Causality Networks of Financial Assets

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Abstract: Through financial network analysis we ascertain the existence of important causal behavior among certain financial assets, as inferred by eight different causality methods. To our knowledge this is the first extensive comparative analysis of financial networks as produced by various causality methods. Additionally, some specific non-linear causalities are used for the first time in the financial network research. Our results contradict the Efficient Market Hypothesis and open new horizons for further investigation and possible arbitrage opportunities. Moreover, we find some evidence that two of the causality methods used, at least to some extent, could warn us about the financial crisis of 2007-2009. Furthermore, we test the similarity percentage of the eight causality methods and we find that the most similar pair of causality-induced networks is on average less than 50% similar throughout the time period examined, rendering thus the comparability and substitutability among those causality methods rather dubious. We also rank the assets in terms of overall out-strength centrality and we find that there is an underlying bonds regime almost monopolising in some cases the realm of causality. Finally, using the network visualization, we observe an established pattern (i.e., across all causalities) of oil's rising role as the financial network faces the Chinese stock market crash.

Keywords: Causality, Efficient Market Hypothesis, Network Theory, Bonds, Oil

1 Introduction

In the dawn of the 21st century, we faced a financial maelstrom that had such a global impact, rippling stock markets across countries like a cataclysmic domino. This so-called global financial crisis of 2007-2009 still echoes in traders, scientists as well as laymen' minds, shook the very foundations of traditional economics and forecasting methods; both of which not only failed to prevent, but also failed to predict the calamity to come. One possible explanation of such a failure could be the fact that traditional economics focus in the "isolated" analysis of individual financial assets, e.g. market indices, bonds, stocks and commodities. By isolated here we mean disconnected from their kindred, i.e., ignoring their interactions with other financial assets. Nonetheless, there are many reasons to defy the bias for dis-

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connection among assets. First of all, assets are more often than not traded in groups, or portfolios, containing at least a dozen of them which are subject to a common strategy. In fact, portfolios of assets are the norm against single asset trading. This common trading pattern suggests that the selling and buying orders of some bundles of assets are governed by the same person (or a small group of people), thus they are to some extent interrelated. Secondly, if we think of the assets' prices as financial embodiments of companies (equities, bonds), national governments (sovereign bonds) and essential market products (commodities), one cannot neglect the causal interactions among them. For example, an increase in oil prices can cause a decrease in airlines services demand, a disruptive innovation in telecoms industry can be patented and turn the tables in the market share of the competitors; not to mention that an increase in the rates of government bonds directly impacts the stock market investments. Last but definitely not least, the psychology of people involved in a specific (national) stock market may at least partly be affected by the fluctuations of stock markets in other countries, e.g. the news of a stock market crash can cause overwhelming sentiments of fear and panic beyond the national bounds, thus impacting the international big game. Reckoning up to that, the cases of large capitalization international funds that invest in many stock markets, and we have more than enough reasons to put under scrutiny the causality among financial assets.

Causality is the relationship between a variable (the cause), whose past performance influences the future output of another variable (the effect) (Pearl, 2003). Scientists from various disciplines have developed methods to quantify causality in time series, despite the fact that not all of them use the term "causality" exclusively. In this paper, we shall use a collection of eight causality methods. Statisticians, by evolving the notion of correlation, introduced the methods of linear intertemporal cross correlation (Hawawini, 1980) and nonlinear intertemporal cross correlation (Pijn et al, 1989) in their endeavor to quantify lead-lag relationships among time series. Econometricians driven by the need to quantify common integrated behavior in time series developed the methods of linear (Granger, 1981) and nonlinear cointegration (Granger and Hallman, 1991). Moreover, the known index of Granger causality, both in its linear (Granger, 1969) and nonlinear (Hiemstra and Jones, 1994) form, was established in the field of econometrics as well. Lastly physicists, mostly from the discipline of information theory, introduced the indices of shadow correlation (Granger and Lin, 1994) and transfer entropy (Schreiber, 2000) that quantify in a model-free way relationships between variables. We use the eight aforementioned methods in order to capture with each one of them the evolution of average causality in a financial network of assets, consisting of various national market indices, sovereign bonds and oil prices, in the period engulfing before, during and after the global financial crisis.

1.1 Motivation

Our motivation to delve into the realm of causality in financial assets is threefold. On the one hand, we feel committed to examine the possibility of causality being able to serve as an early warning signal of the systemic financial collapse. On the other hand, we are also interested to explore whether or not any arbitrage opportunities arise through for example persistent and strong causal relationships between assets. Lastly, we are intrigued to put under scrutiny the less explored and more vestal (as compared to correlations) discipline of causalities in financial networks.

Our choice of assets from various national markets and not from an individual stock market is not random. Given that we settled to study the evolution of causality throughout the global financial crisis we choose both indices and bonds from countries most representative of the turmoil that ensued. Specifically, we choose market indices from USA, China, Brazil, Germany, France, Japan, Hong Kong, Australia and India given that they are countries with large stock market capitalization. For government bonds, we choose those of USA, UK, Germany, Japan, Australia, Switzerland, Spain, Italy and Greece, because we consider those governments as the ones most involved or affected by the crisis. We also include oil prices in our analysis, a commodity strong enough to cause a crisis on its own, as in the case of the 1973 oil crisis. The period we choose for analysis (2000-2016) demands in itself data from various countries given that the extensive use of the web and social media has enabled the international transmission of stock market news and shocks faster than ever before. We believe that our study is an attempt to study a significant portion of the global financial system during a period involving extreme disorder, via the lenses of multidisciplinary causality methods.

1.2 Results

We study the evolutionary behavior of the average causality lying in our financial network. This analysis is conducted for each of the eight causality methods displayed in this paper. Our results ascertain the existence of significant causal behavior among assets throughout the time period examined. According to Hawawini (1980), Atkinson et al. (1987), Lo and Mackinlay (1990), Chowdhury (1991) and Fiedor (2014) the very existence of causality in financial assets challenges the foundations of the well-known Efficient Market Hypothesis (EMH). EMH has three forms: ”weak,” ”semi-strong,” and ”strong” form. The weak form of the EMH claims that asset prices already reflect all publicly available information. The semi-strong form of the EMH includes the weaks form’s characteristic and also claims that prices instantly change to reflect new public information. Finally, the strong form of the EMH additionally claims that prices instantly reflect even hidden ”insider” information. Our results evidently defy the EMH at least in its strong and maybe also in its semi-strong form given that causality has to do with assimilation of not only current but also past information. We consider for our analysis that the global crisis was born on the 9th of August in 2007 as this is the most widespread view based on Google search. More specifically, results from linear intertemporal cross correlation do not imply any predictive capabilities, given that the average causality as measured by it, begins to drop in parallel with the development of the global financial crisis and not before. However, average causality as measured by nonlinear intertemporal cross correlation, could be a candidate for early warning signal given that almost half a year before the crash (on the eve of 2007) it started dropping to all-time lows, and then immediately during the unfolding of the crisis it started rising more steeply than ever before. Linear cointegration analysis does not produce any different causality behavior before or during the global crisis. Its nonlinear counterpart exhibits a marked plunge just three months before the global crisis and then again rises steeply to higher levels. Both linear and nonlinear Granger causality displayed no change in their average causality before or during the global crisis. Despite the fact that shadow causality (based off shadow correlation) displays no forecasting capabilities, it somehow fits quite characteristically on the crisis period by displaying a dramatic drop right after the crisis birth, after a protracted upward trend. Similarly, hidden causality (based off transfer entropy) simply changes its trend from horizontally-fluctuating to slightly downward after the crisis emergence. Apart from the exceptions of nonlinear intertemporal cross correlation and nonlinear cointegration, the rest methods simply follow up the emergence of financial turbulence, serving at best as contemporaneous crisis indicators and not as early warning signals. However, these results can by no means suggest that the remaining six causality methods are incapable of serving as early warning signals, only that they need to be put to further scrutiny.

In order to assess whether or not any comparative analysis among the eight causality methods is meaningful, we test the similarity percentage of common links that remain in the financial network (after filtering for the optimal links in terms of maximum spanning tree) and find that the most similar pair of causality-induced network is that of linear intertemporal cross correlation and linear cointegration methods scoring 48.74% average similarity throughout the time period examined. Thus, we consider it meaningless to try to compare results among different causality methods, at least through our choice of filtering (maximum spanning tree).

In order to gain portfolio-specific insights we delve to network analysis, and specifically link persistence and asset centrality. To that end we rank the causal links as produced by each causality method and we find that the most intense and protracted relationship across all causality methods is that of 10Y-USA-bond causing the prices of ($\rightarrow$) 2to3Y-Spanish-bond. The latter relationship can be considered as strong candidate for arbitrage opportunities. Last but not least, we rank all (25 in total) of the financial assets under study in terms of averaged causality emanation to the network by means of out-strength centrality, and we find that the most causal asset overall seems to be the USA 10 year-bond. Nevertheless, sovereign bonds ranked in general better than equities and oil especially in the case of linear cointegration and hidden causality, unveiling a hidden regime of bonds. This result could not be better described than in the words of James Carville, President Clinton's political adviser (2012, Arnold) who said: *"I used to think that if there was reincarnation, I wanted to come back as the president or the pope. But now I would like to come back as the bonds market. You can intimidate everybody."*.

In Section 2, we present the formulae, literature review and significance to finance for each of the eight causality methods. In Section 3, we provide details regarding the choice of our dataset. In Section 4, we present our research questions and results and in Section 5, we give our concluding remarks.

2 Causality Methodologies

In our study, causality between financial assets is the quantification of the impact that an asset's past price performance have on another asset's future price parformance. Embedded in the nature of causality is some form of predictive potential, i.e., if we know the causality (quantified) between two assets, then given the price of the cause-asset we can, to some extent and probabilistically speaking, forecast the effect-assets price.

2.1 Linear Intertemporal Cross Correlation

The existence of linear intertemporal cross correlation ($LICC$) implies that asset prices change in a lead-lag manner and not simultaneously (Atchinson et al. 1987). $LICC$ is also known as lead-lag cross correlation or time-delayed cross correlation or time-dependent cross correlation. Hawawini (1980) was the first researcher who implemented it in the finance literature, and below we present the formula:

$$LICC^{xy}_{\Delta t} = \frac{\langle R^x_{\Delta t}(t) R^y_{\Delta t}(t+\tau)\rangle - \langle R^x_{\Delta t}(t)\rangle\langle R^y_{\Delta t}(t+\tau)\rangle}{\sqrt{\langle [R^x_{\Delta t}(t) - \langle R^x_{\Delta t}(t)\rangle]^2\rangle\langle [R^y_{\Delta t}(t+\tau) - \langle R^y_{\Delta t}(t+\tau)\rangle]^2\rangle}}, \tag{1}$$

where $R^x_{\Delta t}(t) = \log[p(t)] - \log[p(t-\Delta t)]$ is the log return of the price, $p(t)$, of an asset at a certain time t. Δt denotes time interval of the log returns, usually, it equals 1-time unit. τ denotes the intertemporal delay among the two assets, and $\langle R^x_{\Delta t}(t)\rangle$ denotes the mean of $R^x_{\Delta t}(t)$, and x and y denote asset x and asset y.

Remark 1. When $\tau = 0$, the LICC coincides with Pearson product moment correlation coefficient. $R^{x}_{\Delta t}(t)$ takes values from -1 to $+1$. When $R^{xy}_{\Delta t}(t) < 0$, this means that asset x has a reverse effect on asset y, i.e., if yesterday's return on asset x increases then today's return on asset y shall decrease, and vice versa. When $R^{xy}_{\Delta t}(t) > 0$, this means that asset x has a same-direction effect on asset y, i.e., if yesterday's return on asset x increases then today's return on asset y shall also increase. If $R^{xy}_{\Delta t}(t) = 0$, this means that asset x has no effect on asset y.

In the finance literature, there are three dominant hypotheses that try to explain the raison d'être of lead-lag relationships among assets. These hypotheses are: 1) Nonsynchronous Trading, 2) Speed of Price Adjustment Hypothesis, and 3) Stock Market Overreaction hypothesis (Lo and Mackinlay 1990). Following the hypotheses behind the existence of lead-lag effects, we found some implications regarding the realization of lead-lag effects and their significance in terms of the well-known financial theory of the EMH. More specifically, the existence of intertemporal cross correlations among asset returns implies deviation from the EMH, and thus, provides a probabilistic glimpse at the future of asset prices (Atkinson et al. 1987; Lo and Mackinlay, 1990; Hawawini, 1980).

Kullmann et al. (2002) employed the LICC index to analyze a network of equities from NYSE. They suggested that the existence of such causal relations is due to the functional interactions between the companies that are represented from the equities in their dataset. Mizuno et al. (2004) examined LICC in data of foreign exchange rates and pinpointed arbitrage opportunities for the Japanese Yen through buying it in one market and selling it in another. Eom et al. (2008) analyzed asset prices from Korea, Japan, Taiwan, Canada and USA and found statistically significant interactions among them. Wang et al. (2011) analyzed the network of 48 stock market indices and concluded that news regarding stock market crashes travel beyond national boundaries impacting stock markets around the world in a domino fashion. Huth and Abergel (2014) found important lead-lag relationships in USA high frequency time series. Curme et al. (2015) analyzed time series of 100 NYSE equities and located non-negligible intertemporal cross correlations suggesting possible arbitrage opportunities.

The advantage of LICC is the fact that it captures the direction of influence among asset returns contrary to Pearson product moment correlation coefficient which captures just naive correlations. However, LICC bears one disadvantage that cannot be ignored, namely it takes into account only linear causal relationships. LICC cannot capture nonlinear causal relationships. To that end we present the nonlinear intertemporal cross correlation, described in the next section.

2.2 Nonlinear Intertemporal Cross Correlation

The inability of $LICC$ to capture nonlinear intertemporal relations can be surpassed by employing the nonlinear intertemporal cross correlation. $NICC$ is a statistical measure developed by Pijn et al. (1989) which quantifies nonlinear as well as linear causality from a time series x to a time series y. They developed $NICC$ (also known as correlation ratio eta) out of need to capture nonlinear time delayed relationships in brain neuron signals. We consider the application of $NICC$ in financial time series, since we are interested in capturing the nonlinear intertemporal relationships among assets. According to Pijn et al. (1989), $NICC^{xy}_{\Delta t}$ describes the contraction in uncertainty of $R^{y}_{\Delta t}(t+\tau)$ that can be achieved by forecasting the $R^{y}_{\Delta t}(t+\tau)$ values from those of $R^{x}_{\Delta t}(t)$ via regression as

$NICC_{\Delta t}^{xy} = (totalvariance - unexplainedvariance)/totalvariance$:

$$NICC_{\Delta t}^{xy} = \frac{\sum_{t=1}^{T} R_{\Delta t}^{y}(t+\tau)^2 - \sum_{t=1}^{T}(R_{\Delta t}^{y}(t+\tau) - f(R_{\Delta t}^{x}(t)))^2}{\sum_{t=1}^{T} R_{\Delta t}^{y}(t+\tau)^2}, \tag{2}$$

where $f(R_{\Delta t}^{x}(t))$ is the linear piecewise approximation of the nonlinear regression curve.
Remark 2. Pijn et al. (1989) commented that contrary to Pearson product moment correlation coefficient, which is always symmetric, (i.e., it is the same for the relationship x, y as for y, x, the $NICC$ more often than not is asymmetric $NICC_{\Delta t}^{xy} \neq NICC_{\Delta t}^{yx}$. Interestingly enough, when the relationship f is linear, then $NICC$ verges on the $LICC$. Worthy to note is also the fact that, the larger the asymmetry in the values of $NICC$ from x to y and vice versa, the more nonlinear the relationship f is. NICC values move strictly between 0 and 1. $NICC_{\Delta t}^{xy}$ is 0 when y is independent of x and 1 when y is completely determined by x (Pijn et al. 1989).

To the best of our knowedge, $NICC$ has never been used before in the field of finance. It has only been employed in the field of brain signal analysis, in order to mine for nonlinear dependencies among neurons, see Pijn et al. (1989), da Silva et al. (1989), Pijn et al. (1990) and Wendling et al. (2001). Thus, $NICC$ is employed for the first time in our paper for the purpose of identifying nonlinear causal relationships among asset returns. Nonlinearities have been important in finance literature, since many phenomena and relations in finance are nonlinear. Frank and Stengos (1989) after conducting econometric analysis in the returns of gold and silver, they found proof that their time series are governed by nonlinear mechanisms rather than linear. Hsieh (1989) analyzed day-by-day variations in major foreign exchange rates through linear correlation and found no significant results. However, after employing econometric $GARCH$ analysis he claimed to identify that nonlinear dependencies saturate the exchange rates under study. Scheinkman and LeBaron (1989) tested dependencies in weekly returns of assets only to realize that no random walk rests in their time series, rather nonlinear functions help explain better those dependencies and also predict future from past prices. Abhyankar et al. (1997) examined real time returns of $S\&P$ 500, DAX, $Nikkei$ 225, and $FTSE$ 100. They found evidence of strong nonlinearities among those major indices.

NICC reveals nonlinearities in the dependencies of asset returns that $LICC$ is unable to reveal. This fact renders $NICC$ superior to $LICC$ in terms of causal relationships detection. However, $NICC$, taking values from 0 to 1, provides no information regarding the sign of causality (positive or negative causality). This means that, $NICC$ cannot tell whether two assets have reverse or same-direction causality, contrary to $LICC$ which may not capture nonlinearities but does capture the sign of the causality among asset returns.

2.3 Linear Cointegration

Lead-lag relationships as examined by $LICC$ and $NICC$ are one form of causalities among assets. Another form of causal relationships is that of assets that move in an integrated way, i.e. they evolve dynamically together and this common evolution can be described by a common function. Firstly, we shall present the case of assets cointegrated in a linear way. Linear cointegration (LCo) is an econometric tool firstly introduced by Granger (1981), and subsequently established by Granger and Weiss (2001), and Engle and Granger (1987). Admittedly, two series can be considered as cointegrated when a linear combination of the two is stationary, while none of those time series is individually stationary (Hakkio and Rush 1989). Following Engle and Granger (1987), we provide the LCo method: We must examine whether or not the two series are integrated of the same order. There are various substitute methods to test the integration order of time series: The Dickey-Fuller (DF) (Dickey and

Fuller, 1979) and the Augmented Dickey-Fuller test (ADF) (Dickey and Fuller, 1981), a generalization of the ADF (Phillips and Perron, 1988) and the Kwiatkoswski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkoswski et al., 1992). Given that two series x_t and y_t are integrated of the same order then in order to be cointegrated there must exist a function z_t such as:

$$z_t \in I(0) : z_t = y_t - \beta * x_t. \tag{3}$$

For our analysis we shall use the ADF test (Hamilton, 1994). For further technical details, the reader is referred to Engle and Granger (1987). In order to quantify the causal links produced by *LCo* analysis in our dataset, we follow and expand the technique of Yang et al. (2014), and assign to every causal relationship of assets the β coefficient from the cointegrating regression and normalize it simply by dividing with the max β coefficient among all asset pairs.

Remark 3. Thus, linear normalized cointegration link values can range from -1 to 1. When $LCo^{xy}_{\Delta t} < 0$, this means that asset x is negatively cointegrated with asset y, i.e., if yesterday's price of asset x increases, then today's price of asset y shall decrease, and vice versa. When, $LCo^{xy}_{\Delta t} > 0$, this means that asset x positively cointegrated with asset y, i.e., if yesterday's price of asset x increases then today's price of asset y shall also increase. If $LCo^{xy}_{\Delta t} = 0$, this means that asset x an asset y are not cointegrated in any way.

In the finance literature, we found that the concept of cointegration (similarly to intertemporal cross correlation) is linked to the Efficient Market Hypothesis. According to Chowdhury (1991), given that market efficiency ordains that the current asset price dynamically and immediately absorbs and reflects all available information and, given past prices, no other information should increase the predictability of assets' prices, then a cointegration between two financial assets implies inefficiency. Cerchi and Havenner (1988) employed *LCo* analysis in a dataset consisting of five randomly chosen industrial stocks. What they found was that despite the individual stock time series could at best be described as random walks, when cointegration enters into play they appear to move in a distinct common trend. Hall et al. (1992) analyzed yields to maturity of USA Treasury bills and found strong evidence that they move in tandem with each other dynamically through time. Liu et al. (1997) put under scrutiny the chaotic behavior of the market indices of Shanghai and Shenzen. Their analysis shed light to an underlying mechanism between the two indices, as they seemed to evolve in a cointegrating manner. Alexander (2001) after conducting robust analysis in commodities, she claimed that related commodity types offer some windows of opportunity, given their strong cointegration. Siliverstovs et al. (2005) investigated a dataset consisting of natural gas markets in Europe, North America and Japan in the time period between the early 1990s and 2004. They found a high level of natural gas market cointegration within Europe, between the European and Japanese markets as well as within the North American market. Yang et al. (2014) investigated 26 stock market indices and found that their cointegration relationship increased after the Lehman Brothers collapse, while the degree of cointegration gradually decreased from the sub-prime to European debt crisis.

LCo is useful enough when we are seeking causality in a sense of assets moving in a linearly integrated manner with an emphasis on longer temporal horizon than *LICC*. However, *LCo* is unable to identify nonlinear cointegrating relationships. This is where its nonlinear counterpart enters into play, as described in the next section.

2.4 Nonlinear Cointegration

Nonlinear cointegration (*NCo*) is the expansion of the well-established linear cointegration (*LCo*) which is capable of capturing nonlinear integrated dependencies from one asset to another. *NCo* was firstly introduced by Granger and Hallman (1991), and further developed by Balke and Fomby (1997), Escribano and Mira (2002) and Escanciano and Escribano (2011). According to Escanciano and Escribano (2011), two extended memory series y_t and x_t are nonlinearly cointegrated if there exists a function f such that:

$$z_t = f(y_t, x_t) \text{ is short in memory.} \tag{4}$$

Crashes in extended memory time series have persisting and intense impact; while in short memory ones, crashes are absorbed and vanish after a short time (Escanciano and Escribano, 2011). Memory in time series, and its characterization as short or extended, can be measured via various means. In our analysis, we use the conditional mean persistence method from the aforementioned paper. A time series x_t is considered to be of short memory in mean if for all t, $M(t, h) = E(y_{t+h}|I_t), h > 0$, tends to a constant μ as h becomes large (for more details see Escanciano and Escribano, 2011). Given that we found no method of quantifying the nonlinear cointegration among two variables in the literature, we devise our own method which is described below.

We propose to assign as the weight of a nonlinear cointegration from asset x to asset y, the weighted average of the coefficients in function f from Eq. (4). We allow in our algorithm to search for candidate functions f up to 10^{th} degree polynomials, thus the higher the terms power the greater the weight assigned to it. For each cointegrating relationship after summing those ten coefficients, we divide with the max of the coefficient averages among all asset pairs, in order to claim a normalized quantity for NCo. Thus, nonlinear cointegration link values (as normalized by us) can range from -1 to 1. When $NCo^{xy} < 0$, this means that asset x is negatively cointegrated with asset y. When $NCo^{xy} > 0$, this means that asset x positively cointegrated with asset y. If $NCo_t^{xy} = 0$, this means that asset x and asset y are not cointegrated in any way.

Li (2002) analyzed the stock market indices of Australia, Japan, New Zealand, UK and USA in terms of both LCo and NCo. His results indicated that nonlinear cointegration relationships among those indices are much stronger and persisting as compared to the linear ones. Ma and Kanas (2004) found strong further empirical evidence to support the intrinsic bubble model of stock prices, developed by Froot and Obstfeld (1991). Athanasenas et al. (2014) conducted analysis between the time series of revenues and expenditures of the Greek government. Their results support the fact that negative rates of expenditures severely impact revenues. Apergis and Payne (2014) analyzed asset returns from the stock markets of the $G7$. They found long-lasting nonlinear dependencies in a significant portion of their dataset.

2.5 Linear Granger Causality

Granger causality is a statistical concept of causality that is based on regression. It has been widely used in the financial econometrics literature to detect causal relationships among assets and other economic variables. According to Granger causality, if a time series x_t "Granger-causes" (or "G-causes") a time series y_t, then past values of x_t should contain predictive information that serves to forecast y_t better than the information contained in past values of y_t alone. The so-called predictive information is modelled through regression, (linear for LGC and nonlinear for NGC in section 2.6) Granger, (1969). Following Granger (1969), given x_t and y_t are stationary, if we consider a linear autoregressive (AR) model of time series y_t:

$$y_t = \sum_{i=1}^{N} a_{11,i} y_{t-i} + \sum_{i=1}^{N} a_{12,i} x_{t-i} + E_t(y), \tag{5}$$

where N is the number of past observations included in the AR-model, $a_{11,i}$ and $a_{12,i}$ are the coefficients of the model, $E_t(y)$ is the residual, also known as prediction errors, for y_t. We can say that $x\ G - causes\ y$ if and only if the coefficients $a_{12,i}$ are significantly different from zero. To test the underlying significance, we employ the F-test with the null hypothesis that $a_{12,i} = 0$. In the literature we found no method of quantifying the weight of a G-causal link from an asset x to an asset y.

So given that asset x Granger causes y we decide to assign as weight of the link the value: $LGC_{xy} = 1 - Pvalue$ of the F-test. Values range from 0 to 1 denoting the intensity of the causality.

Bradshaw and Orden (1990) uncovered important LGC from the exchange rate to export sales, while the evidence on causality from the exchange rate to prices is unclear. Rahman et al. (1997) analyzed USA equities and bonds. Their results attested that the causality emanating from bonds to equities is much more robust than vice versa. Abhyankar (1998) investigated causal relationships between the futures contracts and cash markets. According to his results, futures contracts hold predictive information for the future states of cash market. Dutta (2001) found that causality from levels of telecommunications infrastructure to economic activity is stronger than that for causality in the opposite direction. Foresti (2006) put under scrutiny the possibility of causal relationships between economic growth and stock market returns, concluding that stock market drives the economic growth. Wang et al. (2007) tested for possible linkages among Euro currency, USA, Japanese and German interest rates. Their results indicated that Japanese interest rates exert intense causality overall, and that the German interest rates have a bidirectional causal relationship with a variety of Euro currency rates. Zhang and Wei, 2010, uncovered that crude oil prices have a statistically significant causal relationship to the prices of gold, but the opposite was not supported. Billio et al. (2012) analyzed time series data of hedge funds, banks, broker/dealers, and insurance companies. Their findings support the fact that banks exert the most causality to all the other time series they analyzed. Výrost et al. (2015) uncovered an underlying mechanism of a preferential attachment between stock markets, i.e., the probability of the presence of spillover effects between any given two markets increases with their degree of connectedness to others. Fiedor (2015) analyzed the relationships of companies listed in S&P 100 and found that causal relationships are more prevalent than lagged synchronization relationships.

One drawback of LGC is that it does not provide any information regarding whether the assets under study have positive or negative causality. Another drawback is its inability to capture nonlinearities. The latter drawback is treated with its nonlinear counterpart which is presented below.

2.6 Nonlinear Granger Causality

Nonlinear Granger Causality (NGC) is capable of mining the nonlinear predictive information that a time series can hold for another time series, a feat that LGC fails to accomplish. NGC was firstly introduced by Hiemstra and Jones (1994) and further established by Péguin-Feissolle et al. (2013). Following the definition of Péguin-Feissolle et al. (2013), let y_t and x_t be two stationary and ergodic time series. In order to test the existence of a causal relationship between two series, we denote:

$$y_t = f_y(y_{t-1}, , y_{t-p_1}, x_{t-1}, , x_{t-q_1}; {}_1) + e_{1,t}. \tag{6}$$

Eq. (6) includes all combinations between past values of y and x. We can say that x nonlinearly G-causes y if and only if the coefficients on the terms of x's past values are significantly different from zero. To test the underlying significance, we can use the Wald F-test (for more technical details regarding the methodology of NGC see Pguin-Feissolle et al., 2013). In the literature we found no method of quantifying the weight of a nonlinear G-causal link from an asset x to an asset y. So given that asset x nonlinearly Granger causes y we decided to assign as weight of the link the value: $NGC_{xy} = 1 - P\ value$ of the Wald F-test. Values range from 0 to 1 denoting the intensity of the causality.

Hiemstra and Jones (1994) having used NGC between the equity returns of Dow Jones stocks, and the volume rate of $NYSE$, found statistically important causality in both ways. Qiao et al. (2011) sought for causalities in East Asia stock markets. Despite the fact that LGC tests failed to detect statistically significant dependencies, its nonlinear kindred-NGC captured many causalities. Benhmad (2012) similarly, analyzed oil prices and USA Dollar exchange rate. He found supporting evidence of oil influencing the dollar rate slightly more than vice versa. Zhou et al. (2014) examined a dataset Chinese stock futures and spot markets. The authors claim to have found robust results in favor of futures influencing spot markets. Chu et al. (2015) conducted a research between equity returns and investor sentiment in China. Surprisingly enough, they found that both types of time series influence each other in a nonlinear way.

In the last two sections of causality tools we shall deviate from the disciplines of statistics and econometrics and summon methodologies from information theory.

2.7 Shadow Causality

The previously described causality methods suffer from several important weaknesses. Either they depend to requirements of stationarity ($LICC, NICC, LCo, NCo, LGC, NGC$) or they are unable to capture nonlinearities ($LICC, LCo, LGC$) or they cannot distinguish between positive (homogeneous) and negative (heterogeneous) causality ($NICC, LGC, NGC$). This is where tools from information theory come into play, namely: shadow causality (SC) which is based on mutual information and hidden causality (HC) which is based on transfer entropy. These information theoretic methods are nonparametric, have no requirements of stationary time series to be applied to, capture both linear and nonlinear causality, and with a minor modification we were able to make them distinguish between positive and negative causality. Following Granger and Lin (1994), shadow correlation and inspired by Schreiber (2000), who suggested that one can use a lead-lag in mutual information to imbue directionality in our calculations, we provide the shadow causality formula:

$$SC_{x_{t-\Delta t},y_t} = sgn * \sqrt{1 - e^{-2I(x_{t-\Delta t},y_t)}}, \tag{7}$$

where $I(x_{t-\Delta t}, y_t) = \int\int p_{x,y}(x_{t-\Delta t}, y_t) * \log \frac{p_{x,y}(x_{t-\Delta t},y_t)}{p_x(x_{t-\Delta t})*p_y(y_t)} dx\ dy$ is the mutual information (MI). $p(x, y)$ denotes the joint probability distribution function of time series x_t and y_t. $p(x)$ and $p(y)$ denote the marginal probability distribution functions of x_t and y_t, respectively. The function $SC_{x_{t-\Delta t},y_t}$ captures the overall linear and nonlinear causality from x to y. If causality is homogeneous, then $sgn = +1$ (homogeneous causality takes place when an increase in x causes increase in y more often than decrease in y while at the same time decrease in x causes decrease in y more often than increase in y). If causality is heterogeneous, then $sgn = -1$ (heterogeneous causality takes place when increase in x causes decrease in y more often than increase in y while at the same time decrease in x causes increase in y more often than decrease in y). SC values range from -1 to 1 denoting the intensity and type (negative values denote heterogeneous relationship and positive values denote homogeneous relationship) of the causality.

Dionisio et al. (2007) created a bundle of economic and financial indicators from Portugal and tested for possible dependencies among them via MI analysis. Their analysis showed that there are strong causalities from dividend yield and earnings price ratio time series to the monthly excess returns of investors. Maasoumi and Wang (2008) tested for dependencies in economic growth time series among various municipalities in China. They found significant formations of clubs among municipalities, manifesting before and after reformation periods. Menezes et al. (2012) analyzed equity time series, representative of the $G7$ countries. Comparing their results with other methods like that of LGC they claim that MI provided more information regarding the underlying causalities in the stocks of their dataset. Fiedor (2014) investigated nonlinear relationships of companies listed in the $NYSE$. He found that mutual information rate produces different results than simple correlation. In the next section, we present the last causality tool to conclude our methodology section.

2.8 Hidden Causality

Mutual information which is the basis of shadow causality, needs the time lag to account for directionality and thus causality. Therefore, one can argue that it is not a natural tool of causality inference (much like $LICC$ and $NICC$) rather a manufactured one. Transfer entropy (TE) on the other hand, which is the basis of HC, is a natural tool of causality inference. TE is one of the youngest members of the causality family as it was recently introduced by Schreiber (2000). It exploits past values of time series x_t and y_t to test their predictive power for the future value of y_{t+1}. In a similar fashion to the notion of SC, we introduce at this point the HC method which instead of MI uses the stricter TE (Screiber, 2000). Thus, HC is the normalized version of TE, and for its normalization technique we used the method by Junior (2013). Our contribution lies only in the part of mining the sign of positive or negative in a similar manner as we did in SC. The HC formula:

$$HC_{x_t \to y_t} = sgn * \frac{\sum p(y_{t+1}, y_t, x_t) \log \frac{p(y_{t+1} y_t x_t)}{(p(y_{t+1} y_t)}}{\sum p(y_t, x_t) \log_2 \frac{p(y_t, x_t)}{p(x_t)}}, \tag{8}$$

where $\sum p(y_{t+1}, y_t, x_t) \log \frac{p(y_{t+1} y_t x_t)}{p(y_{t+1} y_t)} = TE_{x_t \to y_t}$, which is the TE of x to y and $\sum p(y_{t+1}, y_t)$ $\log_2 \frac{p(y_{t+1}, y_t)}{p(y_t)} = H_{y^F|y^P}$, which is the conditional entropy of the future of y on its past. For more technical details; see the papers of Schreiber (2000) and Junior (2013). If causality is homogeneous, then $sgn = +1$ (homogeneous causality takes place when an increase in x causes increase in y more often than decrease in y while at the same time decrease in x causes decrease in y more often than increase in y). If causality is heterogeneous, then $sgn = -1$ (heterogeneous causality takes place when increase in x causes decrease in y more often than increase in y while at the same time decrease in x causes increase in y more often than decrease in y). HC values range from -1 to 1 denoting the intensity and type (negative values denote heterogeneous relationship and positive values denote homogeneous relationship) of the causality.

Baek et al. (2005) analyzed via TE a dataset consisting of equities from various industrial sectors, and they found that energy related equities such as oil, gas and electricity saturate the whole market. Kwon and Yang (2008) mined for causal relationships in international stock market indices, uncovered that $S\&P$ 500 emanates the most causality to all the other indices. Kim et al. (2013) examined stock market indices from the majority of the $G20$. Their results stand in favor of the theory that western countries exert stronger causality in eastern countries than vice versa. Sandoval (2014) put under scrutiny the companies that are included in $S\&P$ 100. Their results indicate that TE produces a network that creates much more realistic (in terms of industrial affinity) clusters than $LICC$. Junior (2015) analysed the pairs of 83 stock market indices of various countries and found that TE is an effective way to quantify the information flow between indices. Yook et al. (2016) studied a financial network, and they found that the modular structure from $LICC$ cannot correctly reflect the known industrial classification and their hierarchy opposite to the transfer entropy method which fits much better on the market segmentation.

Table 1 briefly summarizes all the causality methods described in Section 2 and some of their basic properties.

Table 1: Causality Methods Trivia

Causality Method	Type of causality identification	Values range	Need time series to be stationary
Linear Intertemporal Cross Correlation	Linear	$[-1,1]$	Yes
Nonlinear Intertemporal Cross Correlation	Linear and Nonlinear	$[0,1]$	Yes
Linear Cointegration	Linear	$[-1,1]$	Yes
Nonlinear Cointegration	Nonlinear	$[-1,1]$	Yes
Linear Granger Causality	Linear	$[0,1]$	Yes
Nonlinear Granger Causality	Nonlinear	$[0,1]$	Yes
Shadow Causality	Linear and Nonlinear	$[-1,1]$	No
Hidden Causality	Linear and Nonlinear	$[-1,1]$	No

3 Data and Filtering

For our analysis, we use weekly data for stock market indices, sovereign bonds and oil from the Thomson Reuters DataStream for the period of 4th January 2000 to 12th February 2016. By using weekly data we negate the Time Zone effects due to the different operating hours of the stock exchanges in different countries. The idea is to have a broad and global selection of financial assets, and to understand their interactions over time by means of causality analysis. Thus, our dataset consists of 10 stock market indices, namely: $SHANGHAI$, $BOVESPA(BSE)$, $DOW\ JONES$, $S\&P$ 500, DAX 30, $HANGSENG$, CAC 40, $NIKKEI$ 225, ASX 200 and $BOMBAY\ STOCK\ EXCHANGE$; 14 bonds, namely: 2$Y\ USA\ bond$, 10$Y\ USA\ bond$, 10$Y\ UK\ bond$, 2$Y\ German\ bond$, 10$Y\ German\ bond$, 2$Y\ Japanese\ bond$, 10$Y\ Japanese\ bond$, 2$Y\ Australian\ bond$, 10$Y\ Australian\ bond$, 10$Y\ Swiss\ bond$, 2to3$Y\ Spanish\ bond$, 10$Y\ Greek\ bond$, 3$Y\ Italian\ bond$ and 10$Y\ Italian\ bond$; and Oil (see also **Table 2**). We use a rolling window of two years to construct the evolutionary financial network, which evolves week by week from 4th January 2000 until 12th February 2016 (total of 738 weeks of network evolution) for each of the eight causality tools presented in Section 2. The time lag used for our analysis is one week, and the statistical significance to keep a causal link is 95%. In order to negate nonstationarity we take the logreturns of the time series and again test with ADF for nonstationarity. No time series in our dataset are found to be nonstationary after logreturns apply. After constructing 25×25 matrices for each of the 738 weeks and each of the eight causality methods, we apply the filtering method of maximum spanning tree in each matrix (Hu, 1961). That way, we are able to apply the strongest known filtering and keep only the most powerful causal relations. Nevertheless, it is quite common to see other filtering methods being applied in financial networks, such as the minimum spanning tree (mse), which has been thoroughly employed in the works of Rosario Mantegna, who was the first to introduce it in finance (Mantegna, 1999a and 1999b). Minimum spanning tree was also effectively used by Di Matteo et al., (2010), Aste and Di Matteo (2006) who also added their own flavor to filtering. Other filtering methods are that of random matrix theory used by Iori et al. (2007) and Bonferroni statistical filtering which was well-displayed by Iori, Mantegna and collaborators in Iori et al. (2015). Last, but definitely not least, we would like to mention the filtering method of planar maximally filtered graph, which has been applied in the works of Di Matteo et al., (2010), Kenett et al. (2010), Birch et al. (2015) and Musmeci et al (2015, 2016 a, 2016 b).

Table 2: Dataset details and asset numbering for Figures 9 to 16.

No	Asset	Details
1	SHANGHAI	A stock market index of all stocks (A shares and B shares) that are traded at the Shanghai Stock Exchange.
2	BOVESPA	An index of about 50 stocks that are traded on the Sao Paulo Stock, Mercantile and Futures Exchange.
3	DOW JONES	A stock market index, and one of several indices created by Wall Street Journal editor and Dow Jones & Company co-founder Charles Dow.
4	S&P 500	An American stock market index based on the market capitalizations of 500 large companies having common stock listed on the NYSE or NASDAQ.
5	DAX 30	A blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange.
6	HANGSENG	A freefloat-adjusted market capitalization-weighted stock market index in Hong Kong. It is used to record and monitor daily changes of the largest companies of the Hong Kong stock market.
7	CAC 40	It represents a capitalization-weighted measure of the 40 most significant values among the 100 highest market caps on the Euronext Paris
8	NIKKEI 225	It is a price-weighted index of the Tokyo Stock Exchange, and the components are reviewed once a year. Currently, the Nikkei is the most widely quoted average of Japanese equities.
9	ASX 200	A market-capitalization weighted and float-adjusted stock market index of Australian stocks listed on the Australian Securities Exchange from Standard & Poor's.
10	BSE	A free-float market-weighted stock market index of 30 well-established and financially sound companies listed on Bombay Stock Exchange.
11	2Y USA bond	A two years-to-maturity sovereign US bond.
12	10Y USA bond	A ten years-to-maturity sovereign US bond.
13	10Y UK bond	A ten years-to-maturity sovereign UK bond.
14	2Y German bond	A two years-to-maturity sovereign German bond.
15	10Y German bond	A ten years-to-maturity sovereign German bond.
16	2Y Japanese bond	A two years-to-maturity sovereign Japanese bond.
17	10Y Japanese bond	A ten years-to-maturity sovereign Japanese bond.
18	2Y Australian bond	A two years-to-maturity sovereign Australian bond.
19	10Y Australian bond	A ten years-to-maturity sovereign Australian bond.
20	10Y Swiss bond	A ten years-to-maturity sovereign Swiss bond.
21	2to3Y Spanish bond	A two to three years-to-maturity sovereign Spanish bond.
22	10Y Greek bond	A ten years-to-maturity sovereign Greek bond.
23	3Y Italian bond	A three years-to-maturity sovereign Italian bond.
24	10Y Italian bond	A ten years-to-maturity sovereign Italian bond.
25	Oil	Crude Oil as traded in NYMEX.

4 Causality Network Analytics

4.1 Sundial of causality: the casting of a shadow that aligns with varying "financial times"

As we are motivated to examine the predictive capacity of causalities for financial turbulence, we examine how the financial network changes over time. Was the global financial crisis somehow imprinted on the average causality of the market before, during or after the event? In order to seek for answers we examined the evolution of the average causality resting in the network, week by week, in a rolling window of one year. Below we present the results of this analysis for each of the eight methods.

During the bubble burst of early 2000s, *LICC* in **Fig. 1** is on average 33% and displays a slightly upward trend as it peaks during the last breath of the rundown (October 2002). During the pre-crisis period it moves at an average of 27.42%; more specifically, it enters a defined slide down throughout 2003, and then from 2004 up until the July of 2007 it fluctuates with a slight upward trend **(Table 3)**.

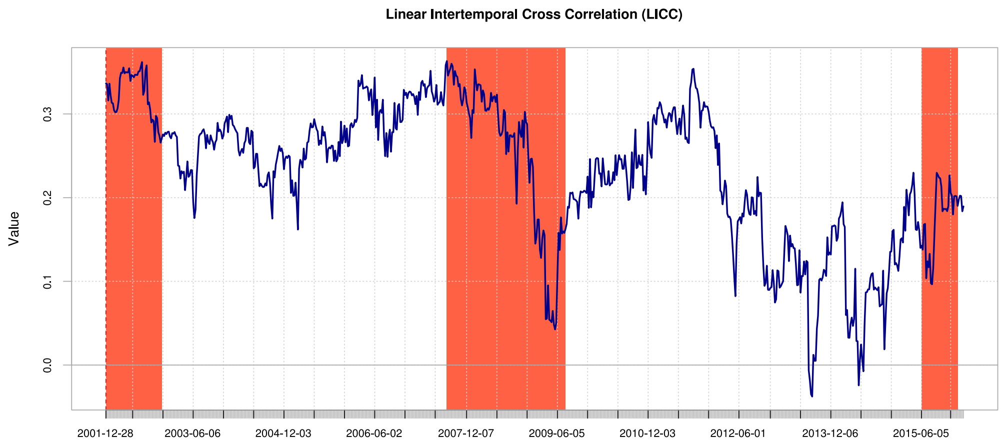

Figure 1: Average of Linear Intertemporal Cross Correlation (LICC) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

The global financial crisis period is characterized by a dramatic drop of *LICC* with an average value of 24.29%, but then at the summer of 2009, we observe a confident rising move as the echoes of crisis die out. The post crisis period is characterized by a generic and fluctuating drop of *LICC*, which is on average 18.95% **(Table 4)**. *LICC* enters the recent financial crash of China in an upward trend, however its levels are already as low as 15.08% **(Table 5)**.

As we observe the evolutionary behavior of *NICC*, see **Fig. 2**, during the stock market rundown of early 2000s, it is on average 29.18% and displays a flat trend throughout that period. During the pre-crisis period it moves at an average of 28.33%; more specifically *NICC* moves slightly downwards from 2004 to 2006 until it suddenly drops even more half a year before the birth of the global financial crisis **(Table 3)**.

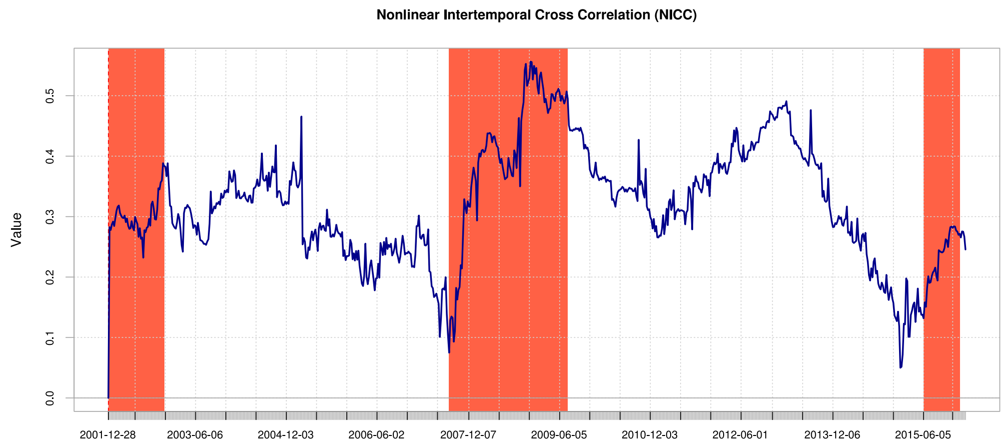

Figure 2: Average of Nonlinear Intertemporal Cross Correlation (NICC) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

The global financial crisis period is characterized by a dramatic increase of $NICC$ with an average value of 40.91%, but then at the summer of 2009 we observe a plunge until the crisis died out. The post crisis period is characterized by a defined increase of $NICC$, which is on average 49.09% **(Table 4)**. $NICC$ enters the stock market plunge of China in an upward trend, however its levels are already as low as 19.38% **(Table 5)**.

Regarding LCo, as seen in **Fig. 3**, during the during the Dotcom bubble burst it is on average 20.34% and displays an upward trend throughout the rundown (October 2002). During the pre-crisis period LCo displays extreme fluctuations around an average of 26.66% and just before the crisis its trend transforms to a rising one **(Table 3)**.

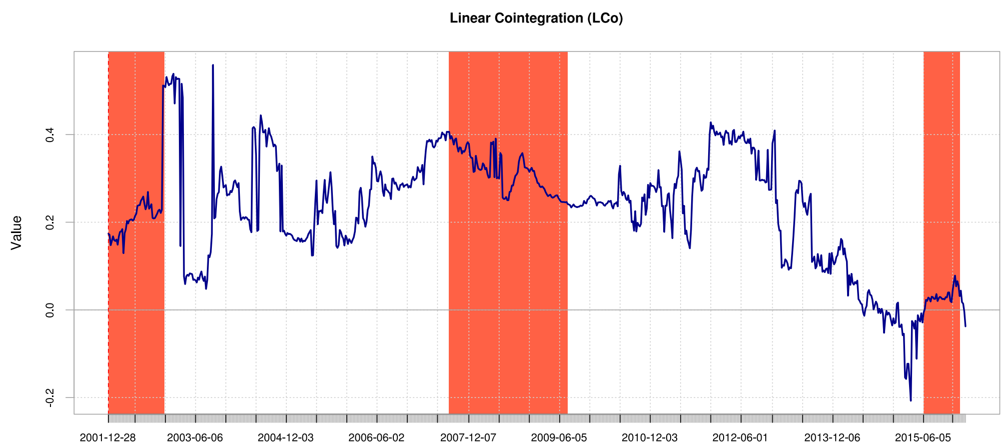

Figure 3: Average of Linear Cointegration (LCo) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

The global financial crisis period is characterized by a smooth drop of LCo with an average value of 30.06% but then at the summer of 2009 it stops falling and moves on a defined support level around 25%. The post crisis period is characterized by a continued move on the same resistance level as before until the end of 2011. Then *LCo* spikes around the summer of 2012 at 40% and begins a defined downward trend at an average of 24.04% **(Table 4)**. *LCo* meets the financial crisis caused by China in a change of trend from negative levels to positive ones, however its levels are already as low as -0.53% **(Table 5)**.

As far as *NCo* is concerned, **Fig. 4**, during the stock market crash of early 2000s it is on the negative side averaging -6.03% and displays a slightly upward trend as it peaks during the last breath of the rundown (October 2002) nearing the zero level. During the pre-crisis period *NCo* moves at an average of 0.44%; more specifically it displays an abrupt spike at the first half of 2003 hitting a ceiling 20%, and then from 2004 up until the July of 2007 it fluctuates with a marked downward trend, joining again the negative side as early as 2006. It bottoms just before the breakout of the crisis at the lowest level ever around -15% **(Table 3)**.

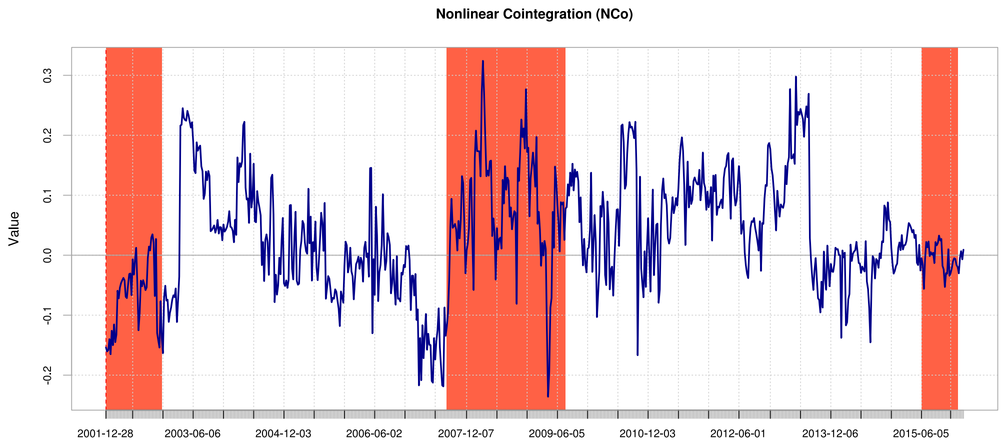

Figure 4: Average of Nonlinear Cointegration (NCo) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

The global financial crisis period is characterized by a wild fluctuation of *NCo* around an average of 7.71%. The post crisis period is characterized by a milder fluctuation of *NCo*, which is on average 6.79% **(Table 4)**. *NCo* enters the Chinese market crash after a prolonged trail with an attractor around zero, being sometimes positive and sometimes negative but always averaging 0.18% **(Table 5)**.

Next we focus in *LGC*, in **Fig. 5**, and we can notice that during the rundown of early 2000s it moves around a support level of 77.52%. During the pre-crisis period it fluctuates a little higher than before at an average of 83.81%. After 2004 however, *LGC* is characterized by a smooth upward trend until the last quarter of 2006 when it started rolling somewhat downwards **(Table 3)**.

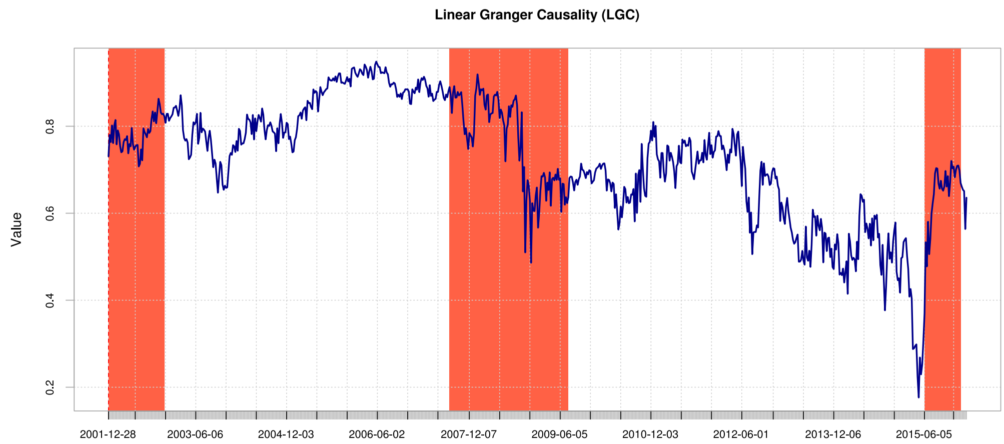

Figure 5: Average of Linear Granger Causality (LGC) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

The global financial crisis period is characterized in the outbreak by a faintly diminishing *LGC* with an average value of 74.8% but then at the end of 2008 we observe a defined drop below 70% finding a new support level at the twilight of the global crisis. The post crisis period is characterized by a generic and fluctuating increase of *LGC* until the summer of 2012, which is on average 64.62%. However, after the third quarter of 2012 the trend changes to a diminishing one hitting as low as 38% **(Table 4)**. *LGC* enters the Chinese rundown in an upward trend, however its levels are already as low as 53.62% **(Table 5)**.

Concerning *NGC*, see **Fig. 6**, emerging from the Dotcom burst it is found on a faintly upward trend averaging 68.81% with the trend becoming steeper as the rundown died out on October 2002. During the pre-crisis period *NGC* plateaued at an average of 77.96% until the end of 2014 when it suddenly dropped at the support level of 60%. Then, in the summer of 2005 it bounced back up, continuing its rising trend until the summer of 2006 when it reached a resistance level of 88% and began falling again, just one year before the breakout of the crisis **(Table 3)**.

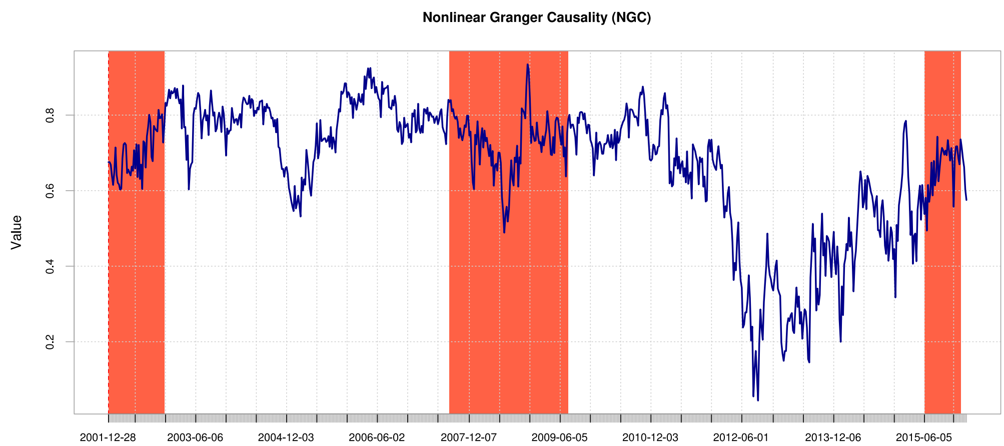

Figure 6: Average of Nonlinear Granger Causality (NGC) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

On the eve of the global financial crisis NGC fall again to same support level as before (60%) while at the end of 2008 it bounced up to between 70% and 80% moving at an average value of 73.14% until the end of the crisis. The post crisis period is characterized by a historically unique drop of NGC reaching a deep support level at just 20% and staying there from the summer of 2012 until the summer of 2013 when it started rising again in a volatile manner **(Table 4)**. The late Chinese shock found NGC still on the rising at an average of 59.41% **(Table 5)**.

Furthermore, the post-Dotcom bubble burst is characterized by an SC, **Fig. 7**, on average 18.77% while its trend is downward. During the pre-crisis period SC enters a marked rising trend averaging 32.16% even after the birth of the global crisis. Throughout the pre-crisis period SC more than doubled from 20% in 2003 to 50% in the summer of 2007 **(Table 3)**.

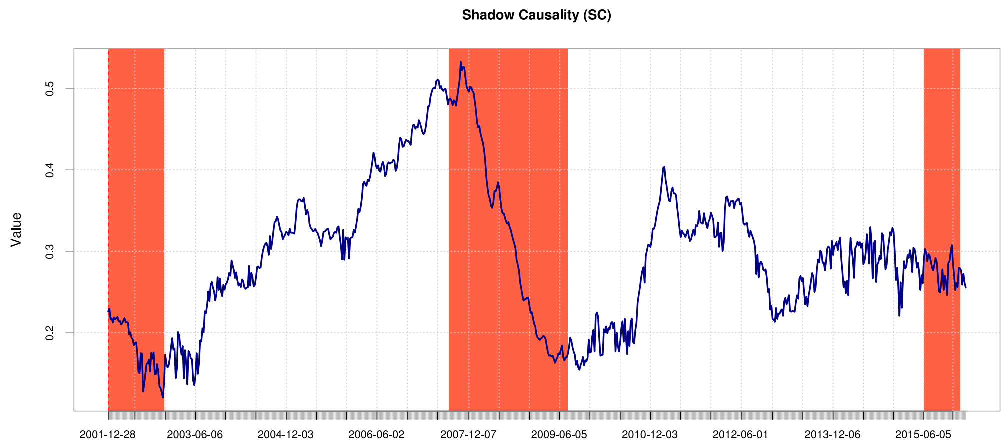

Figure 7: Average of Shadow Causality (SC) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

The global financial crisis period is characterized by an extreme plunge of SC from the resistance level of 50% to a support level of 17% with an average value of 29.97%. In the twilight of the crisis (2009) SC rested at the plateau of 20% entering in that trend the post-crisis period. The post crisis period is characterized by a defined increase of SC to a new support level of 30% from 2011 to 2012 and then in 2013 this support level becomes resistance level forcing the SC to rest beneath 30% with an average of 28.65% **(Table 4)**. SC enters the financial crash of China in a faintly downward trend sliding the plateau of 28.31% **(Table 5)**.

Ultimately, HC in **Fig. 8**, during the stock market rundown of early 2000s is on average 5.48% and displays a slightly upward trend as it peaks on the exhaustion of the rundown (October 2002). During the pre-crisis period it moves at an average of 14.19%; more specifically HC is governed by a steep increase from 2003 all through the summer of 2004 when it hit the resistance level of 25%, and then it enters a prolonged and flat fluctuation downwards to the support level of 10% in the summer of 2006 almost one year before the global crisis **(Table 3)**.

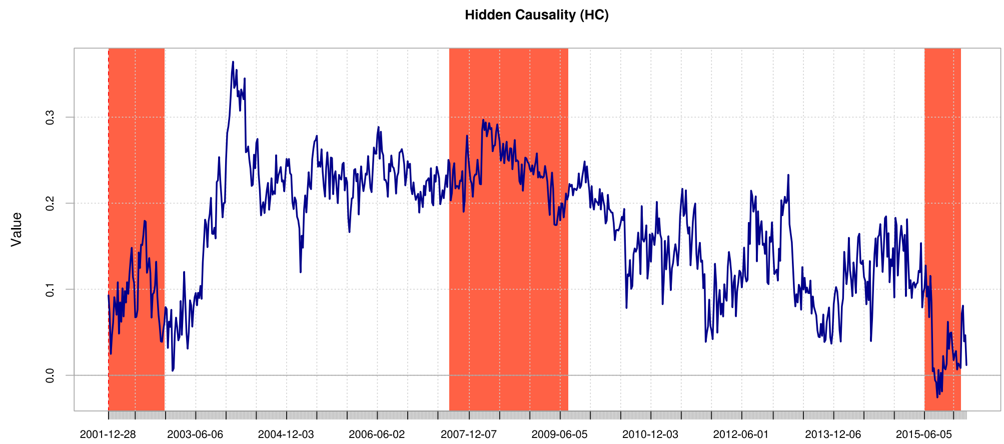

Figure 8: Average of Hidden Causality (HC) for all assets week by week, rolling window of 2 years. **Red Timespans:** Periods of financial turmoil. 2001-2002: Post-Dotcom bubble burst, 2007-2009: Global Finacial Crisis, 2015: Chinese Stock Market Crash

The global financial crisis found *HC* on the rising with an average value of 11.90% but then in the summer of 2008 we witness a marked diminishing trend as the global crisis enters its mature phase. The post crisis period is characterized by an extension of the former downward trend until the eve of 2012 moving at an average of 5.34%. Then *HC* after having fallen to the negative side at around -5%, we can see that it rallies up 15% at the end of 2012 and fluctuating above the support level of 5% until 2014 when it marks a steep decline to again sub-zero levels **(Table 4)**. *HC* enters the financial crisis caused by China in a slightly upward trend, however its levels are already as low as 5.35% **(Table 5)**.

Table 3: Causalities general statistics from the Dotcom Bubble burst until before the Global Financial Crisis

	Stock Market Rundown of Post-Dotcom bubble burst: March 2000 to October 2002					**Pre-crisis period: November 2002 to July 2007**				
Causality Methods	Min	Avg	Max	StDev	Trend	Min	Avg	Max	StDev	Trend
LICC	0.2666	0.3300	0.3620	0.0232	↑	0.1618	0.2742	0.3584	0.0372	↓→↑
NICC	0.2320	0.2918	0.3469	0.0188	→	0.1008	0.2833	0.4655	0.0612	→↓
LCo	0.1294	0.2034	0.2692	0.0339	↑	0.0478	0.2666	0.5589	0.1164	↓↑↓→↑
NCo	-0.1650	-0.0603	0.0348	0.0564	↑	-0.2186	0.0044	0.2452	0.1008	↓
LGC	0.7076	0.7752	0.8631	0.0333	→	0.6472	0.8381	0.9485	0.0684	→↑→
NGC	0.6026	0.6881	0.8138	0.0562	↑	0.5313	0.7796	0.9246	0.0785	→↓↑→
SC	0.1278	0.1877	0.2297	0.0281	↓	0.1203	0.3216	0.5103	0.0965	↑
HC	0.0042	0.0548	0.0903	0.0179	↑	0.0225	0.1419	0.3409	0.0616	↑↓↑↓

LICC: Linear Intertemporal Cross Correlation, **NICC**: Nonlinear Intertemporal Cross Correlation, **LCo**: Linear Cointegration, **NCo**: Nonlinear Cointegration, **LGC**: Linear Granger Casuality, **NGC**: Nonlinear Granger Causality, **SC**: Shadow Causality, **HC**: Hidden Causality.

Min, Avg, Max and **StDev** are calculated in terms of the already average causality among all financial assets throughout the time period declared.

Trend symbols: ↑ denotes an upward trend, ↓ denotes a downward trend, → denotes a flat trend. When two or more trend symbols are written in a row they symbolize consecutive trend changes.

Table 4: Causalities general statistics during and after the Global Financial Crisis

	Global Financial Crisis: August 2007 to December 2009					**Post-crisis period: January 2010 to May 2015**				
Causality Methods	Min	Avg	Max	StDev	Trend	Min	Avg	Max	StDev	Trend
LICC	0.0425	0.2429	0.3632	0.0844	↓↑	0.0377	0.1895	0.3540	0.0903	↑↓↑
NICC	0.0748	0.4091	0.5563	0.1053	↑↓	0.2379	0.3610	0.4909	0.0609	↑↓
LCo	0.2336	0.3006	0.4065	0.0498	↓→	-0.0134	0.2404	0.4281	0.1080	→↑↓
NCo	-0.2359	0.0771	0.3241	0.0900	↑↓↑ ↓↑↓	-0.1667	0.0679	0.2979	0.0890	↑→↓↑ ↓→↑→
LGC	0.4861	0.7480	0.9192	0.0989	→↓→	0.4148	0.6462	0.8098	0.0952	→↓
NGC	0.4887	0.7314	0.9344	0.0752	↓↑→	0.0441	0.5327	0.8754	0.2073	↓↑
SC	0.1545	0.2997	0.5327	0.1269	↓	0.1717	0.2865	0.4037	0.0559	↑→↓→
HC	0.0310	0.1190	0.1996	0.0353	↓	-0.0887	0.0534	0.1625	0.0649	↓↑↓↑

LICC: Linear Intertemporal Cross Correlation, **NICC**: Nonlinear Intertemporal Cross Correlation, **LCo**: Linear Cointegration, **NCo**: Nonlinear Cointegration, **LGC**: Linear Granger Casuality, **NGC**: Nonlinear Granger Causality, **SC**: Shadow Causality, **HC**: Hidden Causality.

Min, Avg, Max and **StDev** are calculated in terms of the already average causality among all financial assets throughout the time period declared.

Trend symbols: ↑ denotes an upward trend, ↓ denotes a downward trend, → denotes a flat trend. When two or more trend symbols are written in a row they symbolize consecutive trend changes.

Table 5: Causalities general statistics during the Chinese Stock Market Crash

	Chinese Stock Market Turbulence: June 2015 to February 2016				
Causality Methods	Min	Avg	Max	StDev	Trend
LICC	0.0187	0.1508	0.2298	0.0495	$\uparrow$
NICC	0.0499	0.1938	0.2839	0.0564	$\uparrow$
LCo	-0.2074	-0.0053	0.0782	0.0525	$\rightarrow$
NCo	-0.1452	0.0018	0.0881	0.0357	$\rightarrow$
LGC	0.1763	0.5362	0.7201	0.1349	$\uparrow$
NGC	0.3172	0.5941	0.7849	0.0998	$\uparrow$
SC	0.2208	0.2831	0.3296	0.0220	$\rightarrow$
HC	0.0535	0.0685	0.1730	0.0642	$\downarrow\rightarrow\uparrow$

LICC: Linear Intertemporal Cross Correlation, **NICC**: Nonlinear Intertemporal Cross Correlation, **LCo**: Linear Cointegration, **NCo**: Nonlinear Cointegration, **LGC**: Linear Granger Casuality, **NGC**: Nonlinear Granger Causality, **SC**: Shadow Causality, **HC**: Hidden Causality.

Min, Avg, Max and **StDev** are calculated in terms of the already average causality among all financial assets throughout the time period declared.

Trend symbols: $\uparrow$ denotes an upward trend, $\downarrow$ denotes a downward trend, $\rightarrow$ denotes a flat trend. When two or more trend symbols are written in a row they symbolize consecutive trend changes.

4.2 The causalities family: convergence or divergence?

Despite the fact that all of the causality methods presented in this article are normalized with values range either $[-1, 1]$ or $[0, 1]$, we cannot conduct a comparative analysis among them because they measure causality through different approaches (for a detailed understanding of what each method measures as causality see Section 2). Instead what we can do is simply attest to each methods reaction and probable predictive capacity to events of the financial market, separately. To further justify the argument of incomparability among the eight causality methods we undertake a similarity analysis (percentage of similar links calculation) for each of the 738 weeks of our evolutionary network and then calculate the average similarity across all weeks for all the possible combinations of the causality methods. The results of this comparison are presented succinctly in **Table 6**. The highest average similarity among any two causality tools is 48.74% of links and occurred between $LICC$ and LGC. The lowest average similarity among any two causality tools is 1.07% of links and occurred between $LICC$ and LCo. Thus we consider comparative analysis out of the question, at least in our experimental context. Maybe with the use of another filtering method, or even no filtering at all, we could possibly find some common ground to lay some comparisons.

Table 6: Averaged Similarity throughout all the time period

Causality Methods	LICC	NICC	LCo	NCo	LGC	NGC	SC	HC
LICC	100%	3.12%	1.07%	5.54%	48.74%	29.69%	3.41%	15.77%
NICC	3.12%	100%	1.67%	8.33%	7.67%	6.65%	3.84%	3.28%
LCo	1.07%	1.67%	100%	1.98%	1.94%	2.27%	4.27%	4.78%
NCo	5.54%	8.33%	1.98%	100%	4.54%	4.04%	4.47%	2.71%
LGC	48.74%	7.67%	1.94%	4.54%	100%	39.44%	2.24%	15.67%
NGC	29.69%	6.65%	2.27%	4.04%	39.44%	100%	2.56%	13.01%
SC	3.41%	3.84%	4.27%	4.47%	2.24%	2.56%	100%	4.36%
HC	15.77%	3.28%	2.71%	2.71%	15.67%	13.01%	4.36%	100%

LICC: Linear Intertemporal Cross Correlation, **NICC**: Nonlinear Intertemporal Cross Correlation, **LCo**: Linear Cointegration, **NCo**: Nonlinear Cointegration, **LGC**: Linear Granger Casuality, **NGC**: Nonlinear Granger Causality, **SC**: Shadow Causality, **HC**: Hidden Causality.

The percentage quantifies the ratio of similar links after the maximum spanning tree filtering is applied. Maximum spanning tree keeps only the strongest links of the network (in absolute values) but still keeps the network connected.

4.3 Causal linkages: time-tested relationships

Having studied the evolution of the eight causality metrics, and after proving their lack of similarity we move on to some distinct features like the most important links and assets. In **Tables 7** through **11** we present the top ten of the links in terms of each causality separately and the overall top 30 links in terms of all causalities together. As we can see from **Table 7**, in terms of $LICC$ the most important causal relationship is that of $10Y{-}USA{-}bond \rightarrow 10Y{-}German{-}bond$ with a $LICC = 44.03\%$. However, in terms of $NICC$ the most causal pair is that of $DAX\ 30 \rightarrow CAC40$ with a $NICC = 72.49\%$. Furthermore, if we take a look at **Table 8**, we notice that in terms of LCo the most important causal relationship is $10Y{-}German{-}bond \rightarrow BOVESPA$ with $LC = 79.40\%$, while in terms of NC the most causal pair is that of $10Y{-}UK{-}bond \overset{-}{\rightarrow} 2Y{-}USA{-}bond$ with $NCo = -28.99\%$. In terms of LGC the most important relationship is that of $3Y{-}Italian{-}bond \rightarrow 2to3Y{-}Spanish{-}bond$, with $LGC = 56.91\%$. However, in terms of NGC, the most important causal pair is that of $10Y{-}Greek{-}bond \rightarrow 2to3Y{-}Spanish{-}bond$ with $NGC = 45.25\%$ **(Table 9)**. In terms of SC the most important causal relationship is that of $DAX30 \rightarrow BSE$ with a score of 24.25%. Nevertheless, the most important causal relationship in terms of HC is that of $10Y{-}USA{-}bond \rightarrow 10Y{-}German{-}bond$ with a score of 48.64% **(Table 10)**. Finally, if we consider the average ranking of all causalities the most important causal pair overall is that of $10Y{-}USA{-}bond \rightarrow 2to3Y{-}Spanish{-}bond$ **(Table 11)**.

Table 7: Top 10 out of 600 Links in terms of strength throughout the time period examined for Linear Intertemporal Cross Correlation and Nonlinear Intertemporal Cross Correlation

Rank	Linear Intertemporal Cross Correlation	Score	Nonlinear Intertemporal Cross Correlation	Score
1	10Y-USA-bond → 10Y-German-bond	0.4403	DAX30 → CAC40	0.7249
2	10Y-USA-bond → 10Y-Australian-bond	0.4105	S&P500 → DOW JONES	0.6951
3	10Y-USA-bond → 10Y-Japanese-bond	0.4092	NIKKEI225 → CAC40	0.5338
4	10Y-USA-bond → 2to3Y-Spanish-bond	0.3956	S&P500 → CAC40	0.4241
5	DOW JONES → NIKKEI225	0.3834	CAC40 → S&P500	0.4065
6	BOVESPA → BSE	0.3766	10Y-Italian-bond → 3Y- Italian bond	0.4010
7	10Y-USA-bond → 10Y-Swiss-bond	0.3509	HANGSENG → CAC40	0.3983
8	BOVESPA → HANGSENG	0.3265	10Y-German-bond → 10Y-UK-bond	0.3807
9	S&P500 → NIKKEI225	0.3075	HANGSENG → BOVESPA	0.3726
10	DOW JONES → BSE	0.3021	HANGSENG → S&P500	0.3699

Causality symbols: x→y denotes that x influences y in the same direction i.e. past x increases cause future y increases (similarly for decreases). While, x$\bar{\rightarrow}$ y denotes that x influences y in the opposite direction i.e. past x increases cause future y decreases and vice versa.

Causality score: the number next to each causal relationship ascribed is the average causal weight from x to y for the time period of 4th January 2000 to 12th February 2016 for the specific causality method

Table 8: Top 10 out of 600 Links in terms of strength throughout the time period examined for Linear Cointegration and Nonlinear Cointegration

Rank	Linear Cointegration	Score	Nonlinear Cointegration	Score
1	10Y-German-bond $\rightarrow$ BOVESPA	0.7940	10Y-UK-bond $\bar{\rightarrow}$ 2Y-USA-bond	-0.2899
2	10Y-UK-bond $\rightarrow$ BOVESPA	0.7899	HANGSENG $\rightarrow$ BOVESPA	0.2547
3	2Y-Australian-bond $\rightarrow$ BOVESPA	0.7493	DOW JONES $\rightarrow$ 3Y- Italian -bond	0.2520
4	10Y-Swiss-bond $\rightarrow$ BOVESPA	0.7249	Oil $\rightarrow$ SHANGHAI	0.2384
5	10Y-Australian-bond $\rightarrow$ BOVESPA	0.7208	NIKKEI225 $\bar{\rightarrow}$ 2Y-USA-bond	-0.2384
6	10Y-USA-bond $\rightarrow$ BOVESPA	0.6937	10Y-UK-bond $\bar{\rightarrow}$ 10Y-USA-bond	-0.2303
7	2Y-German-bond $\rightarrow$ BOVESPA	0.6924	NIKKEI225 $\bar{\rightarrow}$ 2Y-German-bond	-0.2168
8	10Y-Japanese-bond $\rightarrow$ NIKKEI225	0.6815	10Y-USA-bond $\rightarrow$ 2Y-Japanese-bond	0.2046
9	2Y-USA-bond $\rightarrow$ BOVESPA	0.6747	DAX30 $\rightarrow$ 3Y- Italian -bond	0.2018
10	10Y-Japanese-bond $\rightarrow$ BOVESPA	0.6667	10Y-Swiss-bond $\bar{\rightarrow}$ 2to3Y-Spanish-bond	-0.1978

Causality symbols: x$\rightarrow$y denotes that x influences y in the same direction i.e. past x increases cause future y increases (similarly for decreases). While, x$\bar{\rightarrow}$ y denotes that x influences y in the opposite direction i.e. past x increases cause future y decreases and vice versa.

Causality score: the number next to each causal relationship ascribed is the average causal weight from x to y for the time period of 4th January 2000 to 12th February 2016 for the specific causality method

Table 9: Top 10 out of 600 Links in terms of strength throughout the time period examined for Linear Granger Causality and Nonlinear Granger Causality

Rank	**Linear Granger Causality**	**Score**	**Nonlinear Granger Causality**	**Score**
1	3Y-Italian-bond → 2to3Y-Spanish-bond	0.7940	10Y-Greek-bond → 2to3Y-Spanish-bond	-0.2899
2	10Y-USA-bond → 2to3Y-Spanish-bond	0.7899	3Y-Italian-bond → 2to3Y-Spanish-bond	0.2547
3	10Y-Greek-bond → 2to3Y-Spanish-bond	0.7493	10Y-UK-bond → 2to3Y-Spanish-bond	0.2520
4	2Y-German-bond → 2to3Y-Spanish-bond	0.7249	10Y-USA-bond → 2to3Y-Spanish-bond	0.2384
5	10Y-UK-bond → 2to3Y-Spanish-bond	0.7208	10Y-USA-bond → 10Y-Australian-bond	-0.2384
6	10Y-Italian-bond → 2to3Y-Spanish-bond	0.6937	10Y-Italian-bond → 2to3Y-Spanish-bond	-0.2303
7	10Y-USA-bond → 10Y-Australian-bond	0.6924	2Y-German-bond → 2to3Y-Spanish-bond	-0.2168
8	2Y-USA-bond → 2to3Y-Spanish-bond	0.6815	2Y-USA-bond → 2to3Y-Spanish-bond	0.2046
9	DOW JONES → BSE	0.6747	10Y-USA-bond → 10Y-Japanese-bond	0.2018
10	10Y-Australian-bond → 2to3Y-Spanish-bond	0.6667	10Y-Greek-bond → 10Y-German-bond	-0.1978

Causality symbols: x→y denotes that x influences y in the same direction i.e. past x increases cause future y increases (similarly for decreases). While, $x \xrightarrow{-} y$ denotes that x influences y in the opposite direction i.e. past x increases cause future y decreases and vice versa.

Causality score: the number next to each causal relationship ascribed is the average causal weight from x to y for the time period of 4th January 2000 to 12th February 2016 for the specific causality method

Table 10: Top 10 out of 600 Links in terms of strength throughout the time period examined for Shadow Causality and Hidden Causality

Rank	Shadow Causality	Score	Hidden Causality	Score
1	DAX30 → BSE	0.7940	10Y-USA-bond → 10Y-German-bond	-0.2899
2	BSE → BOVESPA	0.7899	10Y-USA-bond → 10Y-Australian-bond	0.2547
3	BSE → S&P500	0.7493	10Y-Italian-bond → 10Y-German-bond	0.2520
4	BSE → Oil	0.7249	2Y-German-bond → 2to3Y-Spanish-bond	0.2384
5	CAC40 → BSE	0.7208	10Y-UK-bond → 10Y-German-bond	-0.2384
6	HANGSENG → BSE	0.6937	DOW JONES → S&P500	-0.2303
7	BSE → ASX200	0.6924	10Y-Greek-bond → 10Y-Italian-bond	-0.2168
8	BOVESPA → BSE	0.6815	2Y-Japanese-bond → 3Y- Italian -bond	0.2046
9	BSE → SHANGHAI	0.6747	10Y-UK-bond → 10Y-Swiss-bond	0.2018
10	DOW JONES → BSE	0.6667	10Y-German-bond → 10Y-Australian-bond	-0.1978

Causality symbols: $x \rightarrow y$ denotes that x influences y in the same direction i.e. past x increases cause future y increases (similarly for decreases). While, $x \overset{-}{\rightarrow} y$ denotes that x influences y in the opposite direction i.e. past x increases cause future y decreases and vice versa.

Causality score: the number next to each causal relationship ascribed is the average causal weight from x to y for the time period of 4th January 2000 to 12th February 2016 for the specific causality method

Table 11: Top 30 out of 600 Links in terms of averaged strength across all causalities

Rank	Causal Relationship	Rank	Causal Relationship
1	10Y-USA-bond → 2to3Y-Spanish-bond	16	10Y-Australian-bond → 2to3Y-Spanish-bond
2	10Y-Greek-bond → 2to3Y-Spanish-bond	17	BOVESPA → BSE
3	3Y-Italian-bond → 2to3Y-Spanish-bond	18	2Y-Australian-bond → 2to3Y-Spanish-bond
4	10Y-USA-bond → 10Y-Australian-bond	19	S&P500 → NIKKEI225
5	10Y-UK-bond → 2to3Y-Spanish-bond	20	BOVESPA → HANGSENG
6	10Y-Italian-bond → 2to3Y-Spanish-bond	21	10Y-German-bond → BOVESPA
7	2Y-USA-bond → 2to3Y-Spanish-bond	22	10Y-Swiss-bond → BOVESPA
8	2Y-German-bond → 2to3Y-Spanish-bond	23	DOW JONES → HANGSENG
9	10Y-USA-bond → 10Y-German-bond	24	DAX30 → BSE
10	10Y-USA-bond → 10Y-Japanese-bond	25	10Y-UK-bond → BOVESPA
11	DOW JONES → BSE	26	2Y-Australian-bond → BOVESPA
12	S&P500 → HANGSENG	27	2Y-USA-bond → 10Y-Swiss-bond
13	10Y-USA-bond → 10Y-Swiss-bond	28	2Y-German-bond → BOVESPA
14	DOW JONES → NIKKEI225	29	BOVESPA → SHANGHAI
15	10Y-Greek-bond → 10Y-German-bond	30	CAC40 → BSE

Causality symbols: x→y denotes that x influences y in the same direction i.e. past x increases cause future y increases (similarly for decreases). While, $x \overset{-}{\rightarrow} y$ denotes that x influences y in the opposite direction i.e. past x increases cause future y decreases and vice versa.

Causality score: the number next to each causal relationship ascribed is the average causal weight from x to y for the time period of 4th January 2000 to 12th February 2016 for the specific causality method

4.4 Causal System: One Attractor to pull them all

In order to rank the assets according to the causality they exert, we employ the out-strength centrality and we average it over the years for every causality method. The complete ranking lists can be seen in **Table 12** , **Table 13** and **Table 14**. As we can see the most causal asset in terms of $LICC$ is the USA 10 $year-bond$, while in terms of $NICC$ the $HANGSENG$ index. Moreover, in terms of LCo the most causal asset is the $Japanese$ 2 $year-bond$, while in terms NCo it is DAX 30 index. LGC coincides with $LICC$ in crowning the USA 10 $year-bond$ as the most causal one, which is again number one causal asset in terms of NGC. However, results are different in terms of SC and HC giving BSE index and $Japanese$ 2 $year-bond$ respectively as the most causal assets. All in all, the most causal asset in terms of all causalities considered appears to be the USA 10 $year-bond$.

What is more, we could not but notice that, in agreement with Rahman et al (1997), LCo along with HC unveil a "hidden" regime of causality occasionally monopolised by the bonds (see **Table 12** and **Table 14**) . This result is astounding because LCo attests that those bonds bear the sceptres of linear and profound long-term influence on the other assets and HC further reveals an active and consistent short-term causality exercised by those bonds.

Table 12: Asset ranking in terms of out-strength centrality

LICC		NICC		LCo	
Asset	**Strength**	**Asset**	**Strength**	**Asset**	**Strength**
10Y USA bond	1.075	HANGSENG	0.871	2Y Japanese bond	1.377
DOW JONES	0.538	DAX 30	0.838	10Y Japanese bond	0.774
S&P 500	0.501	10Y Greek bond	0.830	10Y Swiss bond	0.529
10Y UK bond	0.501	10Y German bond	0.761	10Y UK bond	0.479
2Y USA bond	0.486	S&P 500	0.713	10Y German bond	0.472
BOVESPA	0.416	NIKKEI 225	0.585	2Y German bond	0.464
10Y Greek bond	0.407	10Y Italian bond	0.521	10Y Greek bond	0.410
CAC 40	0.396	CAC 40	0.496	2Y Australian bond	0.393
DAX 30	0.391	10Y Swiss bond	0.383	10Y Australian bond	0.379
3Y Italian bond	0.223	2Y German bond	0.315	10Y USA bond	0.377
2Y Australian bond	0.222	10Y USA bond	0.302	10Y Italian bond	0.370
OIL	0.202	2TO3Y Spanish bond	0.299	2Y USA bond	0.314
10Y Japanese bond	0.185	10Y Australian bond	0.284	3Y Italian bond	0.311
10Y German bond	0.177	DOW JONES	0.282	2to3Y Spanish bond	0.163
BSE	0.170	BSE	0.282	OIL	0.021
2Y German bond	0.169	ASX 200	0.278	SHANGHAI	0.000
SHANGHAI	0.169	BOVESPA	0.262	BOVESPA	0.000
ASX 200	0.160	OIL	0.225	DOW JONES	0.000
10Y Swiss bond	0.145	2Y USA bond	0.186	S&P 500	0.000
10Y Italian bond	0.142	10Y Japanese bond	0.181	DAX 30	0.000
10Y Australian bond	0.137	3Y Italian bond	0.138	HANGSENG	0.000
HANGSENG	0.122	SHANGHAI	0.096	CAC 40	0.000
2Y Japanese bond	0.105	10Y UK bond	0.077	NIKKEI 225	0.000
NIKKEI 225	0.080	2Y Japanese bond	0.076	ASX 200	0.000
2to3Y Spenish bond	0.066	2Y Australian bond	0.059	BSE	0.000

LICC: Linear Intertemporal Cross Correlation, **NICC**: Nonlinear Intertemporal Cross Correlation, **LCo**: Linear Cointegration

Score: Out Strength Centrality is calculated as the average for every node (asset) throughout the period of 4th January 2000 to 12th February 2016 for the specific causality method

Table 13: Asset ranking in terms of out-strength centrality

NCo		LGC		NGC	
Asset	**Strength**	**Asset**	**Strength**	**Asset**	**Strength**
DAX 30	0.637	10Y USA bond	2.429	10Y USA bond	2.098
NIKKEI 225	0.543	S&P 500	1.352	10Y Greek bond	1.480
10Y USA bond	0.440	2Y USA bond	1.267	10Y Swiss bond	1.242
10Y UK bond	0.440	DOW JONES	1.220	DOW JONES	1.195
OIL	0.410	HANGSENG	1.146	2Y USA bond	1.193
3Y Italian bond	0.356	DAX 30	1.122	BOVESPA	1.093
CAC 40	0.324	BOVESPA	1.115	HANGSENG	1.024
2Y Australian bond	0.322	10Y UK bond	1.115	DAX 30	1.021
2Y German bond	0.319	3Y Italian bond	1.047	S&P 500	0.992
DOW JONES	0.306	10Y Greek bond	1.024	10Y UK bond	0.951
2Y USA bond	0.276	2Y German bond	0.835	3Y Italian bond	0.940
BSE	0.273	CAC 40	0.823	OIL	0.920
HANGSENG	0.263	10Y Japanese bond	0.821	10Y Italian bond	0.824
ASX 200	0.251	SHANGHAI	0.811	2to3Y Spanish bond	0.821
SHANGHAI	0.249	2Y Australian bond	0.786	ASX 200	0.815
S&P 500	0.245	10Y Italian bond	0.771	NIKKEI 225	0.808
10Y German bond	0.234	OIL	0.746	10Y Japanese bond	0.705
10Y Australian bond	0.229	BSE	0.729	CAC 40	0.699
10Y Greek bond	0.222	ASX 200	0.728	2Y German bond	0.698
10Y Swiss bond	0.210	10Y Australian bond	0.700	2Y Japanese bond	0.693
10Y Japanese bond	0.200	10Y Swiss bond	0.650	SHANGHAI	0.685
10Y Italian bond	0.174	2Y Japanese bond	0.642	10Y Australian bond	0.678
BOVESPA	0.148	10Y German bond	0.512	BSE	0.675
2to3Y Spanish bond	0.110	NIKKEI 225	0.488	2Y Australian bond	0.521
2Y Japanese bond	0.107	2to3Y Spanish bond	0.460	10Y German bond	0.427

NCo: Nonlinear Cointegration, **LGC**: Linear Granger Causality, **NGC**: Nonlinear Granger Causality

Score: Out Strength Centrality is calculated as the average for every node (asset) throughout the period of 4th January 2000 to 12th February 2016 for the specific causality method

Table 14: Asset ranking in terms of out-strength centrality

SC		HC		Total(mean)	
Asset	**Strength**	**Asset**	**Strength**	**Asset**	**Strength**
BSE	1.150	2Y Japanese bond	0.423	10Y USA bond	0.904
SHANGHAI	0.486	10Y USA bond	0.346	10Y Greek bond	0.630
10Y Greek bond	0.458	2Y German bond	0.257	DAX 30	0.542
S&P 500	0.399	10Y UK bond	0.241	S&P 500	0.540
DOW JONES	0.342	2Y USA bond	0.215	2Y USA bond	0.516
2Y JPN bond	0.323	10Y Greek bond	0.208	DOW JONES	0.507
BOVESPA	0.307	DOW JONES	0.174	10Y UK bond	0.505
ASX 200	0.280	2Y Australian bond	0.156	2Y Japnese bond	0.468
2Y German bond	0.262	10Y Australian bond	0.152	HANGSENG	0.458
CAC 40	0.259	10Y Italian bond	0.140	BOVESPA	0.430
10Y UK bond	0.234	S&P 500	0.121	10Y Swiss bond	0.422
DAX 30	0.225	10Y German bond	0.113	BSE	0.415
10Y Italian bond	0.214	DAX 30	0.100	2Y German bond	0.415
HANGSENG	0.201	BOVESPA	0.099	3Y Italian bond	0.409
NIKKEI 225	0.200	SHANGHAI	0.074	10Y Italian bond	0.395
10Y Australian bond	0.200	3Y Italian bond	0.068	10Y Japanese bond	0.384
OIL	0.195	10Y Swiss bond	0.048	CAC 40	0.379
3Y Italian bond	0.190	BSE	0.040	10Y German bond	0.360
2Y USA bond	0.188	NIKKEI 225	0.039	10Y Australian bond	0.345
10Y German bond	0.184	HANGSENG	0.038	OIL	0.343
2Y Australian bond	0.179	CAC 40	0.034	NIKKEI 225	0.343
10Y Japanese bond	0.176	ASX 200	0.031	2Y Australian bond	0.330
10Y Swiss bond	0.173	10Y Japanese bond	0.028	SHANGHAI	0.321
2to3Y Spanish bond	0.173	OIL	0.024	ASX 200	0.318
10Y USA bond	0.165	2to3Y Spanish bond	0.020	2to3Y Spanish bond	0.264

SC: Shadow Causality, **HC**: Hidden Causality

Score: Out Strength Centrality is calculated as the average for every node (asset) throughout the period of 4th January 2000 to 12th February 2016 for the specific causality method

4.5 Network Visualization

The extraordinary performance of the sovereign bonds led us to further examine our financial network's evolutionary behavior for each of the eight causality methods. To that end, we plot four phases of the network for every causality method (see **Figures 9 to 16**). The phases are recording a) 2002 during the post-Dotcom bubble burst, b) 2008 during the global financial meltdown, c) 2011 during the aftermath of the global crisis and d) 2015 at the heart of the Chinese stock market crash.

On the onset of the $LICC$ network (see **Figure 9 a**), we can observe that the $2Y\!-\!USA\!-\!bond$ is the predominant hub of causality with the only competitive equity indices being those of DAX 30 and CAC 40. During the global financial crisis, $2Y\!-\!USA\!-\!bond$ concedes its central role to the $10Y\!-\!USA\!-\!bond$ while the overall equities performance remained stable. Five years after the outbreak of the global crisis $10Y\!-\!USA\!-\!bond$ still exerts the most causality in the network (see **Figure 9 c**), however its strength is diminished (see **Figure 9 d**). As far as the equities are concerned ASX 200 appears to be the most influential. Ultimately, during the Chinese stock market crisis it is really interesting to see that Oil becomes a hub of causality.

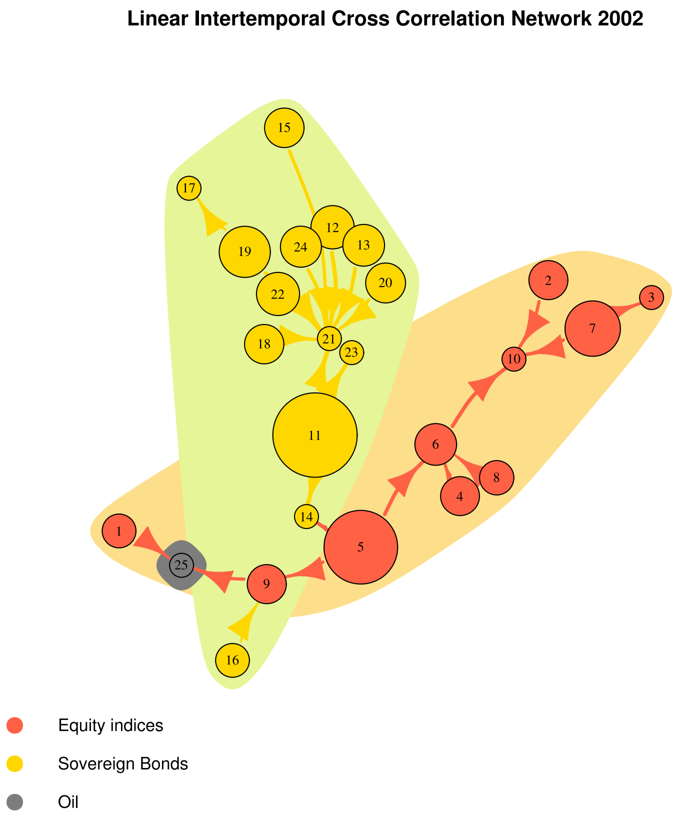

Figure 9 a: Linear Intertemporal Cross Correlation network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

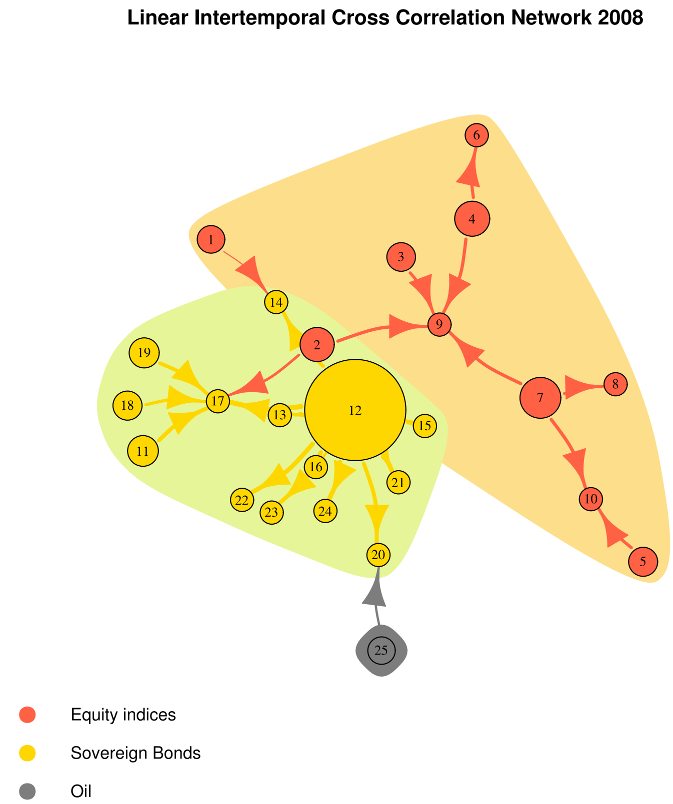

Figure 9 b: Linear Intertemporal Cross Correlation network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

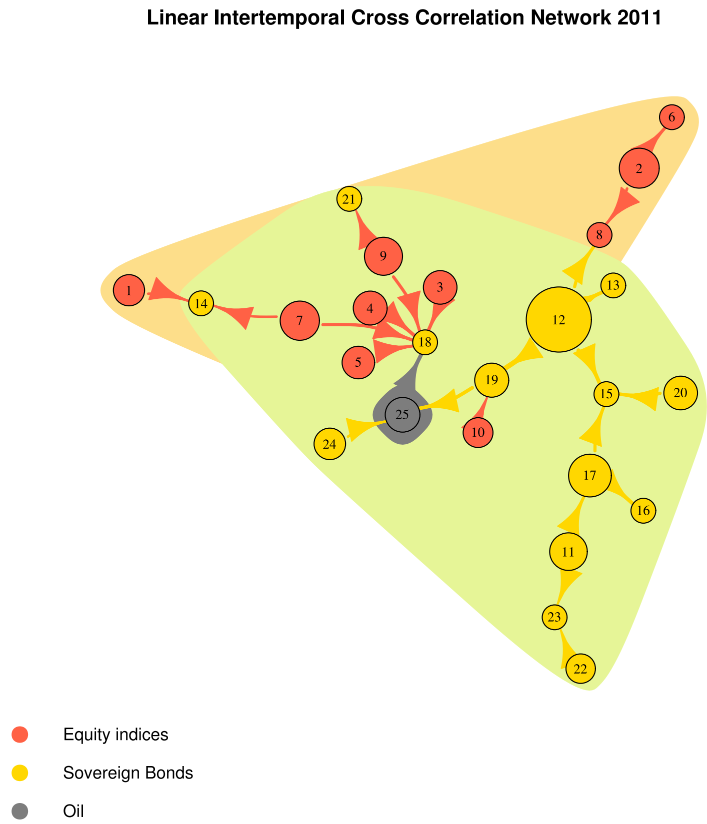

Figure 9 c: Linear Intertemporal Cross Correlation network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

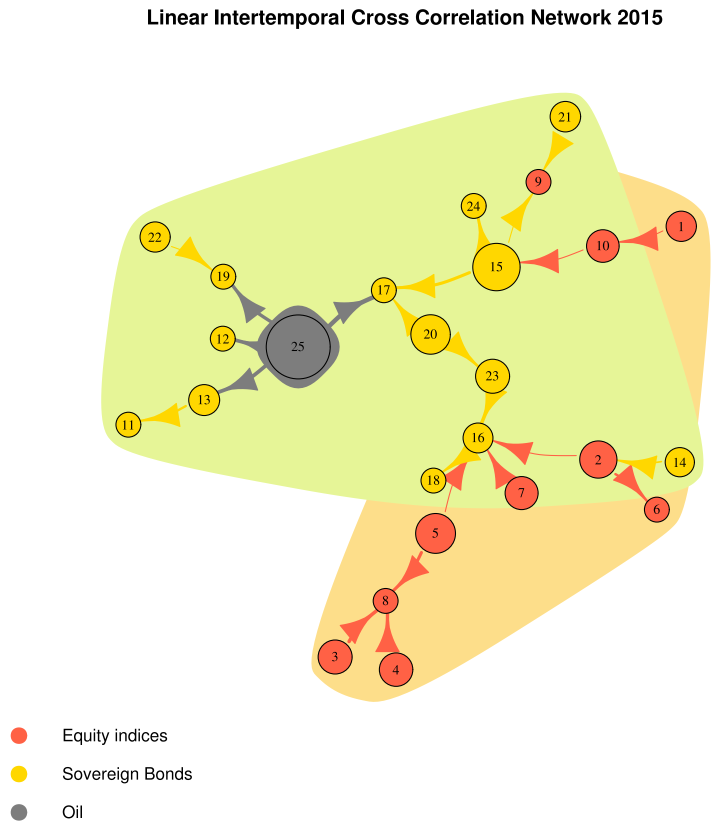

Figure 9 d: Linear Intertemporal Cross Correlation network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

Viewing the same financial network through the lens of $NICC$ (see **Figures 10**) we witness a totally different situation: A disconnected network with substantially weaker relationships and no apparent hubs in all four phases. Contrary to the case of $LICC$ here we see little interaction among assets of different category (equities and bonds). The only similarity appears to be the rising importance of Oil as a key node during the Chinese stock market crash. Overall we observe that $LICC$ produced more stable relationships than $NICC$, however this does not necessarily mean that $LICC$ is better, it could as well mean that $LICC$, being a linear method, overestimated the causality intensity, while $NICC$ as a more "explorative" nonlinear method is stricter in assigning higher scores. This whole association between causality methods and their "meaning" is already part of our future work.

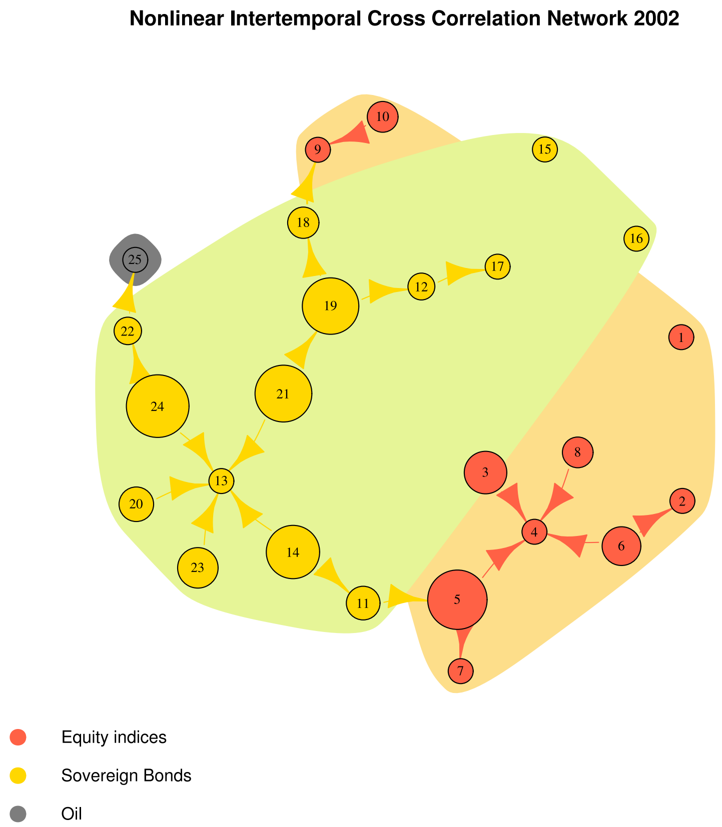

Figure 10 a: Nonlinear Intertemporal Cross Correlation network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

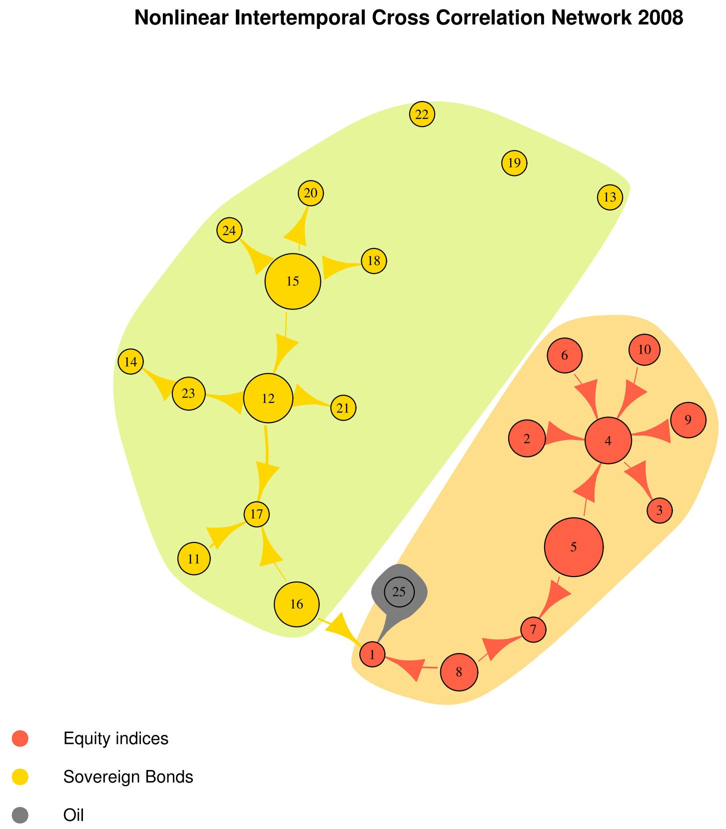

Figure 10 b: Nonlinear Intertemporal Cross Correlation network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

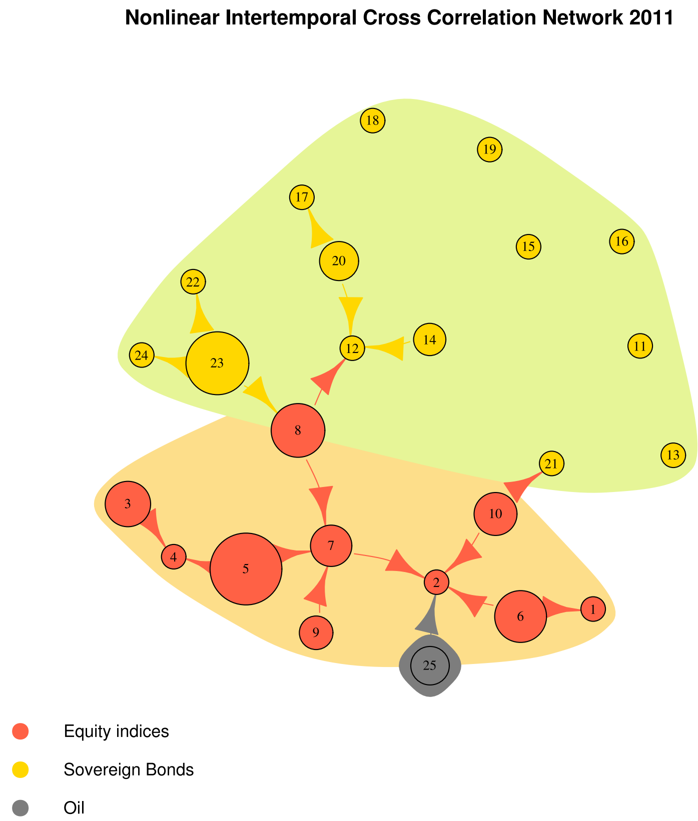

Figure 10 c: Nonlinear Intertemporal Cross Correlation network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

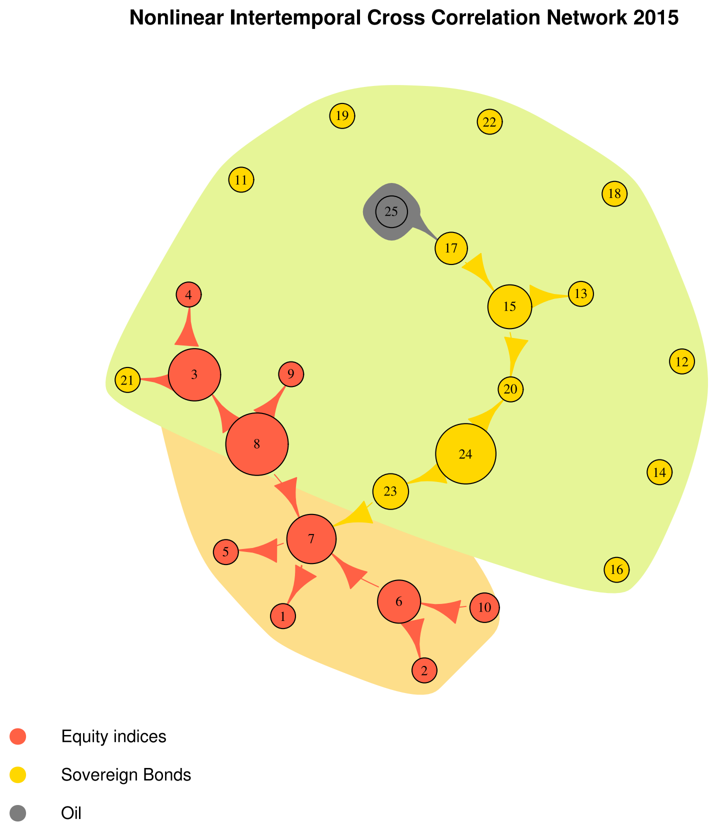

Figure 10 d: Nonlinear Intertemporal Cross Correlation network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

Enter *LCo* in **Figures 11**. Here we clearly see the *reign of bonds* throughout the four phases, with almost all of the linear long-term relationships being initiated from the bonds. Clearly, the equities subgroup is totally broken with the individual equities being strongly influenced of bonds. Noteworthy enough, the $2Y\!-\!Japanese\!-\!bond$ is the hub of the financial network especially in **Figures 11 a, 11 c** where it is obvious that it influences the majority of the equities.

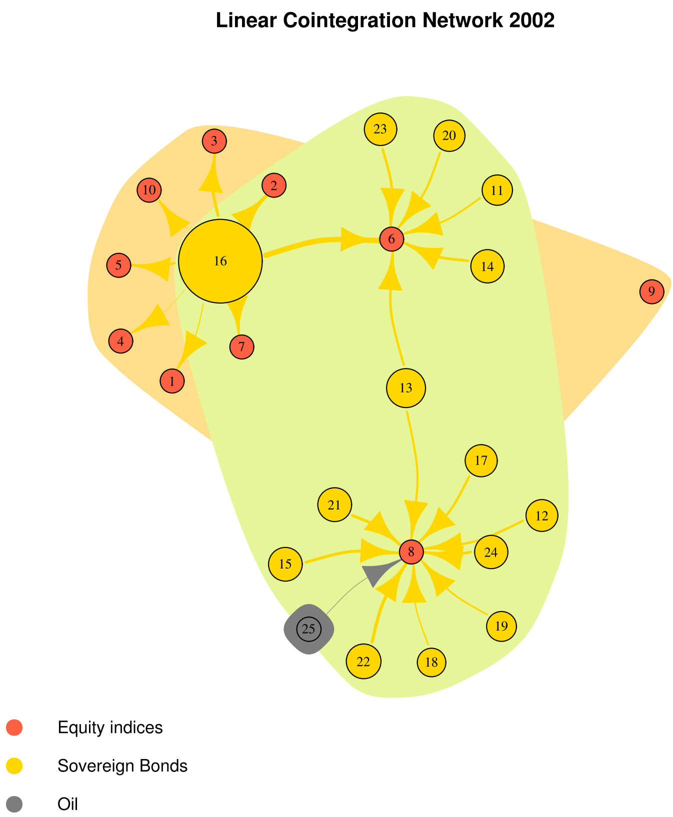

Figure 11 a: Linear Cointegration network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

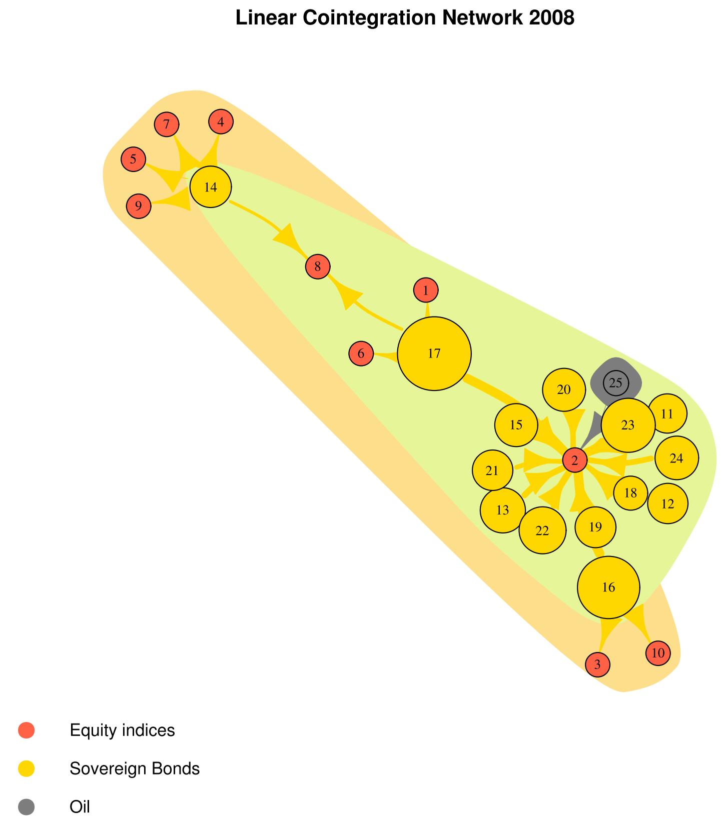

Figure 11 b: Linear Cointegration network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

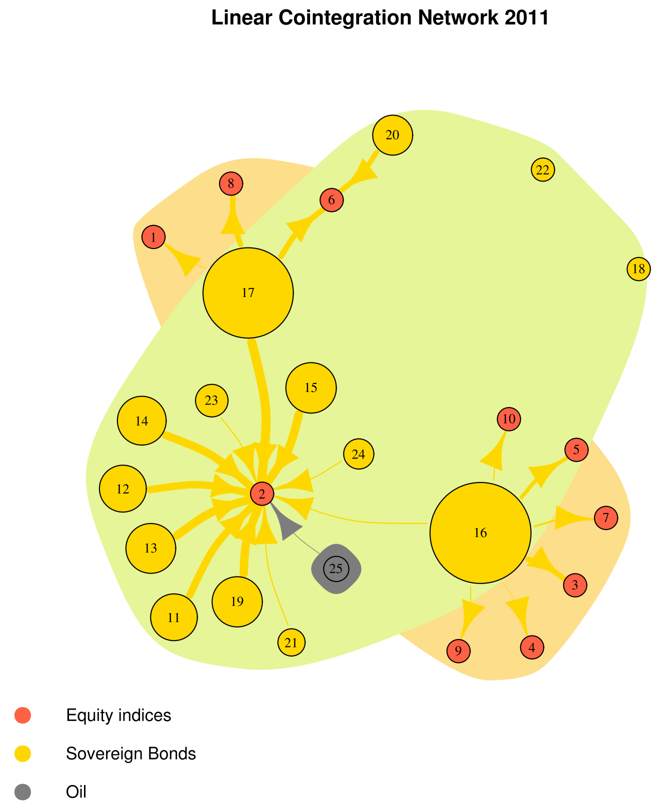

Figure 11 c: Linear Cointegration network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

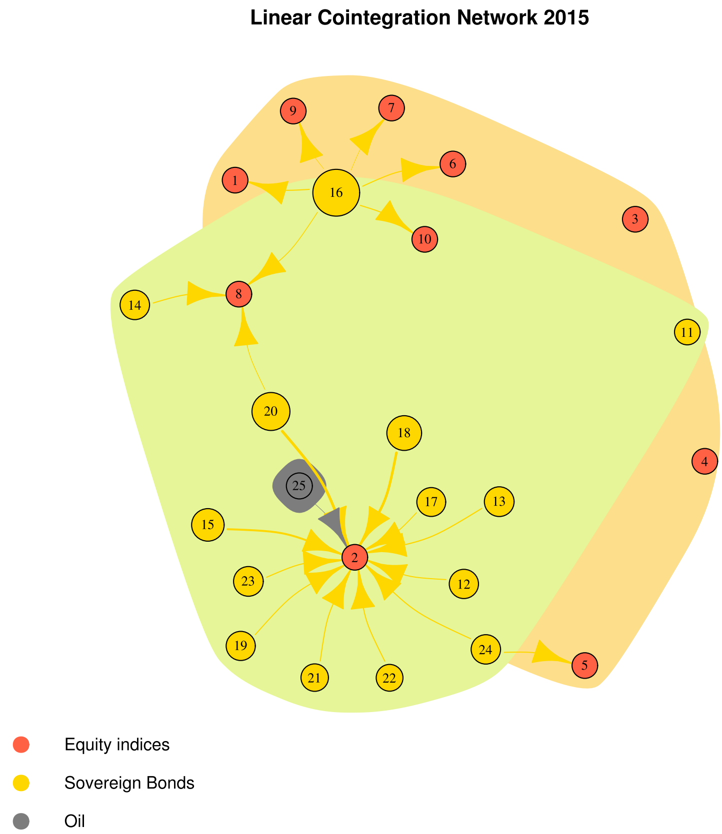

Figure 11 d: Linear Cointegration network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

In the nonlinear form of cointegration network (NCo) bonds still have a stronger presence than equities (see **Figures 12**). During the aftermath of the Dotcom bubble burst the network appears quite mixed, with causal relationships between equities and bonds being formed interchangeably. BSE appears to be the most influential equity and $2Y{-}USA{-}bond$ the most central bond. Into the global crisis, the netwrok appears slighlty more structured, with the leading asset role of equities being handed over to DAX 30, and the stength of $2Y{-}USA{-}bond$ somewhat undermined. After the crisis, $2Y{-}USA{-}bond$, is replaced by the $3Y{-}Italian{-}bond$ as the leading bond, and DAX 30 stands on par with it (see **Figure 12 c**). Finally, when the Chinese stock market crash takes place no evident hub is observed. However the subgroup of bonds is significantly more strongly connected than the subgoup of equities which appears rather scattered.

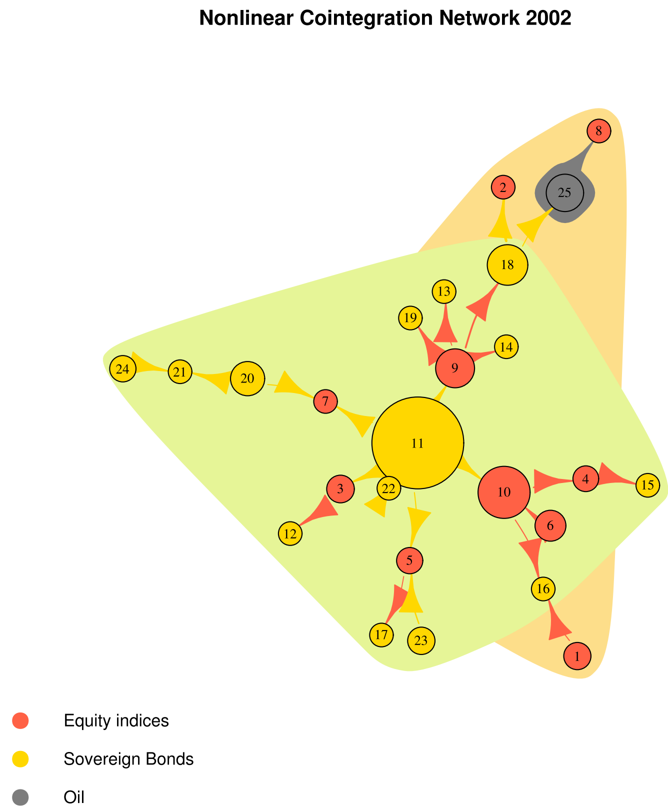

Figure 12 a: Nonlinear Cointegration network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

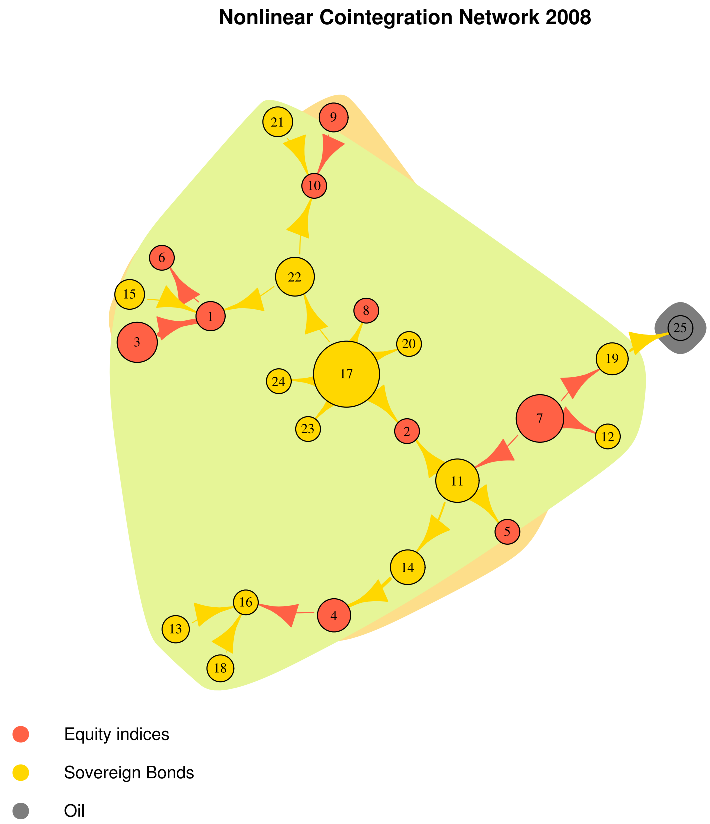

Figure 12 b: Nonlinear Cointegration network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

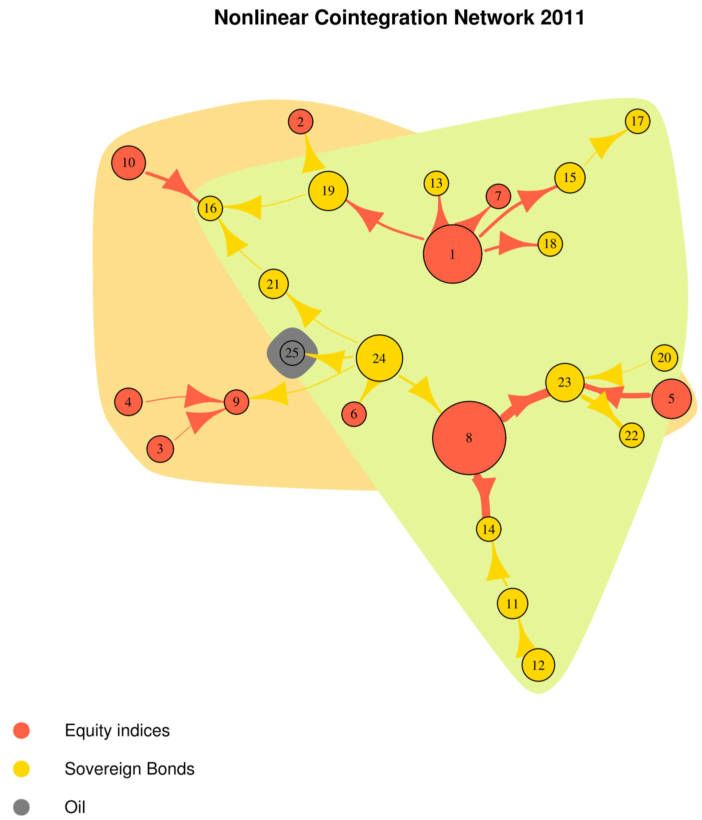

Figure 12 c: Nonlinear Cointegration network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

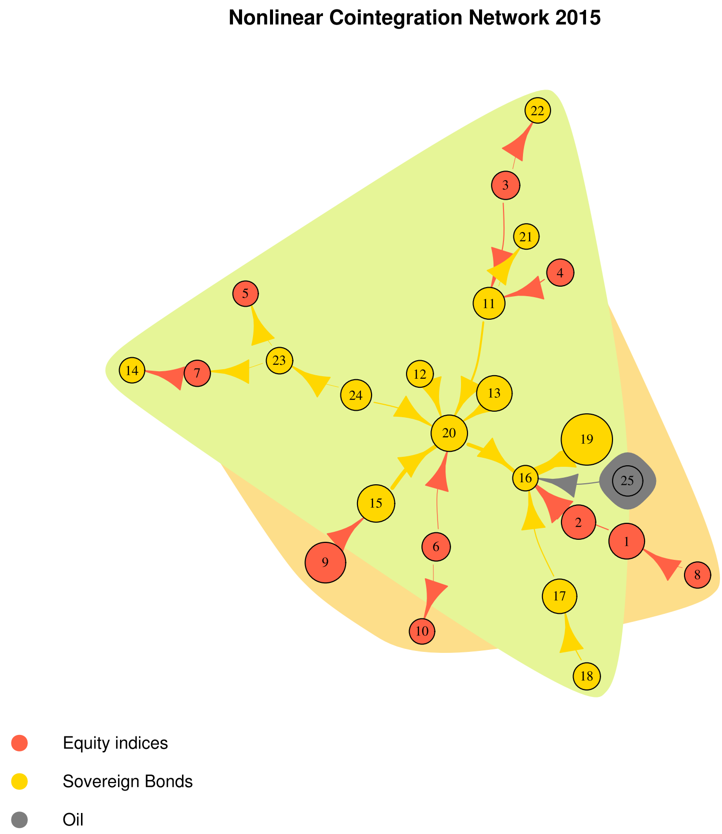

Figure 12 d: Nonlinear Cointegration network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

LGC produces a financial network that during the post-Dotcom bubble burst (see **Figure 13 a**) reveals a strong cluster of bonds and two broken groups of equities. However, during the global financial crisis (see **Figure 13 b**) the equities form a clustered group and in fact outperform the disconnected bonds team. *DowJones*, *BSE* and *BOVESPA* exerted the most causality during that period. After the global financial crisis what we see is a strong presence of bonds with dominant presence of the $10Y{-}UK{-}bond$ and the $2Y{-}USA{-}bond$. As far as the equities are concerned *HANGSENG* appears to be quite central (see **Figure 13 c**). In the Chinese stock market crash, a recurring pattern of rising *Oil* importance is visible (see **Figure 13 d**), while equities and bonds appear to share in almost equal terms the causality flowing in the network.

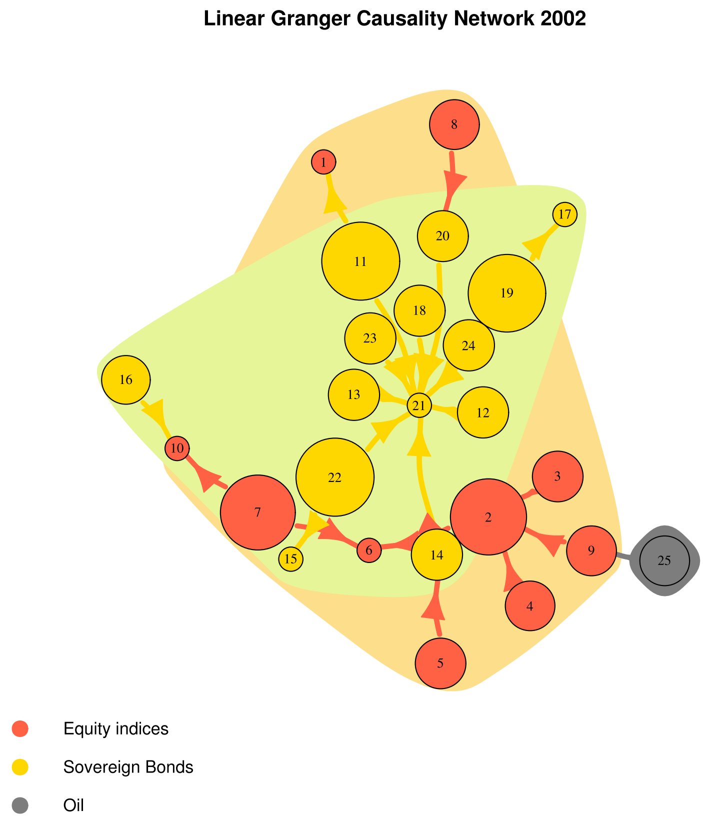

Figure 13 a: Linear Granger Causality network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

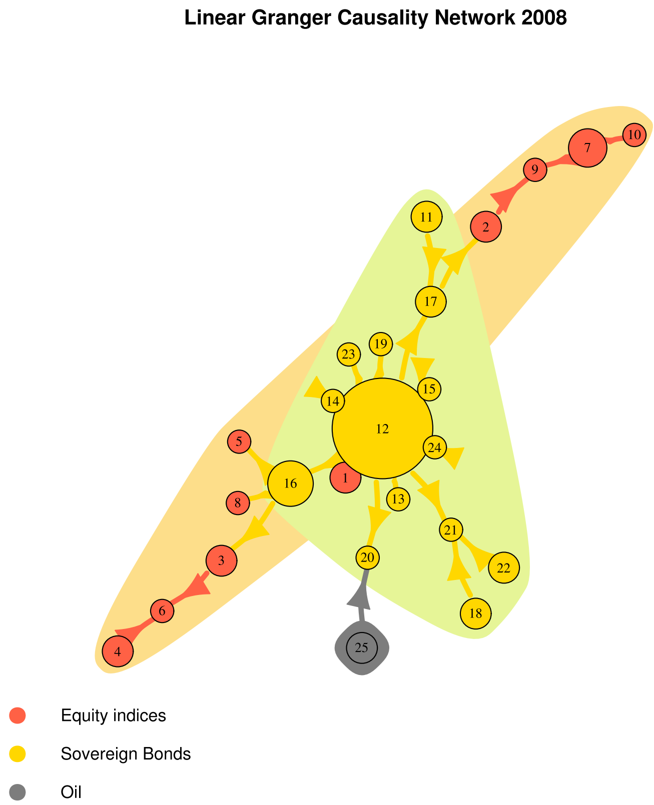

Figure 13 b: Linear Granger Causality network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

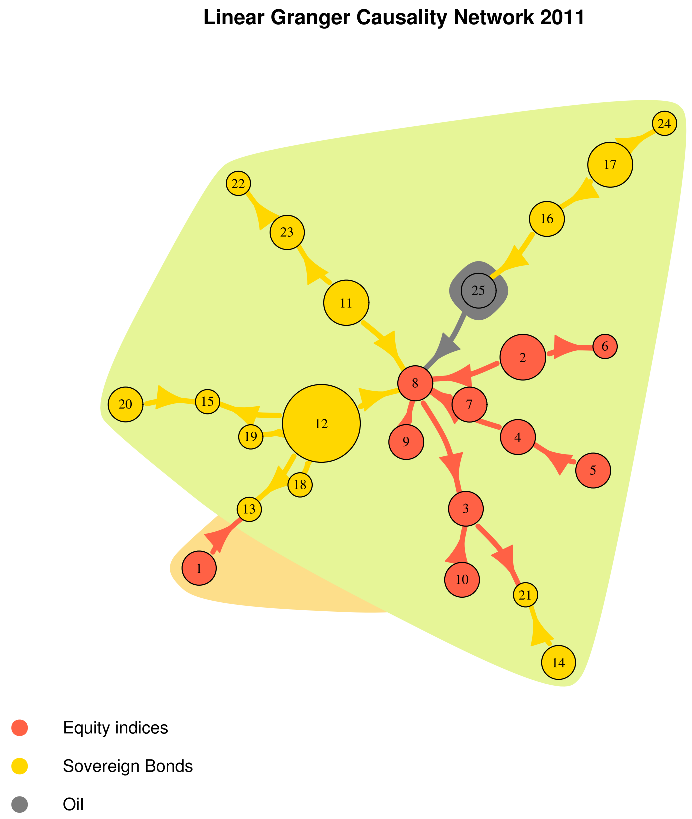

Figure 13 c: Linear Granger Causality network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

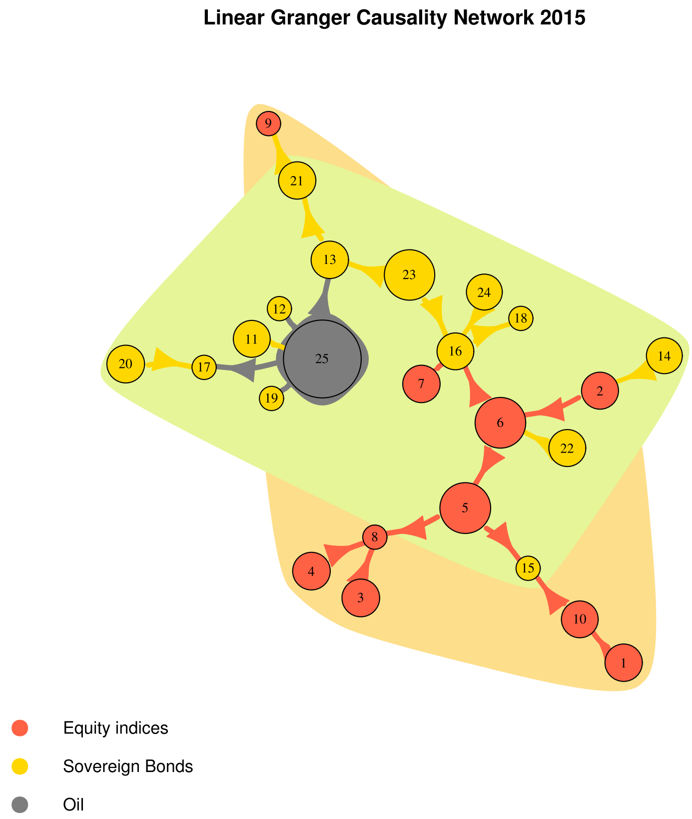

Figure 13 d: Linear Granger Causality network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

NGC appears to evolve in a parallel manner (see **Figures 14**) as that of *LGC*, no wonder given that those processes are quite similar. The only significant difference seems to occur during the global financial crisis. Contrary to the *LGC* case here we can see a very strong cluster of bonds with immense centrality, and on the opposite side an equities subgroup divided in three with *DowJones* as the stronget index. Again, *Oil* rises in significance during the Chinese stock market crash (see **Figure 14 d**).

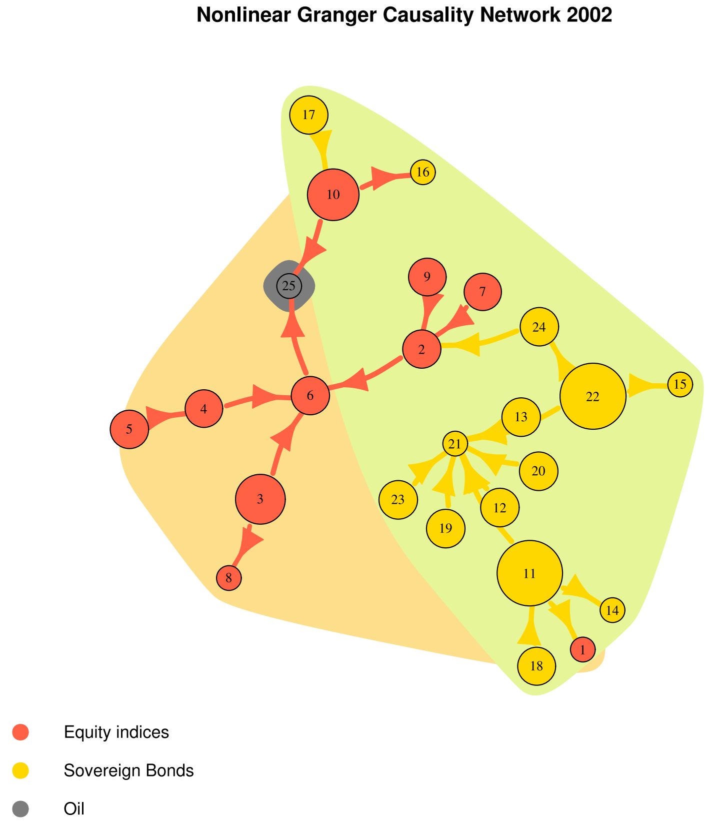

Figure 14 a: Nonlinear Granger Causality network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

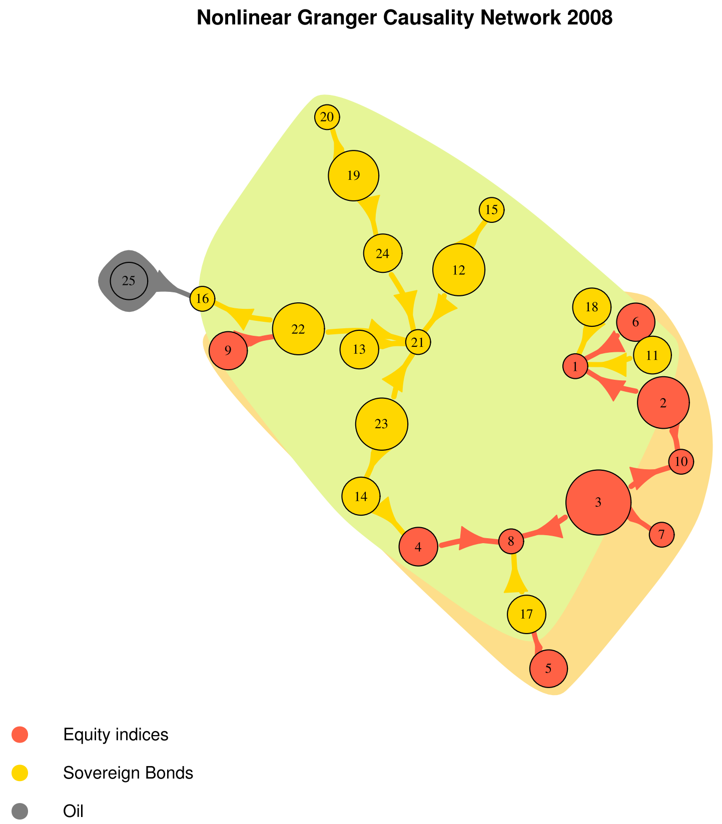

Figure 14 b: Nonlinear Granger Causality network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

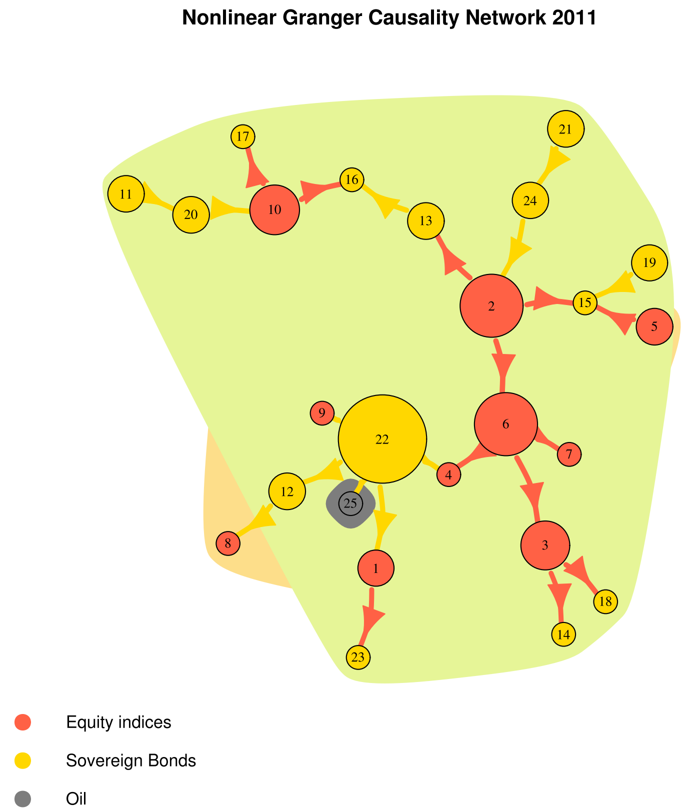

Figure 14 c: Nonlinear Granger Causality network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

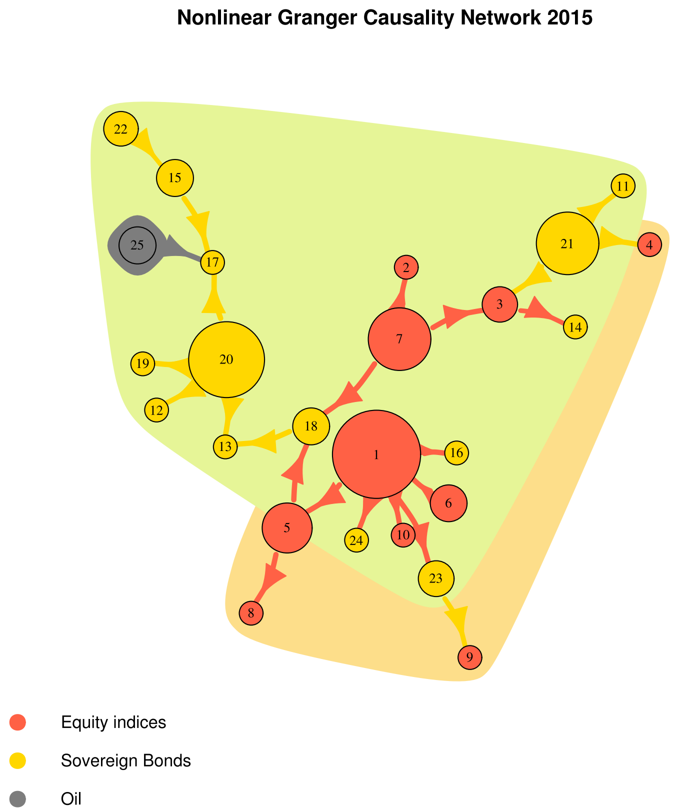

Figure 14 d: Nonlinear Granger Causality network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

Quite intriguing is the newtork as seen through SC (see **Figures 15**). During the post-Dotcom bubble burst we oberve an absolute balance between the equities and bonds, with *Oil* lying in the middle of the network. When the global financial crisis breaks out, the $3Y{-}Italian{-}bond$ (see **Figure 15 b**) polarises the financial network and renders the equities team disconnected. In the aftermath of the crisis, the $10Y{-}Greek{-}bond$ stands as the hub of the financial network (**Figure 15 c**). After four years, and into the Chinese stock market crash, the network appears quite clustered (see **Figure 15 d**) with equities and bonds having trivial and few interactions.

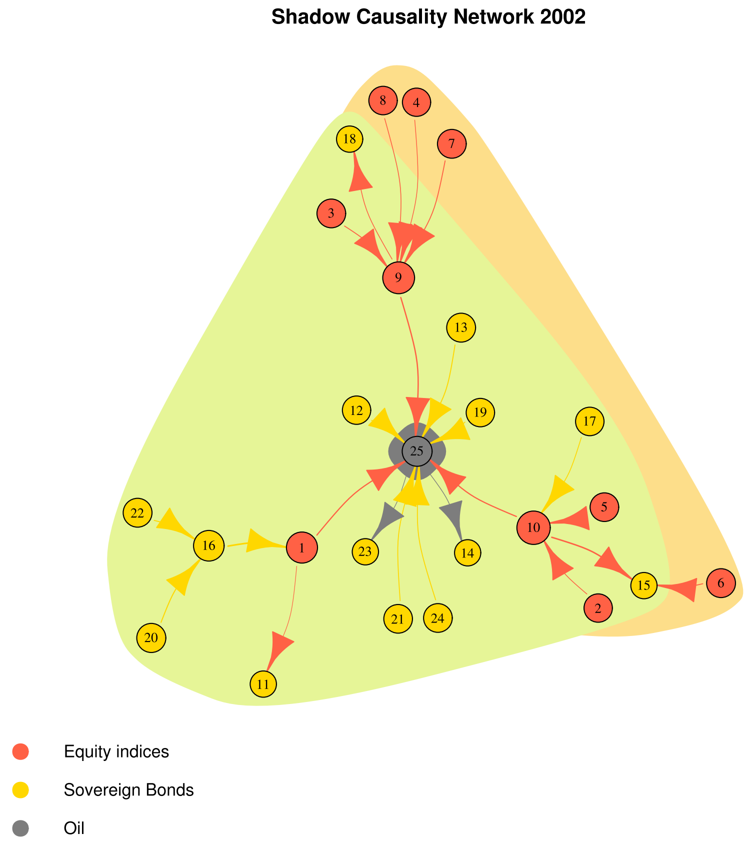

Figure 15 a: Shadow Causality network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

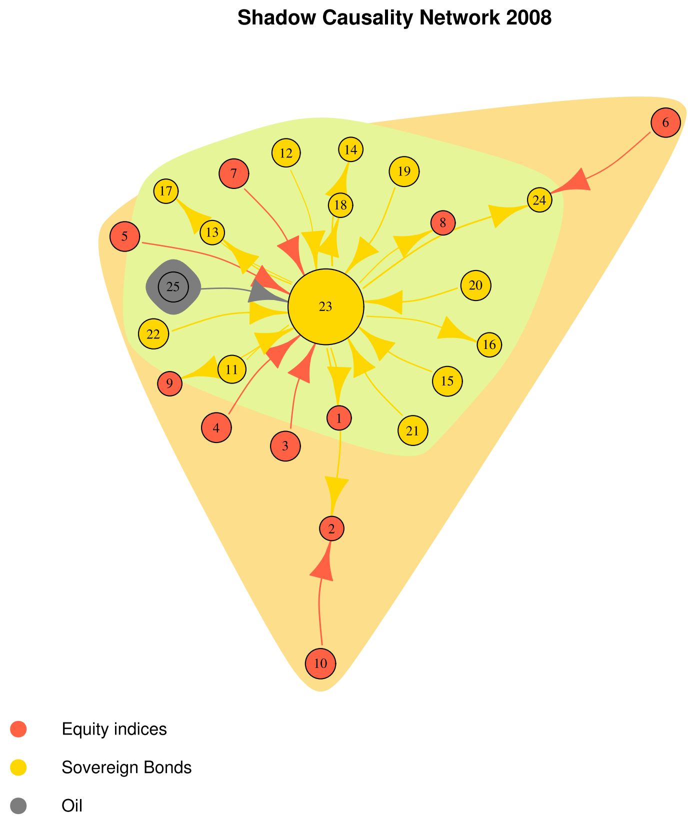

Figure 15 b: Shadow Causality network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

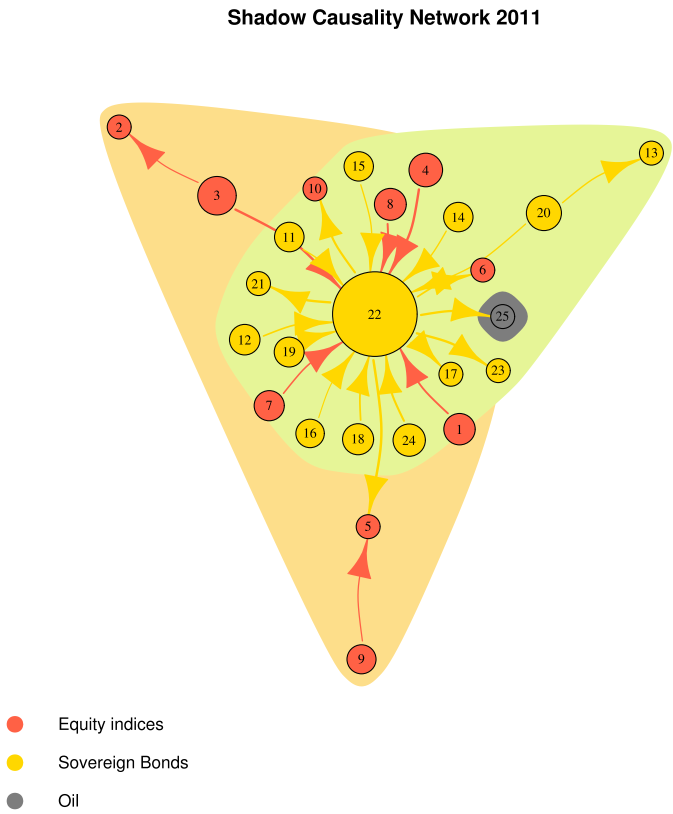

Figure 15 c: Shadow Causality network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

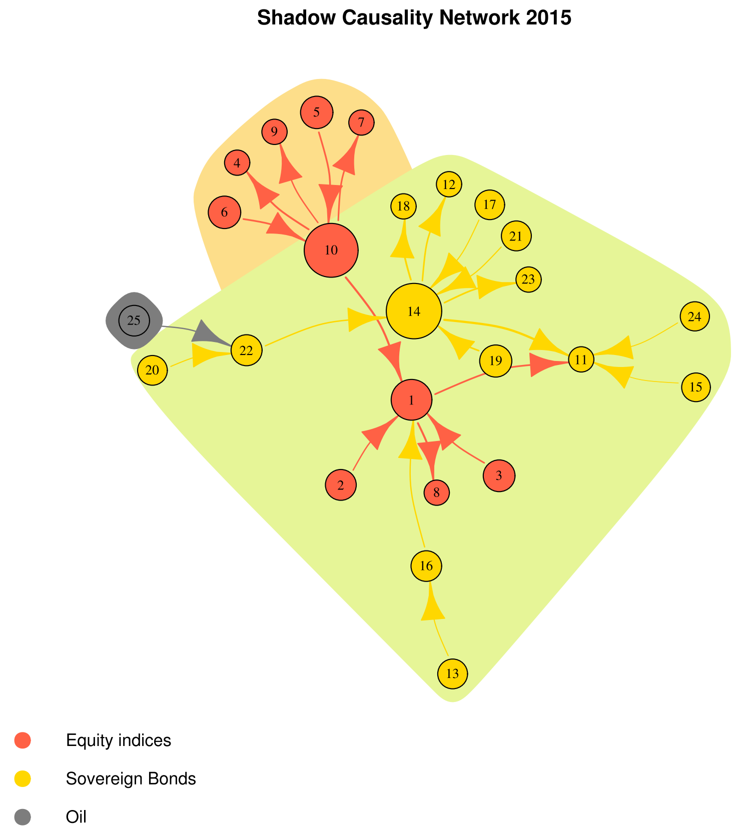

Figure 15 d: Shadow Causality network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

The last prism in our analysis (HC) further consolidates the existence of a *bonds regime* (see **Figures 16**). In the post-Dotcom bubble burst $SHANGHAI$ index with a group of other equities are causally affected by the bonds cluster. The bonds cluster is mostly led by $3Y{-}Italian{-}bond$ and $10Y{-}German{-}bond$ (see **Figure 16 a**). During the global financial crisis the equities group seems further scattered, while on the other hand bonds seem to be connected with even stronger causality relationships (see **Figure 16 b**). In the post-mortem of the global financial crisis the $10Y{-}USA{-}bond$, $2Y{-}USA{-}bond$ and $10Y{-}UK{-}bond$ appear to concentrate the majority of causal relationships. Ultimately, during the Chinese stock market crash we can see a network saturated absolutely by the bonds, with $10Y{-}German{-}bond$ and $10Y{-}Greek{-}bond$ being the undisputed hubs.

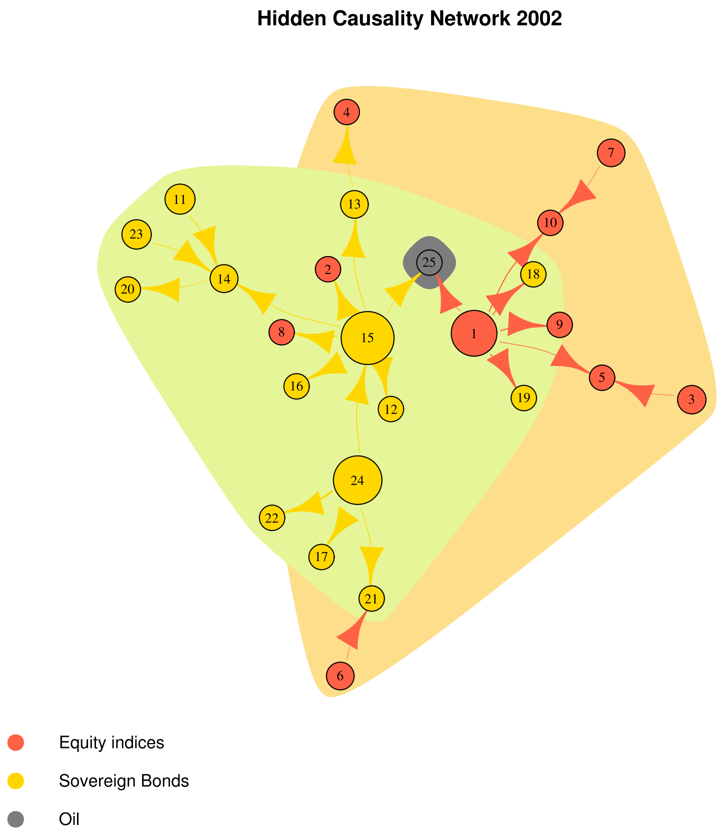

Figure 16 a: Hidden Causality network during the post-Dotcom bubble burst. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

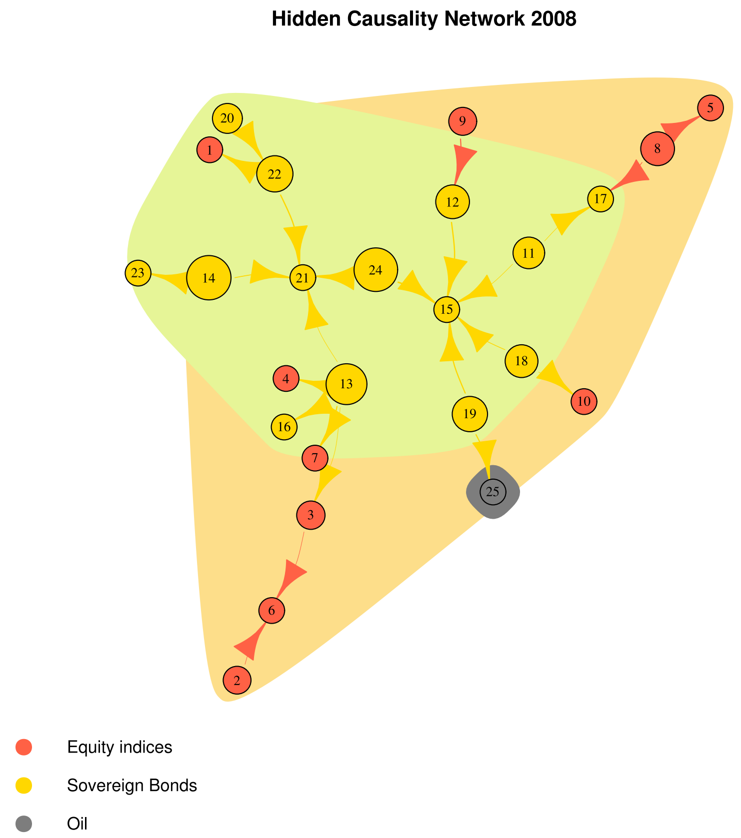

Figure 16 b: Hidden Causality network during the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

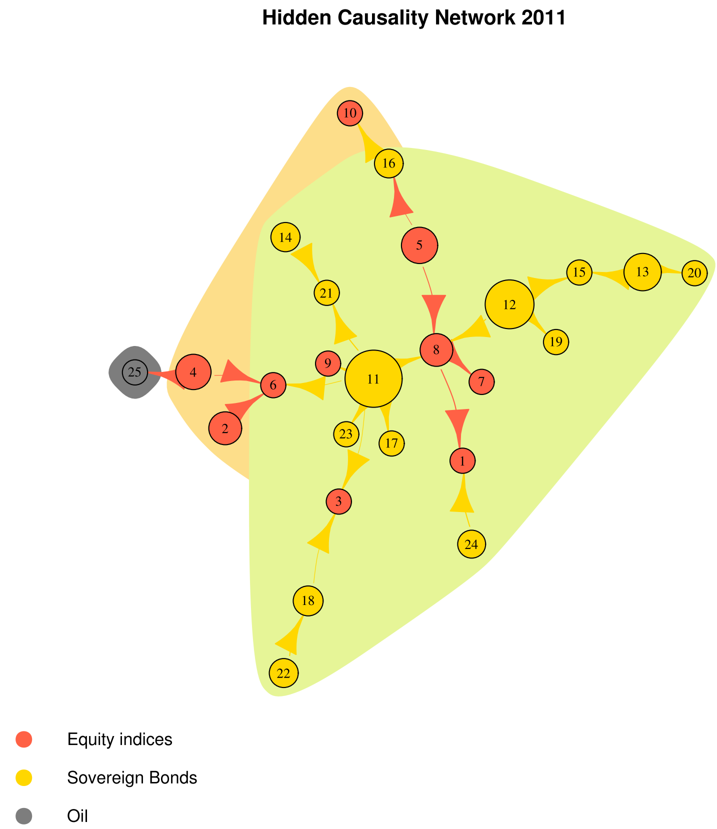

Figure 16 c: Hidden Causality network after the global financial crisis. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

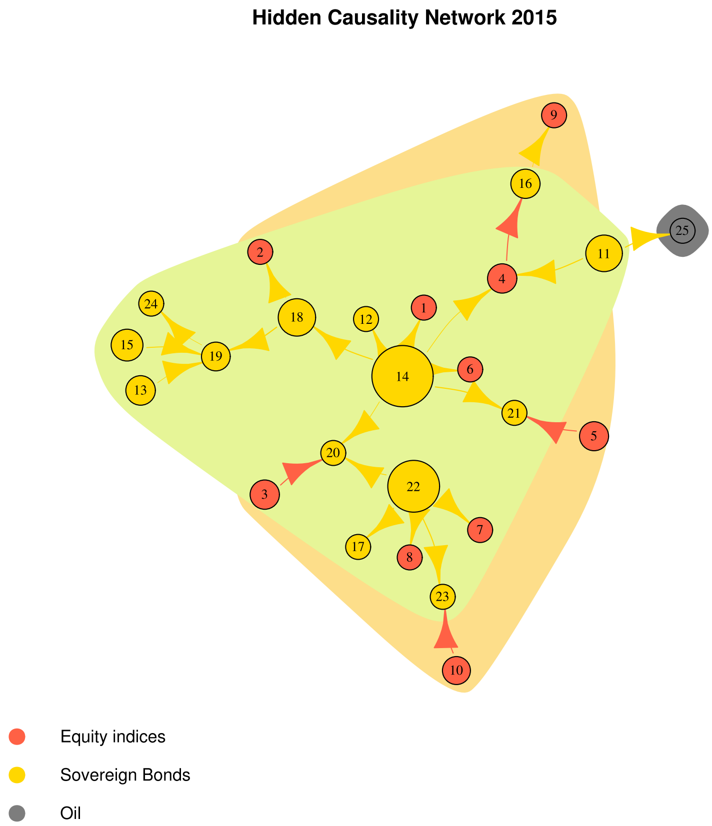

Figure 16 d: Hidden Causality network during the Chinese stock market crash. **Node Size:** analogous to the node's out-strength centrality. **Link Width:** analogous to the causality intensity. **Link Color:** denotes the causality's origin (node category according to legend in each plot) **Colored area:** helps understand visually the *dominant* asset category in terms of network area (light orange-red for equities, light yellow-green is used for bonds and grey for oil.)

5 Conclusion

Our results ascertain the existence of causal behavior among financial assets throughout the time period examined, with varying intensity according to the period under scrutiny. This outcome challenges the strongly supported theory of Efficient Market Hypothesis at least its strong form and opens new horizons for further analysis on market inefficiencies. We tested the similarity percentage of common links among all causality methods and found that the most similar pair of causality-induced network is on average less than 50% similar throughout the time period examined. Thus we consider it meaningless to try to compare results among different causality methods, every method deserves an explanation of their own. However, to our knowledge, our study is the first attempt to try and unify various causalities for the production and analysis of financial networks. Thirdly, we ranked the causal links as produced by each causality method and we found that the most intense and protracted relationship across all causality methods is that of $10Y{-}USA{-}bond \rightarrow (causing\ the\ prices\ of)\ 2to3Y{-}Spanish{-}bond$. Furthermore, we ranked the financial assets in terms of averaged causality emanation, and we uncovered a hidden "bonds regime" with the most causal asset being that of $USA\ 10\ year{-}bond$. Ultimately we observe a recurring pattern of Oil rising in terms of causality exertion as the financial network enters the Chinese stock market crash. Causalities cannot be used for forecasting asset prices directly, rather they are tools to detect causal relationships, and help in the modelling design process. Our future work will involve the use of causal networks as a basis for the scope of modelling and forecasting asset prices.

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