrofinancial imbalances; Global crisis episodes; International Monetary system.

1. Introduction

The events of the first decade of the twenty first century, with equity prices collapsing and their contagion effects spreading from the financial to the real side of the economy and culminated into the so-called Great Recession, bring to mind those experienced by developed economies during the 1929 crisis and the Great Depression of the 1930s. In the search to provide a comprehensive quantitative explanation of such large-scale global events the researchers have adopted an historical perspective by using extended and refined historical data (Reinhart and Rogoff, 2009, Barro, 2009, Alumnia et al. 2010) as well as newly developed long-term cross-country dataset (Schularick and Taylor, 2012, and Jordá et al., 2013). For instance, Reinhart and Rogoff (2009) have examined the association among housing booms, current account deficits, and financial crises, whereas Schularick and Taylor (2012) and Jorda et al. (2013) have investigated the relationship among credit booms, external imbalances and financial crisis events.

Global crisis episodes display several distinct features as to "normal" crisis in terms of frequency, depth and diffusion. First, historically these large drops occur infrequently. Global crises are typically separated by decades, especially in developed economies, so that the cycle length of these crisis episodes "can be a half century or more long, not just 30 years" (Reinhart and Rogoff, 2011, p.1676). Second, large-scale crisis generally imply a severe contraction of the level of economic activity throughout the world whose effects can be long-lasting for the real economy. Third, their effects tend to spread internationally very quickly through fundamentals, trade and capital flows linkages, and "contagious effects". Thus, large-scale crisis can be defined as "rare or extreme events" characterized by synchronous large declines in prices of credit and equity markets across countries and regions and sharp reductions in a broad range of world aggregates which generally culminate with the reform of the existing international monetary and financial system.

Long-term macroeconomic data can provide an exhaustive historical perspective on events occurring at quite a low frequency. The recent global financial crisis has generated renewed interest in macroeconomic and financial history with a proliferation of studies, especially for developed countries (e.g. Reinhart and Rogoff, 2009, Barro, 2009, Alumnia et al., 2010, Schularick and Taylor, 2012, and Jordá et al., 2013), resulting in a wide and growing consensus on the hypothesis that financial crises are "credit booms gone wrong (or bust)".[1] The rationale for taking a longer perspective and adopting the comparative economic history approach in the analysis of international crisis episodes is twofold. The first is that, since history tends to repeat itself, long-term historical time series provide a way to detect empirical regularities among several crisis events. The latter is that, given the low frequency of occurrence of global crisis episodes in developed countries, a long run macro-financial history approach can be pre-

[1] E.g. and Schularick and Taylor (2012).

ferred to standard statistical methods.

In this paper we use the long-term historical database from Schularick and Taylor (2012) and Jordá et al. (2013) in the search for empirical regularities that can offer useful insights for detecting large-scale crisis episodes. For this purpose we examine the relationships among several key macroeconomic and financial variables investigated in the recent literature in the field of macrofinancial history (e.g. Reinhart and Rogoff, 2009, Schularick and Taylor, 2012, and Jordá et al., 2013). Specifically, we investigate the time-frequency dependencies among external imbalances, credit growth and equity price returns measured at global level using the exploratory analysis tools of the continuous wavelet transform. The key finding emerging from the long wave pattern of the CA/GDP ratio, the credit/GDP ratio and equity returns is that major global crisis periods are preceded and accompanied by macroeconomic imbalances in the global economy, current account deficits and credit growth respectively, with crisis episodes occurring at the low end of the contraction phase of equity returns. When this information content on the phase relationships between the long wave components of external imbalances, credit booms and equity price returns is used to construct a composite indicator with the aim of detecting periods of increasing risk of macroeconomic and financial instability at global level we are able to identify three major global crisis periods: two of them, the 1929 crisis and the breakdown of the Bretton-Woods system, correspond to historical crisis episodes at international level that ended with the collapse of existing international monetary systems. The third, the recent global financial crisis of 2008-9, has favored the emergence of a vigorous debate on the reform reforms needed to enhance the stability of international financial markets. Since past global crisis episodes at international level culminated with the collapse of existing international monetary systems, the recent global financial crisis is likely to represent a major turning point in the evolution of the international financial and monetary system. In sum, our results provide important insights for the empirical evidence and for some puzzling questions that have emerged in the macrofinancial historical literature as well as interesting implications for reforming the international financial and monetary system.

The paper is structured as follows: section 2 provides an overview of the evidence provided in the macrofinancial historical literature on the role of credit booms, external imbalances and equity prices in past crisis episodes. Section 3 explores the time-frequency relationships among the variables of our historical dataset using wavelet-based exploratory data tools such as the wavelet coherence and the phase-difference. Section 4 explains the methods used for the extraction of long waves and provides some historical and descriptive evidence on the long wave patterns of the CA/GDP ratio, the credit/GDP ratio and equity returns along with a test of their predictive ability. Section 5 presents the composite index measuring the risk of macroeconomic and financial instability at global level. Section 6 concludes the paper.

2. Global crisis evidence from the macrofinancial historical approach

There is a large growing consensus in the literature on the role played by excessive credit growth for predicting financial crisis episodes. Borio and White (2004) and Eichengreen and Mitchener (2004) have provided empirical evidence that systemic financial crises, and in particular the Great Depression, can be interpreted as "credit booms gone wrong or bust". Similar findings have been recently reaffirmed also for the 2008 global financial crisis. The historical evidence provided by Borio and Lowe (2002b), Mendoza and Terrones (2008), Schularick and Taylor (2012), Jordá et al. (2013), and Taylor (2015) shows that systemic financial crisis are usually preceded by a lending boom and that credit boom is the best indicator of future financial instability. Moreover, the predictive ability of past credit growth values is robust to the inclusion of additional key macroeconomic variables such as global imbalances and equity prices, since these variables, although individually significant as early warning indicators, can provide only limited information about the probability of a future crisis once credit growth is taken into account (Schularick and Taylor, 2012, and Jordá et al., 2013). For example, although there is evidence of accelerating credit growth and external imbalance widening in the years preceding a crisis, "external imbalances do not seem to play as large a role in creating instability as credit boom" (Jordá et al. 2013, p.3). In sum, the main findings stemming from the historical macrofinancial approach on the determinants of the recent financial crisis are twofold: the role of credit growth as a powerful predictor of financial crises (Jordá et al. 2013), and the presence of a global financial cycle in international financial markets (Rey, 2015).[2]

Global imbalances are a matter of concern for policymakers because of the systemic costs associated to large and persistent current account imbalances. Indeed, being symptomatic of underlying relative price, demand, and resource misallocations, global external imbalances represent a systemic threat to financial stability and, as such, are an essential policy target that need to be closely monitored by policymakers (see Obstfeld and Rogoff, 2010, and Obstfeld, 2012). The role of global external imbalances have attracted the attention of many scholars because the persistent imbalance between the United States and the emerging countries has been called for as an underlying cause of the recent global crisis beyond the abuse of derivatives, the systematic deregulation of the financial system and, especially, the role of "excessive" credit growth or credit booms. For example, according to Bini Smaghi (2008) financial imbalances and the crisis are two sides of the same coin. Similarly for Bernanke (2009): "In my view it is impossible to understand this crisis without reference to the global imbalances in trade and capital flows that began in the latter half of the 1990s". And finally, Obstfeld and Rogoff (2010) suggest that imbalances and the financial crisis are intimately connected.

[2] Miranda-Agrippino and Rey (2015) and Rey (2015), looking at international capital flows, have identified a "global financial cycle" in international financial markets in terms of comovements among gross capital flows, credit growth and equity prices around the world.

Notwithstanding this notable convergence of opinions, there is substantial disagreement among academics, policy makers and practitioners about the role played by the widening of global external imbalances started in the late 1990s in the recent financial crisis (Bernanke, 2009, Obstfeld and Rogoff, 2010, Taylor, 2012, 2015). Indeed, the role of global current account imbalances in determining crisis episodes is still controversial because the empirical literature has not yet established robust evidence in support of the predictive ability of the current account for subsequent financial crises.[3] The only notable exception is the paper by Davis et al. (2014) which shows how the combination of credit growth and external deficits is able to explain the significance of the marginal effect of private sector credit growth for the probability of a crisis. In sum, the question whether global imbalances can be considered a useful indicator of potential troubles ahead remains controversial because of the weak empirical evidence on the role of external imbalances, especially if compared with the strong evidence supporting the role of credit booms.

Finally, Borio and Lowe (2002a) and Borio and Drehmann (2009) have documented the role of increasing equity prices as potential indicator of the risk of financial crisis in combination with credit growth. The mechanism works through spill over effects of credit booms for equity prices that tend to increase the risk of financial instability following equity prices boom and bust cycles.[4] Recently, Rey (2015) has detected the presence of a global financial cycle in international financial markets in terms of co-movements among gross capital flows, credit growth and equity prices around the world. Similarly, Jordá et al. (2015) using their newly developed dataset have recently provided evidence about the role that equity prices signal in combination with credit growth in predicting financial crisis looking at house price and mortgage credit booms.

3. Exploratory scale-based analysis of global macroeconomic indicators using wavelets

What is the relationship between current account imbalances and credit or asset-market booms? Studies investigating the links using country-level variables, such as Jordá et al. (2011, p.372), find that the current account deteriorates in the run-up to normal crises, but the evidence is inconclusive in global crises, possibly because both surplus and deficit countries get embroiled in the crisis. Since large-scale crisis episodes are related to macroeconomic and financial conditions at global level, we argue that variables measured at the global level are likely to provide a useful set of indicators for detecting periods of increasing risk of systemic macroeconomic and financial instability.

Allowing for different time scales of variation in the data can provide a fruitful understanding of the complex dynamics of economic relationships among

[3]This is especially true when advanced economies are considered.

[4]The interaction between credit markets and asset price dynamics for boom-bust cycles driven has been also examined in Charpe et al. (2011), Semmler and Bernard (2012) and Chiarella et al. (2014).

variables with non-stationary or transient components, as it is the case with the secular movements in aggregate time series which exhibit structural changes in the trend function so as to be characterized as segmented trend processes (e.g. Gallegati et al., 2017).[5] In particular, wavelet analysis allows to uncover relationships that are veiled when estimated at the aggregate level but may be consistently revealed after allowing for different time scales of variation in the data (Ramsey, 2014).[6]

Among the wide variety of available methods that allow to simultaneously estimate different cyclical components wavelet analysis is gaining popularity, especially in economics and finance,[7] because of its ability to act locally in both frequency and time and to provide a time-frequency representation of a signal that offers good time localization and frequency resolution properties.[8]

The time-frequency relationships among global imbalances, credit growth and equity prices can be easily explored using the bivariate tools of the continuous wavelet transform (CWT): the wavelet coherence and the phase difference.[9]

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[5]Historical datasets where secular or long-run movements in macroeconomic time series are likely to be affected by changes in regime that may occur as a result of wars, economic crises, changes in institutional arrangements (e.g. international monetary system), etc.. This is clearly evident for the long-run trends of money and credit aggregates relative to GDP in the new dataset recently assembled by Schularick and Taylor (2012).

[6]Percival and Walden (2000) provides a technical exposition with many examples of the use of wavelets in a variety of fields, but not in economics. Gencay *et al.* (2002) generate an excellent development of wavelet analysis and provide many interesting economic and finance examples, while Crowley (2007) and Aguiar-Conraria and Soares (2014) provide useful introductions for economists to DWT and CWT, respectively. A brief introduction to wavelets is provided in the Appendix.

[7]E.g. Ramsey and Lampart, (1998a, 1999b), Gencay *et al.*, (2005, 2010), Rua and Nunes (2005), Aguiar-Conraria and Soares (2011), Gallegati *et al.*, (2011), Gallegati and Semmler, (2014).

[8]Using a basis function that is dilated or compressed (through a scale or dilation factor) and shifted (through a translation or location parameter) along the signal the wavelet transform has the ability to decompose a a signal into a set of time scale components, each associated to a specific frequency band and with a resolution matched to its scale. Indeed, the wavelet transform provides a flexible time-scale window that narrows when focusing on small-scale features and widens on large-scale features, thus displaying high time resolution for short-lived high-frequency phenomena, and high frequency resolution for long-lasting low-frequency phenomena.

[9]The application of the CWT requires the specification of the wavelet function. Among the numerous types of wavelet families available, we select the Morlet wavelet, defined as There is a large number of specific wavelets, i.e. Mexican hat, Haar, Daubechies, etc., out of which we choose the Morlet wavelet standardly used in the economic and financial applications. The Morlet wavelet with a central frequency ω_0 is defined as

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} - e^{-\frac{t^2}{2}}.$$

and for $\omega_0 = 6$ it provides a good balance between the time and frequency localization (Grinsted *et al.* 2004) and also simplifies the interpretation of the wavelet analysis because the wavelet scale, s, is inversely related to the frequency, $f \approx 1/s$, which has optimal joint time-frequency concentration and attains the minimum uncertainty value of the corresponding Heisenberg box.

The wavelet coherence measures how the strength of the correlation between two time series changes in the time-frequency plane and represents an expansion of the correlation analysis into the time and the frequency domains, so that it is possible to detect those time scales at which the relationship is statistically significant from those scales at which it is not. The phase difference provides the relative phase between signals' variations, that is their lead/lag relationship.

For our analysis we use the latest vintage of the historical dataset developed by Jordá et al. (2017) available at http://www.macrohistory.net/data/ over the period 1870-2013 for 17 developed countries: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States. In particular, we use the the ratio of the Current account (nominal, local currency) to GDP (nominal, local currency), the ratio of Total plus Mortgage loans to non-financial private sector (nominal, local currency) to GDP (nominal, local currency), and the log difference of Stock prices (nominal index base 2000=100). Given our interest in detecting periods of increasing risk of for the world macroeconomic and financial stability we use aggregate measures for the current account GDP ratio, the credit GDP ratio and equity returns.[10] The extent of global imbalances can be gauged by looking at the average magnitude of the absolute value of world current account positions of the 17 countries as a percentage of their total GDP (e.g. IMF, 2007, and Bracke et al., 2008). As to the credit/GDP ratio and equity returns we compute their global values using a GDP-weighted average[11] of the variables in question across the 17 countries in the sample (e.g. ECB Financial Stability Review, November 2013). As an aside, we may note that the pattern of the credit/GDP ratio presented in the middle panel of Figure 2 is strikingly similar to the plot of the estimated year effects of the bank loans to GDP ratio obtained by running a fixed effects regression in Schularick and Taylor (2012) and Jordá et al. (2013) and to the average global measure of the credit to GDP ratio in Jordá et al. (2017) used to provide support to the so-called 'financial honey stick" hypothesis.

Figure 1 shows the squared wavelet coherence between the current account GDP ratio, the credit GDP ratio and stock market returns measured at global level. Time is recorded on the horizontal axis while the vertical axis gives us the periods in years (and the corresponding scales of the wavelet transform). Reading across the graph one can see how the power of the projection varies across the time domain at a given scale, while reading down the graph at a given point in time shows how the power varies with the scaling of the wavelet (see Ramsey *et al.*, 1995). The wavelet coherence power is indicated by color coding: it ranges from blue (low coherence) to red (high coherence), with high power

[10]Since the database contains a large number of missing data, especially at the beginning of the sample and during war years, aggregate measures allow us to avoid the practice of extensive interpolation.

[11]The average values of the credit to GDP ratio and of stock market returns are weighted by the countrys share in world GDP, where GDP data initially expressed in the national currency are converted into a common currency (the US dollar).

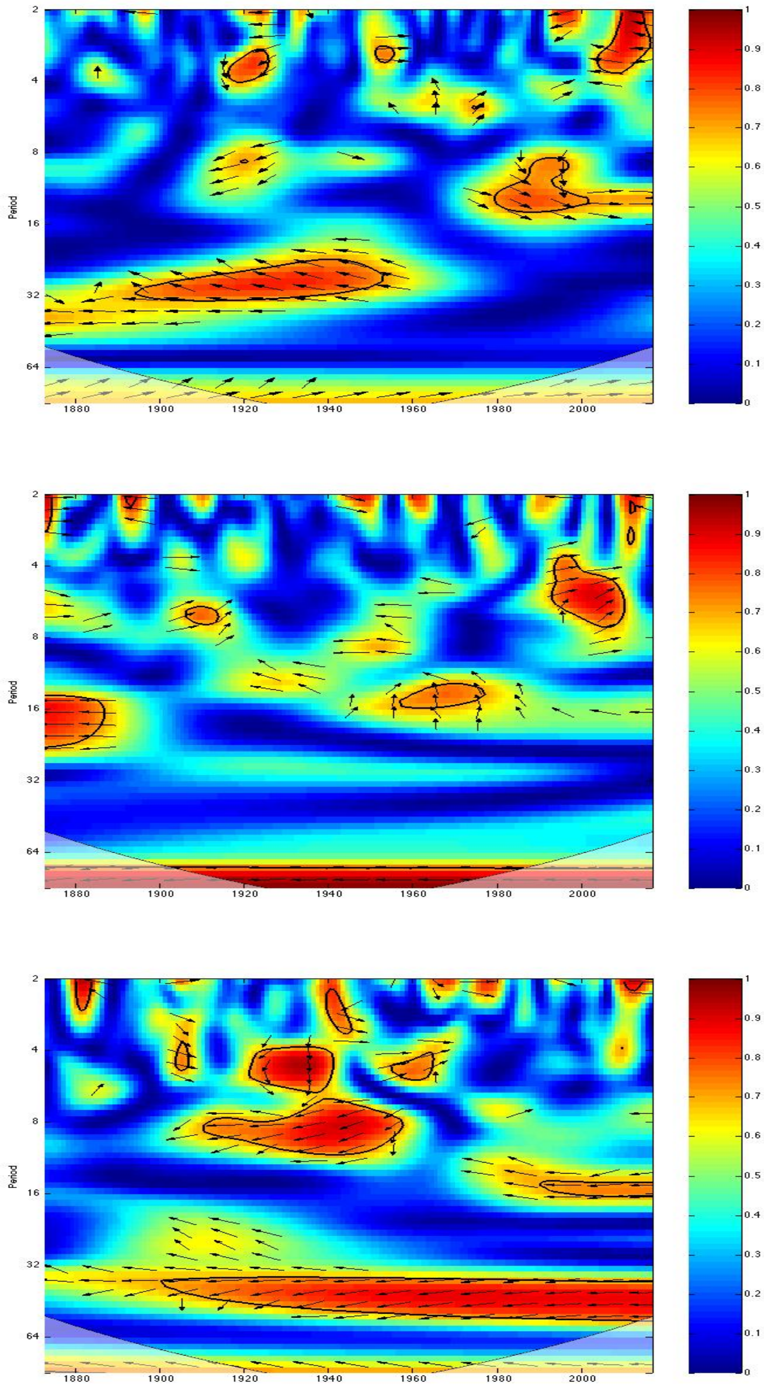

Figure 1: Squared wavelet coherence of CA/GDP and credit/GDP (top panel), CA/GDP and stock market returns (middle panel) and Credit/GDP and stock market returns (bottom panel). The color code for power ranges from blue (low coherence) to red (high coherence). The thick black contour designates the 95% confidence level and the cone of influence (COI) is shown as shaded area. The arrows indicate the phase difference: right (left) pointing arrows indicate in-phase (anti-phase) relationship.

regions associated with warmer colors (red, orange and bright green). High coherence regions detect areas in the time-frequency space where two phenomena have a significant interaction and the strength of their relationship is strong. The thick black contour lines denote regions of statistically significant correlation[12] whereas the cone of influence, represented by a shaded area, corresponds to the region affected by edge effects at the beginning and the end of the time series.[13] Complex-valued wavelets like Morlet wavelet have the ability to provide the phase information, that is a local measure of the phase delay between two time series as a function of both time and frequency. The relative phase information is graphically displayed on the same figure with wavelet coherence by plotting such arrows inside regions characterized by high coherence, so that the coherence and the phase relationship are shown simultaneously.[14]

The results from wavelet coherence analysis show that the relationships among variables are frequency-dependent. At shorter timescales, from interannual to quasi-decadal, there is evidence of statistically significant isolated high coherence regions in the time-frequency plane. At multidecadal timescales there is evidence of a remarkably stable strong negative relationship between the credit GDP ratio and stock market returns, which is significant since the early 1900s. A high coherence region is also evident between CA/GDP ratio and the credit GDP ratio at interdecadal and multidecadal timescales until the early 1960s. By contrast, stable significant bivariate relationships are evident at the highest timescale, i.e. at scales corresponding to periods greater than 64 years, throughout the sample among all variables. However, the cone of influence indicates that at the highest scale levels wavelet coefficients are affected by edge effects for a substantial part of the signal, so that these results should be interpreted with caution.

Since the number of wavelet coefficients suffering from these edge effects decreases in extent as the scale of the wavelet decreases, the size of the cone of influence gradually reduces from highest to lowest scale levels. As a results at the scale level corresponding to periods equal to 64 years the values of the transform which are incorrectly computed due to edge effects are limited to a few observations in the very end and beginning of the sample. Following these

[12]Following Grinsted et al. (2004) and Maraun and Kurths (2004) critical values were calculated as the 95^{th} percentile of the empirical distribution of the simulated wavelet coherencies.

[13]To deal with the influence of border distortions the half-point symmetric (mirror) extension mode at both sides is used to produce extended time series whose length is almost double than the original time series (e.g. Lin and Franzke, 2015). The extended time series have 284 rather than 143 data points. This length is long enough to reduce significantly the size of the "cone of influence" for the maximum scale of 64 years used in this study. Since the annual observations cover a period slightly less than 150 years, they allow to satisfactorily investigate interannual (2-8 years), quasi-decadal (8-16), interdecadal (16-32 years) and multidecadal (32-64 years) timescales.

[14]Following the trigonometric convention the direction of arrows shows the relative phasing of the two time series and can be interpreted as indicating a lead/lag relationship: right (left) arrow means that the two variables are in phase (anti-phase). In addition, if the right arrow points up (down) it means that the first is lagging (leading), while if the left arrow points down (up) means that the first variable is lagging (leading).

considerations, in the remaining of the paper we exclude from our analysis the highest scale levels and focus on the frequency range between 32 and 64 years where the stability of the relationships among global macroeconomic indicators are stronger than at any other timescale.

4. Long wave patterns and global crises: historical evidence and predictive ability

The extraction of unobserved components within specified frequency bands may be pursued using the discrete wavelet transform (DWT) which is a discretized version of the CWT. The key difference between the CWT and the DWT lies in the fact that the DWT uses only a limited number of translated and dilated versions of the mother wavelet to decompose the original signal (see Appendix for details). The application of the DWT with a number of levels (scales) J produces, for each variable, J wavelet details vectors D_1, D_2, ... D_{J-1} and D_J and a smooth scaling vector S_J,

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + ... + D_j(t) + ... + D_2(t) + D_1(t)$$

where S_J represents the smooth long-term component of the signal and the detail components D_j provide the increments at each individual scale level, each corresponding to a specified frequency band.[15]

The same goal can be achieved using Baxter and King (1999) and Christiano and Fitzgerald (1999) approximate pass-band filters. These filters, although performed in the time domain, have their own desired properties formulated in the frequency domain. Although mainly developed in the context of business cycle analysis, these filtering techniques have also been applied for extracting lower frequency components of economic time series because both lower frequency cycles (and trends) and higher frequency components (for example, seasonality and noise) can be filtered out.[16]

However, the optimizing criteria adopted by band-pass filter approximations implicitly define the specific class of model for which the approximating filter

[15]Since the wavelet filter belongs to high-pass filter with passband given by the frequency interval $[1/2^{j+1}, 1/2^j]$ for scales $1 < j < J$, inverting the frequency range to produce a period of time we have that wavelet coefficients associated to scale $j = 2^{j-1}$ are associated to periods $[2^j, 2^{j+1}]$.

[16]The Baxter-King filter has been used by Baxter (1994) to study the relationship between real exchange-rate differentials and real interest rates at low frequencies, and recently by Kriedel (2009) for the analysis of long waves of economic development with a length between 30 and 50 years in six European countries. Christiano and Fitzgerald (2003) have examined the Phillips curve relationship between unemployment and inflation in the short- and the long-run, as well as the correlations between the low-frequency components of monetary growth and inflation with their own asymmetric band-pass filter. Recently, Heap (2005), Jerret and Cuddington (2008) and Erten and Ocampo (2012) have used the Christiano-Fitzgerald filter to isolate the range of cyclical periodicities that constitute super cycles (cycles between 20 and 70 years) in metals and commoditiy prices, respectively.

is optimal. In particular, since a random walk puts more weight on lower frequencies, whereas independent and identically distributed variables weight all frequencies equally, the filter by Baxter and King approximates the ideal band-pass filter for shorter business cycles with higher accuracy than the filter by Christiano and Fitzgerald which, by contrast, provide a worse performance for cycles with short durations. As a consequence, the filter by Christiano and Fitzgerald is expected to approximate the ideal band-pass filter for cycles with long durations better than the filter by Baxter and King, and vice versa (Everts, 2006). By contrast, the application of the wavelet transform provides a systematic way of performing band-pass filtering (Proietti, 2011) that does not require a commitment to any particular class of model. Indeed, the wavelet method allows the simultaneous estimation of different unobserved components without making any explicit assumption about the characteristic of the data generating process, and thus can be considered a "model-free" approach to frequency extraction problems, as they are optimal under any time series representation of the process. This feature is critical with long-term historical data when complexity and nonlinearities are intrinsic features of these datasets. The secular movements in macroeconomic time series are likely to display short-lived transient components like abrupt changes, jumps, and volatility clustering, typical of war episodes or crisis episodes, and to exhibit structural changes in the trend function because of policy changes or paradigm shifts.[17]

In Figure 2 the grey lines shows the raw series for the sum of the absolute value of current account imbalances (percent of GDP), the ratio of total credit to GDP, and equity price returns. In each panel of Figure 2 two smoothed lines are superimposed which represent their corresponding long-term components extracted using the LA(8) wavelet and the CF band-pass filters. The thick smooth line, extracted by applying the maximal overlap discrete wavelet transform (MOWDT)[18] using the Daubechies least asymmetric (LA) wavelet filter of length $L = 8$ based on eight non-zero coefficients (Daubechies, 1992), with reflecting boundary conditions,[19] represents the D_5 detail component. The detail at this level of decomposition gives information about the longest period of 32-64 years. The thin smooth line represents the corresponding component, with periodicity between 32 and 64 years, extracted using the Christiano-Fitzgerald (CF) approximate band-pass filter.[20]

[17]This is evident in the new dataset recently assembled by Schularick and Taylor (2012) where two very different patterns in the long-run trends of money and credit aggregates relative to GDP emerge before and after 1950 when the credit aggregate trends up in the post-WWII period and starts decoupling from money.

[18]The MODWT can accommodate any sample size N, where the DWT requires N to be a multiple of 2^J, and produces the same number of wavelet and scaling coefficients at each decomposition level. The redundancy of the MODWT facilitates alignment of the decomposed wavelet and scaling coefficients at each level with the original time series (Percival and Walden, 2000).

[19]With the reflection boundary conditions the original signal is reflected about its end point to produce a series of length 2N which has the same mean and variance as the original signal.

[20]For the CF band-pass filter as to the stationarity assumption equity price returns are

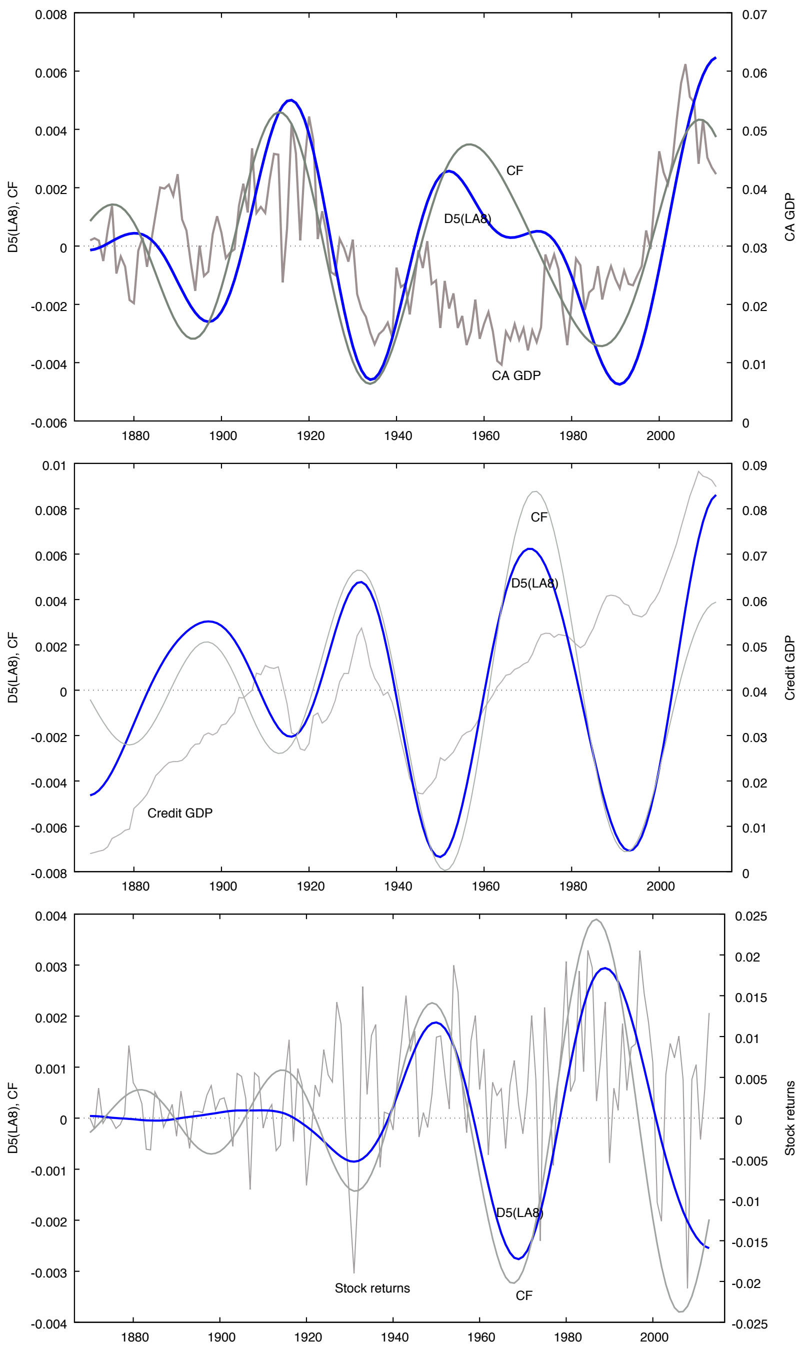

Figure 2: Global measures of the current account/GDP ratio (top panel), the private credit/GDP ratio (middle panel), and equity price returns (bottom panel) along with their long wave components: the thick smooth line is the wavelet filtered D5 component, the thin smooth line the CF filtered component.

The long-term components extracted using the wavelet and band-pass filters display a good pattern of similarity both in terms of the amplitude of cyclical movements and the correct alignment of upper and lower turning points. Exceptions are given by equity returns until 1920s, the CA/GDP ratio in the 2^{nd} half of the XX^{th} century, and the credit/GDP ratio in the early 1970s. Beyond these similarities and differences, relevant divergences emerge as to the filtered values at the right edge of the sample where boundary condition effects seems to affect the ability of wavelet filtering methodology to timely detect turning points in two out of three series.[21]

The historical evidence presented in Figure 1 indicate that periods of rising global current account imbalances are followed by credit booms and equity prices downturns, and precede a number of well known global crisis episodes. In such a pre-crisis dynamics the key mechanism at work is that over the expansion phase of the long-swing the widening of external imbalances provides liquidity at global level and fuels credit growth. The following excessive credit growth undermines the stability properties of the financial system, which evolves from stability to instability,[22] with global crisis events occurring at the low end of the long-term swing in equity returns. This prototype sequence of events is consistent with Davis et al. (2014) findings on the combination of high credit growth and large external borrowing as precursors of crisis and with Schularick and Taylor (2012), and Jordá et al. (2013) results that the onset of global crises occurs in coincidence with equity price boosts and is preceded by credit booms.

The historical long wave patterns of the credit and current account GDP ratios provide several important insights for the interpretation of the findings reported within the macrofinancial history approach (e.g. Schularick and Taylor 2012, Jordá et al., 2013) and for the current debate on the role of global imbal-

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assumed to be an I(0) covariance stationary process without drift, while the current account to GDP ratio and the credit to GDP ratio are assumed to be an I(1) unit root process with drift.

[21]Filtering methods applied to a finite length time series inevitably suffer from border distortions; this is due to the fact that the values of the transform at the beginning and the end of the time series are always incorrectly computed, in the sense that they involve missing values of the series which are then artificially prescribed. Therefore, at the edges of a series the filtered values are likely to suffer from these boundary effects and have to be interpreted carefully.

[22]The recent financial crisis has also generated renewed interest in heterodox contributions that view financial crises as extreme manifestations reflecting endogenous systemic changes in the financial structure of the economy (e.g. Schularick and Taylor, 2012): "our historical data lend some support the ideas of scholars such as Minsky, Kindleberger and others who have argued that the financial system itself is prone to generate economic instability through endogenous credit booms.") Although generally interpreted as a short-term cyclical phenomenon (e.g. Chiarella and Di Guilmi, 2011), the financial instability hypothesis has been recently interpreted as an evolutionary approach generating long waves in financial variables (Ferri and Minsky, 1992, Palley, 2011, and Bernard et al. 2014). According to the "long swings" interpretation of Minsky's financial instability hypothesis (Minsky, 1964, 1995) these endogenous systemic changes in the financial structure occur during the expansion phase of a long swing and have implications for the stability of the financial system (Ferri and Minsky, 1992, Palley, 2011).

ances for financial crises (Obstfeld and Rogoff, 2010, Taylor, 2012, 2015). As to "credit boom vs global imbalances" controversy our findings indicate that, although both long cyclical waves in global imbalances and credit aggregates provide valuable information about approaching major global crises episodes, the temporal sequence of events emerging, with global imbalances preceding lending booms, suggests a sort of "attenuation effect" of the role of global imbalances as to that of credit booms.[23] This is consistent with the greater significance of the credit boom with respect to external imbalances (Jordá et al., 2013), as well as the usefulness of widening imbalances as early warning signals of rising financial instability risk (Reinhardt and Rogoff, 2009). From a policy perspective our evidence suggest that excessive widening global imbalances needs to be carefully monitored by policy makers because, by providing liquidity to the system, they can give rise to credit booms which generally tend to anticipate global crisis periods.

The visual inspection of the long wave components shows three complete well pronounced cycles for external imbalances, three and a half for aggregate private credit and four complete cycles for equity price returns. The top panel of Figure 1, shows the pattern of the sum of the average absolute value of the current account as a percent of GDP. The emergence of global current account imbalances is evident before 1880, in the first two decades of the 20th century, from early 1940s to early 1960s and in the new century. In the middle panel of Figure 1, which depicts the evolution of long cycles patterns in aggregate private credit, periods of "excessive" expansion in credit are clearly evident. These periods of excessive credit variations tend to cluster around four well known historical global crisis periods: the 1890s crises, the great depression after the 1929 crisis, the collapse of the Bretton Woods system and the global contraction following the 2007-8 financial crisis. Finally, the bottom panel of Figure 1 shows that the lowest returns in equity prices occurred around 1900, 1930, 1970, and late 2000s.

The crisis dating chronology emerging from the plots in Figure 1 corresponds to chronology of global crisis episodes reported in the literature. Indeed, in the last 150 years Bordo (2005) identifies two main crises episodes at international level before the recent global crisis, the 1929 Great Depression and the collapse of Bretton Woods international monetary system, which resulted in the collapse of existing international monetary regimes the interwar gold exchange standard and the fixed exchange rate regime.[24] Thus, we can get more insights into the ability of three long term components to provide information about the likelihood of future global crisis episodes using the crisis prediction framework applied in Schularick and Taylor (2012) and Jordá et al. (2013, 2014).

[23]Moreover, the recent phase shift between the current account GDP ratio and the loan GDP ratio is likely to further reducing the significance of external imbalances by posing an additional veil to the usefulness of the evolution of global imbalances as an early warning signal of global crisis episodes.

[24]The early 1890s crises and 1977-79 dollar crisis are also reported, although they are indicated as small imbalances when compared to that of the present period.

The receiver operating characteristic (ROC) curve is a standard tool for evaluating the predictive ability of different binary classifiers and visualizing their performance. The curve plots plots a curve according to its true positive rate, sensitivity, against its false positive rate (true negative rate), specificity (one minus specificity). The area under the estimated ROC curve (AUC) provides a summary measure of classification accuracy (or summarizes the discrimination ability of a model) by means of a simple test of predictive ability against the null value of 0.5 with an asymptotic normal distribution.

The horserace among models using individual classifiers shows that credit/GDP ratio and equity returns are highly significant, yielding values of the AUC of 0.6882 and 0.7399 respectively, whereas the significance of the current account GDP ratio is much lower, the AUC is equal to 0.5916, a value that is above the simple coin toss (AUC = 0.5) by some margin. Figure 5 shows the predictive ability differences among the three models with the ROC curves for credit/GDP and equity price returns very close to each other and almost overlapping, and the CA/GDP ROC curve well below the other two curves at all points. The analysis of the predictive ability of the three long-term components suggests that periods of excessive credit and equity price boosts are helpful in predicting global crisis periods, and that the current account GDP ratio has also a role, although a limited one. These results are in line with those reported in Jordá et al. (2013) except for the role of stock prices whose contribution as a predictive variable they find is negligible.

5. A global crisis index

After the US financial crisis of 2007-8 measures of the degree of stress prevailing in the overall financial system[25] have been developed by government and international institutions with the aim of determining whether financial stress is high enough to be a serious concern for financial stability. Financial stress indexes (FSI) developed at both country and global level, provide a measure of the overall level of financial stress by combining information from different markets, that is interbank, credit, equity, foreign exchange, etc., (e.g. Hakkio and Keeton, 2009, Kliesen and Smith, 2010), with extreme values corresponding to stressful periods and/or financial crises. Financial conditions indexes (FCI) like the Chicago Fed National Activity Index (Brave and Butters, 2011) and the ZEW Financial Condition Indices for the Euro area (Schleer and Semmler, 2015) are similar to FSIs in that they both combine different financial market indicators, but differ as the focus of FCIs is on the link between the financial sector and the real economy (see Kliesen et al., 2012, and Hatzius et al., 2010, for surveys).

[25] Examples are the Financial Stress Indexes of the Federal Reserve Bank of Kansas City (KCFSI), St. Louis (STLFSI), Cleveland (CFSI) and IMF's Financial Stress Index for Advanced Economies (AE-FSI).

The statistical regularities about the timing of global imbalances, credit booms and equity returns lows emerging from the historical analysis of the long cycle components can provide useful information for identifying global crisis events, such as those culminated with the collapse of existing international monetary systems. Hence, in this section we develop a global crisis index with the aim of identifying periods of world economic turbulence corresponding to periods of increasing risk of global macroeconomic and financial instability at system level.[26]

For the purpose of constructing a composite indicator[27] we examine first the timing relationships among long wave components using cross-correlation analysis. The left panel of Figure 3 shows that the relationship between the current account to GDP ratio and the credit to GDP ratio is strong and positive. The average leading time of global current account imbalances for credit is seventeen years with a correlation coefficient of 0.70, with a shifting phase relationship between widening imbalances and excessive credit variation from leading to contemporaneous in the last decades where the surplus of emerging countries is financing the deficit of the industrialized countries, and the US in particular.[28] The pairwise correlation is high and negative between the current account to GDP ratio and equity returns (middle panel of Figure 3) with a coefficient value of 0.61 and an average leading time of 16 years. A negative relationship is also evident between the credit to GDP ratio and equity returns (right panel of Figure 3), with an average leading time of equity price returns with respect to the credit to GDP ratio of four years and a pairwise correlation coefficient equal to -0.91.

Figure 4 shows the global crisis index for the period 1871-2013 calculated by aggregating the long wave components of the CA/GDP ratio, the credit/GDP ratio and equity returns. For the period 1870-1990 the composite index is obtained using the D_5 components of the CA/GDP ratio lagged 12 years, and the current values of the credit/GDP ratio and equity returns. From 1990 the CF filtered components are used with the CA/GDP ratio now entering without lags. Values above (below) 0 indicate turbulent (normal) periods in the world economy, with crisis periods identified with peaks of the index and the severity of crises episodes measured by the height of the index.

Following the approach generally used in the literature on financial stress indexes the performance of the global crisis index presented in Figure 4 can be evaluated on the basis of its ability to identify past "significant" global crisis

[26]To our knowledge the only existing global crisis index which proxies of world economic turbulence is the BCDI index (Reinhardt, 2011) which accounts for banking (systemic episodes only), currency, debt (domestic and external), and inflation crisis index.

[27]The pattern of the composite indicator resembles that of a probabilistic model so that the values of the indicator echo the probability prediction from a typical binary model (such as a probit, logit, etc.), a linear probability model, a factor model, ...

[28]This phase shift is consistent with the findings reported by Jordá et al. (2013) that in recent decades the correlation between credit growth and external imbalances has increased considerably: "In the past decades ..... higher loan growth went increasingly hand in hand with widening imbalances" (Jordá et al. (2013), p.).

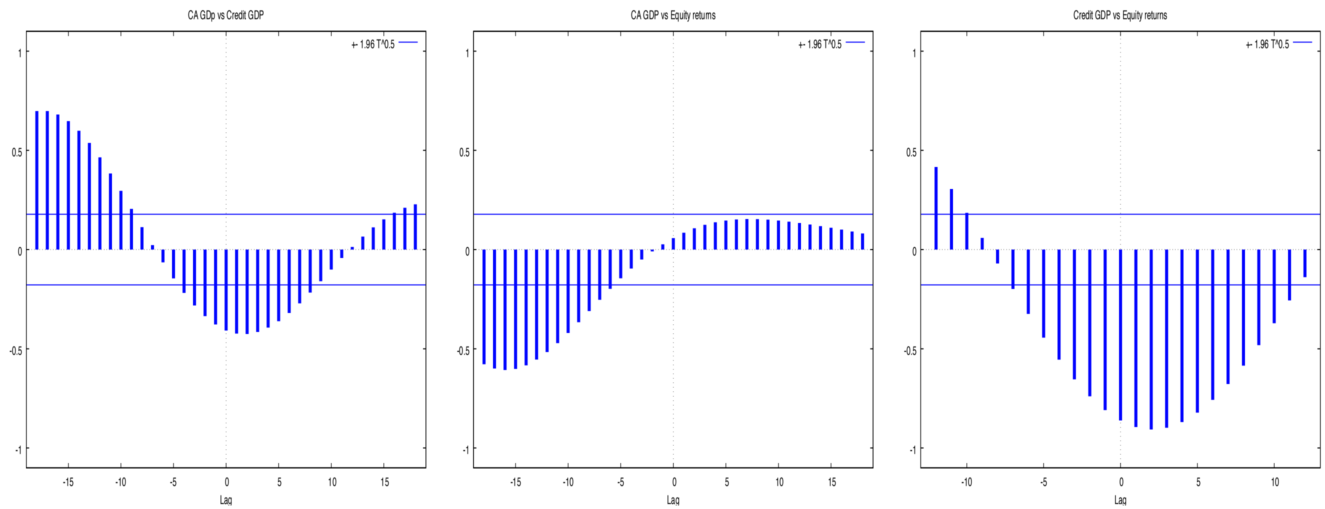

Figure 3: Cross-correlation results between the D_5 wavelet filtered components of: current account and the credit GDP ratios (left panel), the current account to GDP ratio and equity returns (middle panel), and the credit to GDP ratio and equity returns (right panel).

episodes both in absolute and in relative terms. Four peaks are clearly identified by the historical record of the index, one minor in 1889, and three major in 1930, 1969 and 2009, each corresponding to well known global crisis periods at international level: the early 1890s, the 1929 crisis, the break-down of the Bretton Woods system of fixed exchange rates and the recent financial crisis. As before, we can evaluate the predictive ability of the global crisis index using the ROC curve. The global crisis index yields a value of the AUC of .9065, a value that is above that of its individual components by a good margin, as shown in Figure 6.

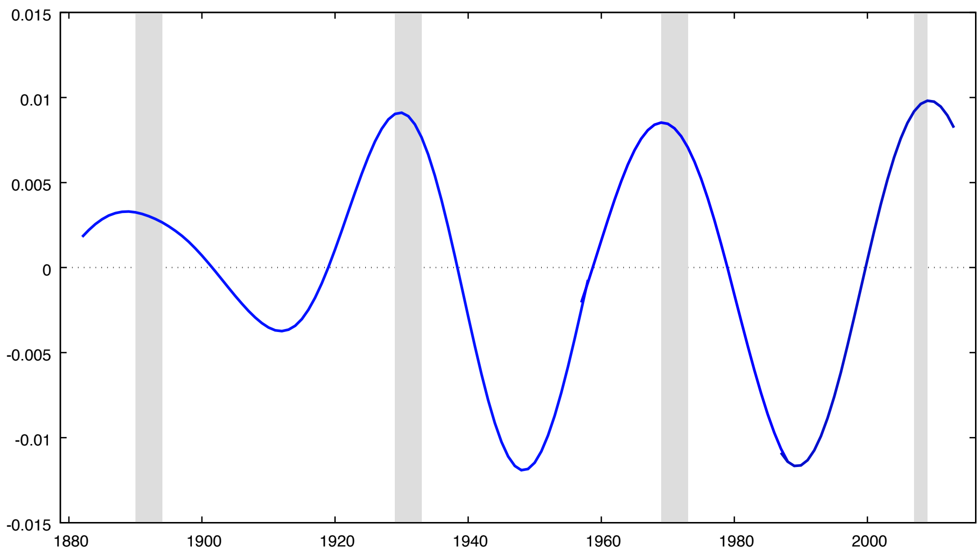

Figure 4: Global crisis index constructed by aggregating the long wave components of the CA/GDP ratio, the credit/GDP ratio and equity returns. Grey shaded area represents the most "significant global" crisis events according to Bordo (2005) and Jordá et al. (2013).

The highest values of the global crisis index include the two past systemic global financial crises and the worst large-scale international non-financial crisis episode.[29] Previous historical global crisis episodes culminated with the collapse of existing international monetary systems. The vigorous debate about the fundamental reforms needed in the international financial and monetary system, that started immediately thereafter the recent global financial turmoil (Uzor, 2009), can be interpreted as evidence that the 2008-9 global financial crisis represents a major turning point in the evolution of the international monetary

[29]The reasons why the Bretton Woods period was immune to financial crises is still a puzzling question in the literature (Taylor, 2012). From a policy perspective the design and regulation of the financial system, consisting of tight domestic financial regulation and external capital controls, is likely to have been a determinant factor in preserving financial stability.

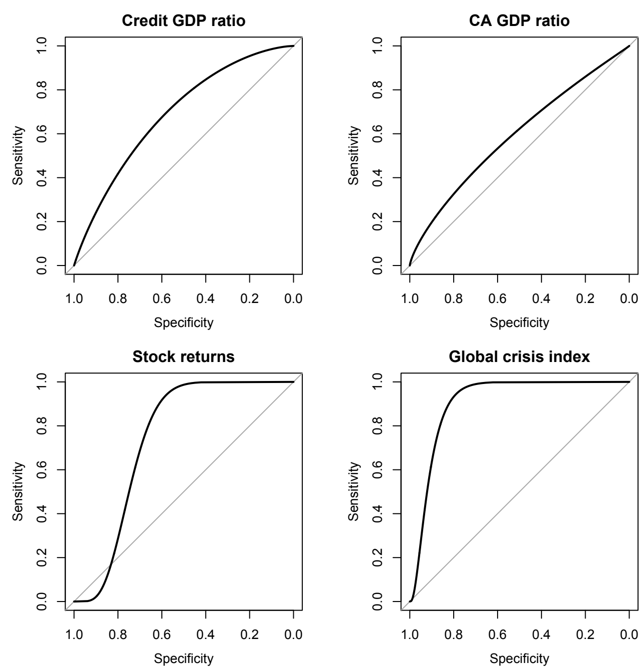

Figure 5: Receiver Operating Characteristic Curve.

and financial system. Our findings suggest that the way towards a stable and effective international monetary regime in a world of financial innovation and globalization, beyond addressing the weakness of the current financial regulatory framework, should also contrast the emergence of large and persistent global macro-imbalances over the medium and longer term.

6. Conclusions

After the recent global financial crisis a lot of attention has been devoted to analyze the dynamics of macroeconomic and financial variables in the run-up to a crisis from an historical perspective. Taking the long-run view of the macrofinancial history approach and using filtering techniques we find evidence of a regular sequential temporal pattern of the long cyclical components before global crisis periods, with global current account imbalances preceding credit booms and equity returns downturns at global level. When we use this information to construct a global crisis index with the aim of signaling periods of increasing risk of macroeconomic and financial instability at system level we are able to identify three major crisis episodes at international level: the 1929 crisis, the Bretton-Woods system collapse and the recent financial crisis. Since past historical global crisis episodes ended with the collapse of existing international monetary systems, the 2008-9 global financial crisis is likely to represent a major turning point in the evolution of the international monetary and financial system. Our findings suggest that the agenda for reforming the international monetary and financial system, in addition to coping with the weakness of the current financial regulatory framework, should focus on contrasting large and persistent global macro-imbalances over the medium and longer term.

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Appendix: A brief introduction to the wavelet transform

We begin this section by recalling the basic structure of the wavelet approach to modeling time series data. Wavelets are particular types of function $\psi(.)$ that are localized both in time and frequency domain and used to decompose a function $f(x)$, *i.e.* a surface, a series, etc.., in more elementary functions which include informations about the same $f(x)$. The essential characteristics of wavelets are best illustrated through the development of the continuous wavelet transform (CWT). At the simplest level, a "wavelet" is a function $\psi(.)$ such that:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{1}$$

$$\int_{-\infty}^{\infty} \psi(t)^2 dt = 1 \tag{2}$$

The cosine function is a "large wave" because its square does not converge to 1, even though its integral is zero; a wavelet, a "small wave" obeys both constraints. We see from these relationships that wavelets involve weighted differences, integral of $\psi(.)$ is zero; and has a normalized scale. The import of the latter is that for any $\varepsilon > 0$, there exists a finite T such that:

$$\int_{-T}^{T} \psi(t)^2 dt < 1 - \varepsilon \tag{3}$$

In short, the squared contribution to the variance is vanishingly small outside the range (-T, T). In addition, there is a requirement on the choice of wavelet function that is called the "admissibility condition" which ensures that the original function can be reconstructed from the wavelet decomposition (see Percival and Walden, 2000).[30]

[30]By means of the inverse transform, the original signal can be recovered by integrating over all scales λ and locations τ, respectively.

For any arbitrary mother wavelet function ψ, the continuous wavelet transform of the function $x(t)$ is given by:

$$W_x(\lambda, \tau) = \int_{-\infty}^{\infty} \psi_{\lambda,\tau}(t) x(t) dt \tag{4}$$

$$\tag{5}$$

where

$$\psi_{\lambda,\tau}(t) \equiv \frac{1}{\sqrt{\lambda}} \psi\left(\frac{t-\tau}{\lambda}\right).$$

$W_x(\lambda, \tau)$ represents a set of wavelet daughters obtained by scaling and translating the mother wavelet ψ with parameters λ and τ denoting the dilation (scale factor) and translation (time shift), respectively (see Percival and Walden, 2000).

Continuous wavelet transform (CWT) can provide us with the (local) wavelet power spectrum (sometimes called scalogram or wavelet periodogram) which displays, in time (space) and frequency (scale), the frequency content of signals as a function of time and discover thus the way the dynamics of the sequence evolve. Let $W_x(\lambda, t)$ be the continuous wavelet transform of a signal $x(.)$, with respect to the wavelet ψ, where λ is a scaling or dilation factor that controls the length of the wavelet and t a location parameter that indicates where the wavelet is centered. $|W_x|^2$ represents the wavelet power which depicts the local variance of $x(.)$. The wavelet power spectrum provides an unfolding of the characteristics of a process in the scale-space plane and can be quite revealing about the structure of a particular process, as it can clearly show the presence of multiscale features and can easily identify their temporal locations.

Although useful for revealing potentially interesting features in the data, like characteristic scales, the wavelet power spectrum is not necessarily the best tool to deal with the time-frequency dependencies between two time-series. Indeed, even if two countries share a similar high power region, one cannot infer that their business cycles look alike. To detect and quantify relationships between variables, cross-wavelet tools like wavelet coherency and wavelet phase-difference have to be used.

Wavelet tools suitable for the analysis of time-frequency dependencies between two time series are the cross-wavelet power, wavelet coherency and wavelet phase difference. Let W_x and W_y be the continuous wavelet transform of the signal $x(t)$ and $y(t)$, the cross-wavelet power of the two series is given by $|W_{xy}|$=$|W_x W_y|$ and depicts the local covariance of the two time series at each scale and frequency (see Hudgins *et al.*,1993, Torrence and Compo, 1998, Grinsted *et al.*, 2004). The wavelet coherence is defined as the modulus of the wavelet cross spectrum normalized by the wavelet spectra of each signal,

$$R_{xy}^2 = \frac{|S(\lambda^{-1} W_{xy})|^2}{S(\lambda^{-1}|W_x)|^2) S(\lambda^{-1}|W_y)|^2)}, \tag{6}$$

where S is a smoothing operator. The squared wavelet coherence coefficient R^2_{xy}, ranging between 0 and 1, can be considered a direct measure of the local correlation between two time series in time-frequency domain and is especially useful in highlighting the time and frequency intervals where two phenomena have strong interactions. The wavelet coherence is especially useful in highlighting the time and frequency intervals where two phenomena have strong interactions. It can be considered as the local correlation between the time series in time frequency space.

Finally, the phase difference can be useful to characterize the phase relationships between two time series as a function of frequency, *i.e.* phase synchronization of two time series. The wavelet coherence phase difference θ is the ratio between the imaginary and the real part of the wavelet coherence:

$$\theta_{xy} = arctan(\frac{\Im[S(\lambda^{-1}W_{xy})]}{\Re[S(\lambda^{-1}W_{xy})]}). \tag{7}$$

The phase of a given time-series $x(t)$ can be viewed as the position in the pseudo-cycle of the series and it is parameterized in radian ranging from $-\pi$ to π.

The CWT is a highly information redundant transform representing each datum by a pair of data, designating time, or space, and scale. As a consequence it it is computationally impossible to analyze a signal using all wavelet coefficients. In addition, as noted by Gencay *et al.* (2002), $W(\lambda;\tau)$ is a function of two parameters and as such it contains a high amount of redundant information. A one to one transformation is obtained by discretizing the transform over scale and over time. We therefore move to the discussion of the discrete wavelet transform (DWT), since the DWT, and in particular the MODWT, a variant of the DWT, is largely predominant in economic applications.[31]

The DWT is based on similar concepts as the CWT, but is more parsimonious in its use of data. In order to implement the discrete wavelet transform on sampled signals we need to discretize the transform over scale and over time through the dilation and location parameters. Indeed, the key difference between the CWT and the DWT lies in the fact that the DWT uses only a limited number of translated and dilated versions of the mother wavelet to decompose the original signal. The idea is to select τ and λ so that the information contained in the signal can be summarized in a minimum number of wavelet coefficients. The number of observations at each scale is given by $N/2^j$ $j = 1, 2, ...J$. The discretized transform is known as the discrete wavelet transform, DWT.

The discretization of the continuous time-frequency decomposition creates a discrete version of the wavelet power spectrum $W(\lambda,\tau)$ in which the entire time-

[31]The number of the papers applying the DWT is far greater than those using the CWT. As a matter of fact, the preference for DWT in economic applications can be explained by the ability of the DWT to facilitate a more direct comparison with standard econometric tools than is permitted by the CWT (e.g. time scales regression analysis, homogeneity test for variance, nonparametric analysis,).

frequency plane is partitioned with rectangular cells of varying dimensions but constant area, called Heisenberg cells.[32] Higher frequencies can be well localized in time, but the uncertainty in frequency localization increases as the frequency increases, which is reflected as taller, thinner cells with increase in frequency. Consequently, the frequency axis is partitioned finely only near low frequencies. The implication of this is that the larger-scale features of the signal get well resolved in the frequency domain, but there is a large uncertainty associated with their location. On the other hand, the small-scale features, such as sharp discontinuities, get well resolved in the time domain, even if there is a large uncertainty associated with their frequency content. This trade-off is an inherent limitation due to the Heisenberg‘s uncertainty principle that states that the resolution in time and frequency cannot be arbitrarily small because their product is lower bounded. Therefore, owing to the uncertainty principle, an increased resolution in the time domain for the time localization of high-frequency components comes at a cost of an increased uncertainty in the frequency localization, that is one can only trade time resolution for frequency resolution, or vice versa.

The general formulation for a continuous wavelet transform can be restricted to the definition of the "discrete wavelet transform", by discretizing the time-scale parameters λ and τ. In order to obtain an orthonormal basis a transform of the scaling parameter, $\lambda = \lambda_0^j$, and the Nyquist sampling rule, $\tau = k\lambda_0^j T$, are used. The generating wavelet functions are then

$$\psi_{j,k}(t) = \lambda_0^{-j/2}\psi\left(\frac{t - k\lambda_0^j T}{2^j}\right) \tag{8}$$

where j and k are integers. If T is small enough and the computation is done octave by octave, i.e. $\lambda_0 = 2$, the "mother wavelet"results in the following equation

$$\psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t - 2^j k}{2^j}\right) \tag{9}$$

This function represents a sequence of rescalable functions at a scale of s $= 2^j, j = 1, 2, ..., J$, and with time index k, $k = 1, 2, 3, ..., N/2^j$. The wavelet transform coefficient of the projection of the observed function, $f(t)$, $k = 1, 2, 3, ..., N, N = 2^J$ on the wavelet $\psi_{j,k}(t)$ is given by:

$$\begin{aligned} d_{j,k} &\approx \int \psi_{j,k}(t) f(t) dt, \\ j &= 1, 2, ..J \end{aligned} \tag{10}$$

For a complete reconstruction of a signal $f(t)$, one requires a scaling function, $\phi(.)$, that represents the smoothest components of the signal. While the wavelet

[32] Their dimensions change according to their scale: the windows stretch for large values of λ to measure the low frequency movements and compress for small values of λ to measure the high frequency movements.

coefficients represent weighted "differences" at each scale, the scaling coefficients represent averaging at each scale. The scaling function, also know as the "father wavelet", is defined by:

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right) \tag{11}$$

and the scaling function coefficient is given by:

$$s_{J,k} \approx \int \phi_{J,k}(t)f(t)dt, \tag{12}$$

The discrete wavelet transform DWT re-expresses a time series in terms of coefficients that are associated with a particular time and a particular dyadic scale. For the DWT, where the number of observations is $N = 2^J$, the number of coefficients at each dyadic scale is:

$$N = N/2^J + N/2^J + N/2^{J-1} + ... + N/4 + N/2 \tag{13}$$

that is, there are $N/2^J$ coefficients $s_{J,k}$, $N/2^J$ coefficients $d_{J,k}$, $N/2^{J-1}$ coefficients $d_{J-1,k}$... and $N/2$ coefficients $d_{1,k}$.

By construction, we have an orthonormal set of basis functions, whose detailed properties depend on the choices made for the functions, $\phi(.)$ and $\psi(.)$; see for example the references cited above as well as Daubechies (1992), Silverman (1998) and Strang and Nguyen (1996).[33]

At each scale, the entire real line is approximated by a sequence of "non-overlapping" wavelets. The deconstruction of the function $f(t)$ is therefore:[34]

$$\begin{aligned} x(t) \quad \approx \quad & \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + ... + \\ & \sum_k d_{j,k}\psi_{j,k}(t) + ... + \sum_k d_{1,k}\psi_{1,k}(t) \end{aligned} \tag{15}$$

The above equation is an example of the Discrete Wavelet Transform (DWT) based on an arbitrary wavelet function, $\phi(.)$.

[33] The orthonormal properties can be demonstrated by the equations:

$$\begin{aligned} \int \phi_{J,k}(t)\phi_{J,k^*}(t)dt &= \delta_{k,k^*} \\ \int \psi_{j,k}(t)\psi_{j^*,k^*}(t)dt &= \delta_{j,j^*}\delta_{k,k^*} \\ \int \psi_{j,k}(t)\phi_{J,k^*}(t)dt &= 0 \end{aligned} \tag{14}$$

where $\delta_{i,j}$is the Kronecker delta.

[34] The degree of relative error in many cases of economic variables is approximately on the order of 10^{-13}, so that one can reasonably claim that the wavelet decomposition in (10) is very good.

Further, the approximation can be re-written in terms of collections of coefficients at given scales as:

$$
\begin{aligned}
S_J &= \sum_k s_{J,k}\phi_{J,k}(t) \\
D_J &= \sum_k d_{J,k}\psi_{J,k}(t) \\
D_{J-1} &= \sum_k d_{J-1,k}\psi_{J-1,k}(t) \\
&\;\;\;\;\;\cdots\cdots \\
D_1 &= \sum_k d_{1,k}\psi_{1,k}(t)
\end{aligned}
\tag{16}
$$

Finally, in terms of coefficient crystals, the approximating equation can be restated as:

$$x(t) \approx S_J + D_J + D_{J-1} + ...D_2 + D_1 \tag{17}$$

where S_J contains the "smooth component" of the signal, and the $D_j, j = 1, 2, ..J$, the detail signal components at ever increasing levels of detail. Hence, S_J provides the large scale road map, while D_1 shows the pot holes. Since any term in (12) represents a component of the signal $x(t)$ with a different resolution, the previous equation indicates what is termed the multiresolution decomposition (MRD).

Finally, in this short introduction to wavelet analysis, we might mention the maximum overlap, or non-decimated wavelet transform, MODWT. This transform is a compromise between the CWT, with continuous variations in scale, and DWT where the power of the transform is highly localized. The MODWT is highly redundant, so that the transformations at each scale are not orthogonal; but the offsetting gain is that applying the transform leaves the phase invariant, a very useful property in analyzing transformations, and the transform is not restricted to limitations imposed by the dyadic expansion used by the DWT. Thus, the MODWT can be applied to data sets of length not divisible by 2^J and returns at each scale a number of coefficients equal to the length of the original series.