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LETTER FROM THE EDITORS-IN-CHIEF

Kimmo Soramäki and Tiziana Di Matteo
Financial Network Analytics Ltd. and King’s College London

Before discussing this issue of *The Journal of Network Theory in Finance*, we would like to welcome all the new members of our editorial board (www.risk.net/static/journal-of-network-theory-in-finance-editorial-board): an impressive team that we are honored to work with.

This issue contains three papers. The first paper, “Visibility graph combined with information theory: an estimator of stock market efficiency” by Bruna Amin Gonçalves and A. P. F. Atman, continues the flow of contributions generated by discussions and talks given at the Econophysics Colloquium in Brazil (www.econophysics-colloquium.org). This paper combines for the first time the visibility graph technique with information theory quantifiers, specifically the Shannon–Fisher plane, to study several stock market indexes from thirty-two different countries and perform an analysis in different time periods. The main outcome is that emerging countries display more persistence features than developed countries. This type of study demonstrates that techniques from statistical physics can be powerful when studying problems in finance and economics.

In the second paper, “Causality networks of financial assets”, Stavros K. Stavroglov, Athanasios A. Pantelous, Kimmo Soramäki and Konstantin Zuev present a comparative analysis of financial networks as produced by various causality methods. Their results contradict the efficient market hypothesis, opening new horizons for further investigation and possible arbitrage opportunities. The authors’ conclusion that causalities cannot be used for forecasting asset prices directly – rather, they are tools to detect causal relationships and help in the model-design process – raises questions and challenges standard approaches. The network visualization they provide will also help practitioners and scientists to see insights they could not have seen otherwise.

Silvio Schumacher provides evidence on the functioning of interbank money markets and the impact of market participants’ interconnectedness in “Networks and lending conditions: empirical evidence from the Swiss franc money markets”, this issue’s third and final paper. The author offers an empirical study of trading volume and interest rates in the secured and unsecured Swiss interbank markets. He computes various network statistics for both markets and uses these as exogenous variables in panel regressions for volume and interest rates. As it turns out, past network measures often appear as significant explanatory variables, and most of the effects found appear to be economically plausible.
Research Paper

Visibility graph combined with information theory: an estimator of stock market efficiency

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ABSTRACT

The visibility graph (VG) is a technique that acts as a bridge between dynamic systems and graph theory, and has been applied in recent years to analyze different systems in an innovative way. In this paper, we use information theory quantifiers to analyze the graphs generated by the VG method as applied to the return rate time series of stock markets from different countries between 1995 and 2016. In particular, we consider the degree probability distribution of the generated graphs to calculate Shannon entropy and Fisher information, in order to build the Shannon–Fisher plane. By analyzing the pattern of the countries along this plot, we demonstrate by this methodology that, on average, developed countries are concentrated at the top right-hand side of the plane, while emerging countries appear mostly at the bottom of the plane; we also identify markets that form a community. Moreover, when a separate analysis is applied to data considering two periods (before and after 2008), it is possible to detect significant
changes in the patterns, mainly for developed countries; this indicates a possible quantifier for the impact caused by the 2008 European crisis in the global markets.

**Keywords:** visibility graph; return rate time series; Shannon entropy; Fisher information; developed countries; emerging countries.

## 1 INTRODUCTION

Since the pioneering work of the French mathematician Bachelier in 1900, the analysis and modeling of financial markets has become an active field of research in economics. Ettore Majorana developed an analogy between statistical physics and economics (Fidomanzo and Majorana 2002), but it was only in the 1990s that several physicists began to get interested in this interdisciplinary subject (Chakrabarti *et al* 2007; de Oliveira *et al* 1999; Mandelbrot 1997; Sato and Takayasu 1998; Takayasu *et al* 1992). These efforts have culminated in a new interdisciplinary field, econophysics (Mantegna and Stanley 2000), gathering mathematicians, physicists and economists together to apply ideas, methods and models from statistical physics in order to analyze the market as a complex system (Atman and Gonçalves 2012; Cajueiro and Tabak 2004; Fan *et al* 2009; Horta *et al* 2014; Sensoy and Tabak 2016; Stefan and Atman 2015; Wei *et al* 2003).

In the last few decades, the study of financial time series has been attracting much of this community’s interest, particularly the analysis of trade market asset prices (Atman and Gonçalves 2012; Chakrabarti *et al* 2007; de Resende *et al* 2017; Fidomanzo and Majorana 2002). Several methodologies have been proposed by many authors in the quest to find a robust measure to quantify market efficiency (Cajueiro and Tabak 2008; Di Matteo *et al* 2005; Sun *et al* 2016; Zunino *et al* 2010). Due to the stochastic nature of these temporal series, tools from statistical physics, such as fractal geometry and the Hurst exponent, \( H \) (Hurst *et al* 1965), have been used to perform qualitative analyses of stock market return rate time series (Barabási and Vicsek 1991; Peng *et al* 1994; Simonsen *et al* 1998). For instance, Cajueiro and Tabak (2004, 2008) and Di Matteo *et al* (2005), among others, have observed that markets from emerging countries tend to display many persistence characteristics, while markets from developed countries present features of random walks, a behavior that is to be expected when considering the efficient market hypothesis. Recently, Horta *et al* (2014) and Sensoy and Tabak (2016) proposed that changes took place in time series characteristics after the financial crises of 2008 and 2010, mostly in developed countries, which have since become more persistence features.

Another technique commonly used to analyze financial time series comes from information theory. Many authors have proposed the use of quantifiers to measure
the risk of market crises; for instance, Risso (2008) used the Shannon entropy to evaluate the efficiency of five different countries (Japan, United States, Malaysia, Mexico and Russia). He considered the return rate of these markets and noted that in crisis periods the markets became less efficient. Risso (2008) also concluded that the United States seemed to be the most efficient market out of the countries surveyed. Zunino et al (2010), using two quantifiers of information theory combined with the Bandt and Pompe (BP) method (see Bandt and Pompe 2002), built a plane to evaluate the statistical complexity of the markets (Lamberti et al 2004; Rosso et al 2007). They were also able to classify their level of development.

Recently, a new approach was proposed to analyze time series of complex systems by mapping them to graphs (visibility graphs (VGs) (Lacasa et al 2008)). Some authors have successfully applied this technique to different economic systems, such as Wang et al (2012), who used quantifiers from graph theory (degree distribution, the clustering coefficient and the assortativity coefficient) to analyze the macroeconomic time series of Chinese banks. The authors concluded that government policies in China have a major influence on gross domestic product (GDP) dynamics. Long (2013) applied the methodology proposed in Lacasa et al (2009), combining the Hurst exponent with VG, to study the long-run correlation of price time series and return rates for gold in the London Bullion Market Association (LBMA). Zhuang et al (2014) analyzed the time series of financial markets from twenty-two developed countries via VG to show that it is possible to correlate such results with important incidents that affect the market, such as the financial crisis of 2008.

In a recent work, Ravetti et al (2014) proposed combining a horizontal visibility graph (HVG) with quantifiers from information theory to quantify the information dynamics across a time series, distinguishing stochastic processes from chaotic ones. Along the same lines, Gonçalves et al (2016) applied this methodology to characterize the temporal dynamics during the Holocene epoch by means of El Niño–Southern Oscillation (ENSO) proxy records.

In this paper, we propose combining the VG technique with quantifiers of information theory, specifically the Shannon–Fisher plane built from degree distribution, to study stock market indexes from thirty-two countries according to the degree of development of those countries. Also, considering two separate periods for the data temporal span, one from 1995 to 2007 and another between 2007 and 2016, it is shown that the pattern displayed in the Shannon–Fisher plane has experienced a significant change since 2008.

This work is organized as follows. In Section 2, we describe the VG and quantifiers of information theory used. In Section 3, our results and discussions are presented. Finally, we present our conclusions and acknowledgements in Section 4.
2 METHODS

2.1 Visibility graph

Lacasa et al (2008) proposed the VG method for mapping a time series in a graph while maintaining the inherent characteristics of the transformed time series. To construct a graph using this method, the nodes should have the same order as the data set of the corresponding time series. If a straight line can be drawn that connects two points of the data series without crossing the height of the intermediate terms between them, the corresponding nodes are connected by an edge, ie, there is visibility between this data.

Formally, the criterion established for visibility is the following: two arbitrary values of the time series \((x_a, y_a)\) and \((x_b, y_b)\) share visibility and, thus, become two nodes connected by an edge in the corresponding graph, if all other intermediate terms \((x_c, y_c)\) between them satisfy the relationship

\[
y_c < y_b + (y_a - y_b) \frac{x_b - x_c}{x_b - x_a}.
\]

In the VG, the nodes can see at least their nearest neighbors and incorporate the time causality in a natural way. Figure 1 shows the mapping by VG, amplifying the first twenty data points obtained from a return rates time series of Argentina, the graph and degree distribution.

The transformation of a time series into a graph is quite promising, because it allows us to use the tools developed in graph theory to investigate, quantify and analyze several systems. Among these tools, we highlight network quantifiers and different possibilities of extracting the probability distribution function (PDF), such as the classic degree distribution, the distribution of edge amplitudes and the distance-between-edges distribution. Thus, these PDFs may be used both in the evaluation of the quantifiers of information theory and in the analysis of parameters of the functional that relates the PDF to a given quantity, eg, the entropy (Donner and Donges 2012; Gonçalves et al 2016; Lacasa et al 2009; Ravetti et al 2014).

Distribution of degree \(P_{\text{deg}}\)

For a given network \(G\) with \(N\) nodes, the degree distribution, \(P_{\text{deg}}(\kappa)\), is associated with the probability that a randomly chosen node has degree \(\kappa\). This discrete distribution is defined on the set \(\{0, 1, \ldots, N - 1\}\).

2.2 Shannon entropy \(S\)

When considering the probability distribution \(P = \{p_i; i = 1, \ldots, N\}\) of a discrete random variable, with \(\sum_{i=1}^{N} p_i = 1\), the calculation of Shannon entropy \(S\) (Shannon 1948) is given by \(S[P] = -\sum_{i=1}^{N} p_i \ln(p_i)\).
FIGURE 1  Example of the transformation of a time series into a graph (VG) and the corresponding degree distribution.

(a) Stock market time series of Argentina (ARGENTINA MERVAL INDEX) and the associated return rate series. (b) Network building procedure by the VG technique. For better visualization, only the first twenty data points from the return rate time series were considered. We have added a baseline to the data to improve visualization, avoiding negative return rate values. (c) VG generated considering the entire time series (about 5,200 nodes). (d) Degree distribution $P_{\text{deg}}$ obtained from the graph shown in (c).

In Shannon (2001), the calculation of entropy is analyzed in the case of two probabilities $p$ and $q = 1 - p$, so we have that $S = -p \ln p - q \ln q$. Therefore, it is observed that

- $S = 0$ if and only if $p = 0$ or $p = 1$; that is, only if one has complete knowledge of the system; and
- $S_{\text{max}}$ is equal to $\ln 2$ when both odds are equal, $p = q = \frac{1}{2}$; that is, when knowledge of the system is uncertain.

For the case of networks, our knowledge of the underlying process is maximal for regular networks, where entropy is $S_{\text{min}} = S_{\text{regular}} = 0$ (same degree for all nodes).
However, our ignorance is maximal for a random network with a uniform distribution of links, in which the entropy $S_{\text{max}} = S_{\text{random}}$ is maximum. For a given distribution $P$, the “normalized Shannon entropy” is thus computed as $\delta[P] = S[P]/S_{\text{max}}$. For the case of degree distribution, $S_{\text{max}} = \ln(M)$, where $M$ is the number of nodes in the network. In this paper, we consider the degree distribution to calculate Shannon entropy.

### 2.3 The Fisher information measure

The Fisher information measure $\mathcal{F}$, a very important estimator in statistics, quantifies uncertainty regarding an orderly space when a given probability distribution is being considered. $\mathcal{F}$ constitutes a measure of the gradient content of the distribution; it is quite sensitive even to small localized perturbations (Fisher 1922; Friden 2004).

In the case of a discrete distribution function, the more suitable Fisher information measure (Fisher 1922) is defined as

$$\mathcal{F}[P] = F_0 \sum_{i=1}^{N-1} [(p_{i+1})^{1/2} - (p_i)^{1/2}]^2. \tag{2.2}$$

Here, the normalization constant $F_0$ reads as follows (Sánchez-Moreno et al 2009): $F_0 = 1$ if $p_{i^*} = 1$ for $i^* = 1$ or $i^* = N$ and $p_i = 0$ for all $i \neq i^*$, and $F_0 = 1/2$ otherwise.

An important consequence of this definition is that if $\mathcal{F}[P] = \mathcal{F}_{\text{max}}$, it is possible to predict with certainty the possible outcomes of $i$, ie, knowledge of the system is maximal. However, when $\mathcal{F}[P] = 0$, there is a complete incertitude about the system. That is, one can state that the general behavior of the Fisher information measure is the opposite of that exhibited by the Shannon entropy.

### 2.4 Shannon–Fisher information plane

The causal Shannon–Fisher plane, $(\delta \times \mathcal{F})$, introduced by Vignat and Bercher (2003), is a planar representation. Here, the axes are functions of the probability density considered, the normalized Shannon entropy in the abscissa and the Fisher information measure in the vertical axis. This tool is a convenient way to represent, in the same information plane, global and local aspects of the discrete distribution function associated with the system being studied. In the last few years, the $(\delta \times \mathcal{F})$ plane has been applied in several works (Gonçalves et al 2016; Olivares et al 2012; Ravetti et al 2014).
TABLE 1  World stock indexes.

<table>
<thead>
<tr>
<th>Country</th>
<th>Classification</th>
<th>Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Argentina</td>
<td>E</td>
<td>ARGENTINA MERVAL INDEX</td>
</tr>
<tr>
<td>2 Australia</td>
<td>D</td>
<td>ALL ORDINARIES INDEX</td>
</tr>
<tr>
<td>3 Austria</td>
<td>D</td>
<td>AUSTRIAN TRADED ATX INDEX</td>
</tr>
<tr>
<td>4 Belgium</td>
<td>D</td>
<td>BEL 20 INDEX</td>
</tr>
<tr>
<td>5 Brazil</td>
<td>E</td>
<td>BRAZIL BOVESPA STOCK INDEX</td>
</tr>
<tr>
<td>6 Canada</td>
<td>D</td>
<td>S&amp;P/TSX COMPOSITE INDEX</td>
</tr>
<tr>
<td>7 Chile</td>
<td>E</td>
<td>CHILE STOCK MARKET SELECT INDE</td>
</tr>
<tr>
<td>8 Denmark</td>
<td>D</td>
<td>KFX COPENHAGEN SHARE INDEX</td>
</tr>
<tr>
<td>9 Finland</td>
<td>D</td>
<td>HEX GENERAL INDEX</td>
</tr>
<tr>
<td>10 France</td>
<td>D</td>
<td>CAC 40 INDEX</td>
</tr>
<tr>
<td>11 Germany</td>
<td>D</td>
<td>DAX INDEX</td>
</tr>
<tr>
<td>12 Greece</td>
<td>E</td>
<td>ASE GENERAL INDEX</td>
</tr>
<tr>
<td>13 Hong Kong</td>
<td>D</td>
<td>HANG SENG INDEX</td>
</tr>
<tr>
<td>14 Hungary</td>
<td>E</td>
<td>BUDAPEST STOCK EXCHANGE INDEX</td>
</tr>
<tr>
<td>15 India</td>
<td>E</td>
<td>MUMBAI SENSEX 30 INDEX</td>
</tr>
<tr>
<td>16 Indonesia</td>
<td>E</td>
<td>JAKARTA COMPOSITE INDEX</td>
</tr>
<tr>
<td>17 Ireland</td>
<td>D</td>
<td>IRISH OVERALL INDEX</td>
</tr>
<tr>
<td>18 Japan</td>
<td>D</td>
<td>NIKKEI 225 INDEX</td>
</tr>
<tr>
<td>19 Korea</td>
<td>E</td>
<td>KOREA COMPOSITE INDEX</td>
</tr>
<tr>
<td>20 Malaysia</td>
<td>E</td>
<td>KUALA LUMPUR COMP INDEX</td>
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<tr>
<td>21 Mexico</td>
<td>E</td>
<td>MEXICO BOLSA INDEX</td>
</tr>
<tr>
<td>22 Philippines</td>
<td>E</td>
<td>PHILIPPINES COMPOSITE INDEX</td>
</tr>
<tr>
<td>23 Poland</td>
<td>E</td>
<td>WSE WIG INDEX</td>
</tr>
<tr>
<td>24 Portugal</td>
<td>E</td>
<td>LISBON BVL GENERAL INDEX</td>
</tr>
<tr>
<td>25 Sri Lanka</td>
<td>E</td>
<td>COLOMBO STOCK EXCHANGE</td>
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<tr>
<td>26 Spain</td>
<td>D</td>
<td>S&amp;P 500 INDEX</td>
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<tr>
<td>27 Sweden</td>
<td>D</td>
<td>OMX STOCKHOLM INDEX</td>
</tr>
<tr>
<td>28 Switzerland</td>
<td>D</td>
<td>SWISS MARKET INDEX</td>
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<tr>
<td>29 Taiwan</td>
<td>E</td>
<td>TAIWAN WEIGHTED INDEX</td>
</tr>
<tr>
<td>30 Thailand</td>
<td>E</td>
<td>STOCK EXCHANGE OF THAILAND INDEX</td>
</tr>
<tr>
<td>31 United Kingdom</td>
<td>D</td>
<td>FTSE 100 INDEX</td>
</tr>
<tr>
<td>32 United States</td>
<td>D</td>
<td>S&amp;P 500 INDEX</td>
</tr>
</tbody>
</table>

Emergent and developed stock markets are denoted as E and D, respectively.

3 EMPIRICAL RESULTS

In this paper, we analyze the prices of thirty-two equity indexes for different countries during the period between January 1995 and May 2016. The names of these indexes are presented in Table 1. All data was collected from the Bloomberg database (Bloomberg 2016).
We calculated the exchange index return rates temporal series for each index. Then, the data was mapped by VG, and the values of normalized Shannon entropy $\delta$ and the Fisher information measure $\mathcal{F}$ were computed using the degree distribution $P_{\text{deg}}$. Thus, we were able to construct the Shannon–Fisher plane, $\delta \times \mathcal{F}$. The Shannon entropy values were normalized using the maximum entropy value $S_{\text{max}} = \ln(M)$, where $M$ is the length of the series (in number of points). Figure 1 exemplifies how the degree distribution is obtained from the return rate time series.

Initially, a global analysis considering the whole series from 1995 to 2016 (approximately 5300 points) was made, as shown in Figure 2(a). Then, a second analysis was made, taking two sets of data separately: one from 1995 to 2007 (approximately 3200 points) and another comprising the period 2008–16 (approximately 2100 points), thus separating the periods before and after the crisis of Europe in 2008, as shown in Figures 2(b) and 2(c).

In each plane, a linear fit was drawn in the values of $S$ and $\mathcal{F}$. Then, two straight lines perpendicular to the adjusted line were drawn; these were shifted, with the first (in blue) moving to the highest point of an emerging country and the second (in red)
moving to the lowest point of a developed country. Thus, the triangles in blue and red were formed from these lines. (The constructions are presented in our online supplementary material.)

### 3.1 Degree distribution of $P_{\text{deg}}$

From the degree distribution, it is possible to note that, for data comprising the entire period from 1995 to 2016, developed countries, on average, present the highest values of $\mathcal{F}$ and lower values of $\delta$, as seen in the Shannon–Fisher plane (Figure 2). The developed countries are concentrated at the top left-hand side of the plane, as indicated by the blue triangular area. The emerging countries appear mostly at the bottom of the plane, as indicated by the red triangular area.

If we consider an analogy with the VG results applied to fractional Brownian motion (fBm) and fractional Gaussian noise (fGn) series, correlated with the Hurst exponent $H$ (Lacasa et al 2009), where the authors have demonstrated that there is a monotonic relation between the degree distribution and the Hurst exponent, we are able to extract persistence information about the markets analyzed. An increase in persistence can be
associated with longer sequences of increasing and/or decreasing values, a behavior that generates deep “valleys” and high “mountains” in the profiles, increasing the visibility of certain nodes. So, the corresponding VG will reflect this effect by increasing the degree of certain nodes, leading to a less concentrated degree distribution and higher values of Shannon entropy (lower values of the Fisher information measure). This behavior is illustrated in our online supplementary material.

Another feature observed in the degree distribution is the leptokurtic nature of the distributions. The kurtosis calculations indicate that, on average, the degree distributions of emerging countries are more flattened (with average kurtosis values equal to $-2.8048$ for emerging markets and $-2.784$ for developed ones), a behavior that explains the higher values of $\delta$ observed for these countries. Therefore, this result confirms those of previous works, which have claimed that, on average, indexes of emerging countries tend to display more persistence than those of developed countries; this is by means of Hurst exponent analysis of the return rate indexes (Cajueiro and Tabak 2004, 2008; Di Matteo et al 2005).

Another feature we can extract from these distributions is the power law behavior of the degree distribution, $P_{\text{deg}}(k) \sim k^{-\alpha}$, with $2 < \alpha < 3$, as shown in Figure 3. This
FIGURE 3  Degree probability distributions, $P_{\text{deg}}$, of Germany and Sri Lanka.

(a) Degree distribution $P_{\text{deg}}$ extracted from the graph for Germany (black squares) and Sri Lanka (blue circles).
(b) Distribution on logarithmic scales for Germany (green line) and Sri Lanka (red line). The power law distribution for the degree distributions, $P_{\text{deg}}(k) \sim k^{-\alpha}$ from $k = 3$, is quite evident, with exponents $\alpha = 2.56$ for Germany and $\alpha = 2.31$ for Sri Lanka. The period considered for the power law fitting was January 1995–May 2016.

This figure compares Sri Lanka with Germany. (Additional results for the other countries are presented in our online supplementary material.)

When the data is analyzed in separated periods, for the first range from 1995 to 2007, one can observe that, on average, the developed countries have larger values of $F$ and lower values of $S$, and, thus, lower entropies. In the subsequent period (2008–2016), we observe that these countries perform a displacement to the right-hand side in the plane $F \times S$, occupying the upper-right side, as evinced by the blue triangular area in Figure 2(c). This is a remarkable confirmation that changes are occurring in the persistence features of the indexes for these countries. Regarding the emerging countries that are initially concentrated in a central-lower position, as indicated by the red triangular area, our analysis comparing the two separate temporal ranges indicates a displacement toward the right, but one that is a bit less remarkable than
that observed for the developed countries. These results indicate a possible change in
the persistence characteristics of the market indexes after the 2008 crisis, especially
for developed countries; this corroborates previously reported observations (Cajueiro

4 CONCLUSIONS

In this work, the stock market series of thirty-two countries were analyzed using the
Shannon–Fisher plane built from the degree PDF, obtained via the VG technique.
Analyses were performed in three different periods: January 1995–May 2016, Janu-
ary 1995–December 2007 and January 2008–May 2016. As was observed in all peri-
ods, the emerging countries have, on average, larger values for the Shannon entropy
and lower values for the Fisher information measure. Correlating these results with
analyses made with fBm and fGn, we conclude that emerging countries display more
persistence features than developed ones. In addition, it was possible to verify that
in the period between January 2008 and May 2016, significant changes caused by
Europe’s 2008 crisis affected the persistence features in these markets. In summary,
we propose an alternative methodology that can be considered a statistical physics
approach and should be very useful for studying problems in economics.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the
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REFERENCES

Atman, A., and Gonçalves, B. A. (2012). Influence of the investor’s behavior on the com-
fvrwc).


Visibility graph combined with information theory


Research Paper

Causality networks of financial assets

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ABSTRACT

Through financial network analysis we ascertain the existence of important causal behavior between certain financial assets, as inferred from eight different causality methods. To the best of our knowledge, this is the first extensive comparative analysis of financial networks as produced by various causality methods. In addition, some specific nonlinear causalities are used for the first time in 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 have warned us about the financial crisis of 2007–9. 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, thus rendering the comparability and substitutability of these 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 monopolizing (in some cases) the causality methods. Finally, using network visualization, we observe an established
pattern (ie, across all causalities) of oil’s increasing role as the financial network faced the Chinese stock market crash.

Keywords: causality; efficient market hypothesis; network theory; bonds; oil.

1 INTRODUCTION

At the dawn of the twenty-first century, we faced financial turbulence that rippled across stock markets throughout the world in a domino effect. The global financial crisis of 2007–9 still echoes in the minds of traders, scientists and laymen and shook the very foundations of traditional economics and forecasting methods, which failed not just to predict but also to prevent the calamity to come. One possible explanation of such a failure could be the fact that traditional economics focuses on the isolated analysis of individual financial assets, eg, market indexes, bonds, stocks and commodities. By “isolated” we here mean disconnected from their kin-dred, ie, by ignoring their interactions with other financial assets. Nonetheless, there are many reasons to defy the bias for disconnection between assets. First, assets are more often than not traded in portfolios of at least a dozen and subject to a common strategy. In fact, portfolios of assets are the norm, as opposed to 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), and are thus to some extent interrelated. Second, if we think of the asset prices as financial embodiments of companies (equities, bonds), national governments (sovereign bonds) and essential market products (commodities), we cannot neglect the causal interactions between them. For example, an increase in oil prices can cause a decrease in demand for airline services; an innovation in the telecommunications industry can be patented and reverse the market share of the competitors; an increase in the rates of government bonds directly affects stock market investments. Finally, the psychology of people involved in a specific (national) stock market may be at least partly affected by the fluctuations of stock markets in other countries, eg, the news of a stock market crash can cause fear and panic beyond the national borders, affecting the international “big game”. Add to these the cases of large capitalization international funds that invest in many stock markets, and we have more than enough reasons to scrutinize the causality between financial assets.

The relationship between a variable (the cause), whose past performance influences the future output of another variable (the effect), is known as “causality” (Pearl 2003). Scientists from various disciplines have developed methods to quantify causality in time series, despite the fact that not all of them use this terminology exclusively.
Statisticians, in 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 in 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, in both its linear (Granger 1969) and nonlinear (Hiemstra and Jones 1994) forms, was also established in their field. Last, physicists, mostly from the discipline of information theory, created indexes of mutual information (Granger and Lin 1994) and transfer entropy (Schreiber 2000) that quantify, in a model-free way, the relationships between variables. In this paper, we shall use the above collection of eight causality methods to capture the evolution of average causality in a financial network of assets consisting of various national market indexes, sovereign bonds and oil prices, in the periods 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. We want to examine the ability of causality to serve as an early warning signal for systemic financial collapse. We are also interested in exploring whether or not any arbitrage opportunities arise, through, for example, persistent and strong causal relationships between assets. Last, we wish to scrutinize the less explored discipline (compared with correlation) of causalities in financial networks.

Our choice of assets from various national markets rather than from an individual stock market is deliberate. Given that we aim to study the evolution of causality throughout the global financial crisis, we choose both indexes and bonds from countries most representative of the ensuing turmoil. Specifically, we choose market indexes from the United States, China, Brazil, Germany, France, Japan, Hong Kong, Australia and India, as they are countries with large stock market capitalization. For government bonds, we choose the United States, the United Kingdom, Germany, Japan, Australia, Switzerland, Spain, Italy and Greece, because we consider these governments to have been the most involved in or affected by the crisis. In our analysis we also include the price of oil: a commodity strong enough to cause a crisis on its own (as in the case of the 1973 oil crisis). As the period we choose for analysis (2000–16) saw extensive use of the Web and social media to enable the international transmission of stock market news and shocks faster than ever before, this necessitates the use of data from many countries. Our study looks at a significant portion of the global financial system during a period of extreme disorder, through the lens of multidisciplinary causality methods.
1.2 Results

We study the evolutionary behavior of the average causality in our financial network. This analysis is conducted for each of the eight causality methods mentioned above. Our results ascertain the existence of significant causal behavior between assets throughout the time period examined. According to Hawawini (1980), Atchinson et al (1987), Lo and MacKinlay (1990), Chowdhury (1991) and Fiedor (2014a,b) the very existence of causality in financial assets challenges the foundations of the well-known “efficient market hypothesis”. The efficient market hypothesis has three forms: “weak”, “semi-strong” and “strong”. The weak form claims that asset prices already reflect all publicly available information. The semi-strong form includes the weak form’s characteristic and additionally claims that prices change instantly to reflect new public information. The strong form additionally claims that prices instantly reflect even hidden “insider” information.

Our results evidently defy the efficient market hypothesis in its strong form, and possibly also in its semi-strong form, given that causality has to do with assimilation of not only current but also past information. For our analysis we consider that the global crisis was “born” on August 9, 2007, as this is the most widespread view based on a Google search. More specifically, results from linear intertemporal cross-correlation do not imply any predictive capabilities, given that the average causality it measures begins to drop in parallel with the development of the global financial crisis, rather than before it. However, average causality as measured by nonlinear intertemporal cross-correlation could be a candidate for an early warning signal, given that almost half a year before the crash (at the start of 2007) it started dropping to all-time lows, and then as the crisis unfolded it started to rise more steeply than ever before. Linear cointegration analysis does not show 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 rises steeply. Both linear and nonlinear Granger causality showed no change in their average causality before or during the global crisis. Despite the fact that shadow causality (based on mutual information) displays no forecasting capabilities, it somehow “fits” the characteristics of the crisis period by displaying a dramatic drop right after the “birth” of the crisis, after a protracted upward trend. Similarly, hidden causality (based on transfer entropy) simply changes its trend from horizontally fluctuating to slightly downward after the emergence of the crisis. With the exception of nonlinear intertemporal cross-correlation and nonlinear cointegration, the methods simply follow the emergence of financial turbulence, serving at best as contemporaneous crisis indicators and not as early warning signals. However, these results by no means suggest that the remaining six causality methods are incapable of serving as early warning signals, only that they must be subjected to further scrutiny.
In order to assess whether or not any comparative analysis of the eight causality methods is meaningful, we test the similarity of common links that remain in the financial network (after filtering for the optimal links in terms of the maximum spanning tree) and find that the most similar pair of causality-induced networks is that of linear intertemporal cross-correlation and linear cointegration methods, which score a 48.74% average similarity throughout the time period examined. Thus, we consider it meaningless to try to compare the results of different causality methods, at least through our choice of filtering (maximum spanning tree).

In order to gain portfolio-specific insights, we delve into network analysis, and specifically link persistence and asset centrality. Toward that end we rank the causal links produced by each causality method and find that the most intense and protracted relationship across all causality methods is that of the ten-year US bond causing the prices of the two- to three-year Spanish bond (where price causation is denoted by “→”). The latter relationship can be considered a strong candidate for arbitrage opportunities. Finally, we rank all twenty-five of the financial assets under study in terms of averaged causality issuing to the network by means of out-strength centrality, and find that the most causal asset overall seems to be the ten-year US bond. Nevertheless, in general, sovereign bonds ranked better than equities and oil, particularly 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 (Arnold 2011), 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 formulas and review the literature for each of the eight causality methods and discuss their significance to finance. In Section 3 we provide details regarding our choice of data set. 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 quantified as the impact that an asset’s past price performance has on another asset’s future price performance. Embedded in the nature of causality is some form of predictive potential, ie, 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 asset’s 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, time-delayed cross-correlation or time-dependent cross-correlation. Hawawini (1980) was the first researcher to implement it in the finance literature, and we present the formula below:

$$\text{LICC}_{\Delta t}^{xy} = \frac{(R_{\Delta t}^x(t)R_{\Delta t}^y(t + \tau)) - (R_{\Delta t}^x(t))(R_{\Delta t}^y(t + \tau))}{\sqrt{\left[(R_{\Delta t}^x(t)) - (R_{\Delta t}^x(t))\right]^2\left[(R_{\Delta t}^y(t) - \tau) - (R_{\Delta t}^y(t + \tau))\right]^2}}, \quad (2.1)$$

where $R_{\Delta t}^x(t) = \log[p(t)] - \log[p(t - \Delta t)]$ is the log return of the price, $p(t)$, of an asset at a certain time $t$. $\Delta t$ denotes the time interval between the log returns, usually one time unit. $\tau$ denotes the intertemporal delay between the two assets, $(R_{\Delta t}^x(t))$ denotes the mean of $R_{\Delta t}^x(t)$, and $x$ and $y$ denote the two assets.

**Remark 2.1** When $\tau = 0$, the LICC coincides with the Pearson product moment correlation coefficient. $R_{\Delta t}^x(t)$ takes values from $-1$ to $+1$. When $R_{\Delta t}^{xy}(t) < 0$, this means that asset $x$ has a reverse effect on asset $y$, ie, if yesterday’s return on asset $x$ increases, then today’s return on asset $y$ will decrease, and vice versa. When $R_{\Delta t}^{xy}(t) > 0$, this means that asset $x$ has a same-direction effect on asset $y$, ie, if yesterday’s return on asset $x$ increases, then today’s return on asset $y$ will also increase. If $R_{\Delta t}^{xy}(t) = 0$, this means that asset $x$ has no effect on asset $y$.

In the finance literature, there are three dominant hypotheses that aim to explain the lead–lag relationships between assets. These hypotheses are (Lo and MacKinlay 1990)

(1) nonsynchronous trading,

(2) the speed of price adjustment hypothesis, and

(3) the stock market overreaction hypothesis.

We found some implications of these hypotheses regarding the realization of lead–lag effects and their significance in terms of the efficient market hypothesis. More specifically, the existence of intertemporal cross-correlations between asset returns implies a deviation from the efficient market hypothesis, and thus provides a probabilistic glimpse at the future asset prices (Atchinson et al 1987; Lo and MacKinlay 1990; Hawawini 1980).

Kullmann et al (2002) employed the LICC index to analyze a network of equities from the New York Stock Exchange (NYSE). They suggested that the existence of such causal relations is due to the functional interactions between the companies that are represented by the equities in their data set. Mizuno et al (2004) examined LICC in data for 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 the United States and

The advantage of LICC is that it captures the direction of influence between asset returns, unlike the Pearson product moment correlation coefficient, which just captures naive correlations. However, LICC has one disadvantage that cannot be ignored: it only takes into account linear causal relationships. It cannot capture nonlinear causal relationships. Therefore, next we present nonlinear intertemporal cross-correlation.

### 2.2 Nonlinear intertemporal cross-correlation

The inability of LICC to capture nonlinear intertemporal relations can be overcome by employing the nonlinear intertemporal cross-correlation (NICC). This is a statistical measure, developed by Pijn et al (1989), which quantifies both nonlinear and linear causality from a time series $x$ to a time series $y$. Pijn et al developed NICC (also known as “correlation ratio eta”) out of the need to capture nonlinear time-delayed relationships between neuron signals. We here consider the application of NICC to financial time series, since we are interested in capturing the nonlinear intertemporal relationships between assets. According to Pijn et al (1989), $NICC_{x \rightarrow y}^{xy}$ describes the reduction 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 $NICC_{x \rightarrow y}^{xy} = \frac{(total\ variance - unexplained\ variance)}{total\ variance}$:

$$\begin{align*}
NICC_{x \rightarrow y}^{xy} & = \frac{\sum_{t=1}^{T} R_y^{\Delta t}(t + \tau)^2 - \sum_{t=1}^{T} (R_y^{\Delta t}(t + \tau) - f(R_x^{\Delta t}(t)))^2}{\sum_{t=1}^{T} R_y^{\Delta t}(t + \tau)^2},
\end{align*}$$

(2.2)

where $f(R_x^{\Delta t}(t))$ is the linear piecewise approximation of the nonlinear regression curve.

**Remark 2.2** Pijn et al (1989) commented that, unlike the 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 ($NICC_{x \rightarrow y}^{xy} \neq NICC_{y \rightarrow x}^{yx}$). Interestingly enough, when the relationship $f$ is linear, then NICC converges on the LICC. Note also that the larger the asymmetry in the values of NICC from $x$ to $y$, and vice versa, the more nonlinear the relationship $f$. NICC values move strictly between 0 and 1. $NICC_{x \rightarrow y}^{xy}$ 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 knowledge, NICC has never previously been used in the field of finance. It has only been employed in the field of brain signal analysis, in order to determine nonlinear dependencies between neurons (see Pijn et al 1989, 1990; Lopes da Silva et al 1989; Wendling et al 2001). NICC is employed to identify nonlinear causal relationships between asset returns. Nonlinearities are important in the finance literature, since many phenomena and relations in finance are nonlinear. Frank and Stengos (1989), after conducting econometric analysis of the returns of gold and silver, found proof that their time series are governed by nonlinear rather than linear mechanisms. Hsieh (1989) analyzed day-by-day variations in major foreign exchange rates through linear correlation and found no significant results. However, after employing econometric generalized autoregressive conditional heteroscedasticity (GARCH) analysis he identified 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 remains in their time series; rather, nonlinear functions better explain those dependencies and also predict future prices from past prices. Abhyankar et al (1997) examined real time returns of the Standard & Poor’s 500 (S&P 500), Deutscher Aktienindex (DAX), Nikkei 225 and Financial Times Stock Exchange 100 (FTSE 100) and found evidence of strong nonlinearities between them.

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 relationship detection. However, NICC, which takes values from 0 to 1, provides no information about the sign (positive or negative) of causality. This means that NICC cannot tell whether two assets have reverse or same-direction causality, unlike LICC, which may not capture nonlinearities but does capture the sign of the causality between asset returns.

2.3 Linear cointegration

Lead–lag relationships as examined by LICC and NICC are one form of causality between assets. Another form of causal relationship is that of assets which move in an integrated way, ie, they evolve dynamically together, and this common evolution can be described by a common function. First, we present the case of assets cointegrated in a linear way. Linear cointegration (LCo) is an econometric tool introduced by Granger (1981), and subsequently established by Engle and Granger (1987) and Granger and Weiss (2001). Admittedly, two series can be considered cointegrated when a linear combination of the two is stationary, while neither of the 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 to the same order. There are various substitution methods to test the integration order.
of time series: the Dickey–Fuller (Dickey and Fuller 1979), the augmented Dickey–Fuller (ADF) test (Dickey and Fuller 1981), a generalization of the ADF (Phillips and Perron 1988) and the Kwiatkowski–Phillips–Schmidt–Shin test (Kwiatkowski et al 1992). Given that two series, $x_t$ and $y_t$, are integrated to the same order, in order to be cointegrated there must exist a function

$$z_t \in I(0): z_t = y_t - \beta x_t.$$  \hspace{1cm} (2.3)

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 data set, we follow and expand the technique of Yang et al (2014): assign to every causal relationship between assets the $\beta$ coefficient from the cointegrating regression, and normalize it simply by dividing by the maximum $\beta$ coefficient of all the asset pairs.

**Remark 2.3** Thus, linear normalized cointegration link values can range from $-1$ to $1$. When $\text{LCo}_{xy}^{\Delta_t} < 0$, this means that asset $x$ is negatively cointegrated with asset $y$, ie, if yesterday’s price of asset $x$ increases, then today’s price of asset $y$ will decrease, and vice versa. When, $\text{LCo}_{xy}^{\Delta_t} > 0$, this means that asset $x$ is positively cointegrated with asset $y$, ie, if yesterday’s price of asset $x$ increases, then today’s price of asset $y$ will also increase. If $\text{LCo}_{xy}^{\Delta_t} = 0$, this means that assets $x$ and $y$ 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 further information should increase the predictability of the assets’ prices, a cointegration between two financial assets implies inefficiency. Cerchi and Havenner (1988) employed LCo analysis in a data set consisting of five randomly chosen industrial stocks. They found that, despite the fact that the individual stock time series could at best be described as random walks, when cointegration enters into play the series appear to have a distinct common trend. Hall et al (1992) analyzed yields to maturity of US treasury bills and found strong evidence that they move in tandem dynamically through time. Liu et al (1997) scrutinized the chaotic behavior of the Shanghai and Shenzen market indexes. Their analysis shed light on an underlying mechanism between the two indexes, as they seemed to evolve in a cointegrated manner. Alexander (2001) claimed, after conducting robust analysis of commodities, that related commodity types offer some windows of opportunity, given their strong cointegration. Siliverstovs et al (2005) investigated a data set consisting of natural gas markets in Europe, North America and Japan between the early 1990s and 2004. They
found a high level of natural gas market cointegration within Europe, and between the European and Japanese markets as well as within the North American market. Yang et al (2014) investigated twenty-six stock market indexes and found that their cointegration relationship increased after the Lehman Brothers collapse, while the degree of cointegration gradually decreased from the subprime to the European debt crisis.

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

### 2.4 Nonlinear cointegration

Nonlinear cointegration (NCo) is an expansion of the well-established linear cointegration (LCo) that is capable of capturing nonlinear integrated dependencies between one asset and another. NCo was 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

\[
z_t = f(y_t, x_t) \text{ is short in memory.} \tag{2.4}
\]

Crashes in extended memory time series have an enduring and intense effect, while in short memory time series crashes are absorbed and vanish quickly (Escanciano and Escribano 2011). Memory in time series, and its characterization as short or extended, can be measured by various means. In our analysis, we use the conditional mean persistence method from Escanciano and Escribano (2011). A time series, \( x_t \), is considered to be of “short memory in the mean” if, for all \( t \) and \( h > 0 \),

\[
M(t, h) = E(y_{t+h} | I_t) \text{ tends to a constant } \mu \text{ as } h \text{ becomes large (for more details see Escanciano and Escribano 2011).}
\]

Given that we found no method of quantifying the nonlinear cointegration between two variables in the literature, we devised our own method, which is described below.

We assign the weighted average of the coefficients in function \( f \) from (2.4) to be the weight of a nonlinear cointegration from asset \( x \) to asset \( y \). We allow our algorithm to search for candidate functions \( f \) up to tenth-degree polynomials; thus, the higher the term’s power, the greater the weight assigned to it. For each cointegrating relationship, we divide the sum of these ten coefficients by the maximum of the coefficient averages between 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 \(1\). If \( NCo_{xy} < 0 \), asset \( x \) is negatively cointegrated with asset \( y \). If \( NCo_{xy} > 0 \),
asset \( x \) is positively cointegrated with asset \( y \). If \( \text{NCo}_{t}^{xy} = 0 \), asset \( x \) and asset \( y \) are not cointegrated in any way.

Li (2002) analyzed the stock market indexes of Australia, Japan, New Zealand, the United Kingdom and the United States in terms of both LCo and NCo. His results indicated that nonlinear cointegration relationships between those indexes are much stronger and persistent than the linear ones. Ma and Kanas (2004) found further strong empirical evidence to support the intrinsic bubble model of stock prices developed by Froot and Obstfeld (1991). Athanasenas et al (2014) conducted analysis of the time series of revenues and expenditures of the Greek government. Their results support the fact that negative rates of expenditure severely affect revenues. Apergis and Payne (2014) analyzed asset returns from the stock markets of the Group of Seven (G7). They found long-lasting nonlinear dependencies in a significant portion of their data set.

### 2.5 Linear Granger causality

Granger causality is a statistical concept of causality based on regression. It has been widely used in the financial econometrics literature to detect causal relationships between 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 modeled through regression (linear regression for linear Granger causality (LGC), and nonlinear regression for nonlinear Granger causality (NGC) in the next section).

Following Granger (1969), given \( x_t \) and \( y_t \) are stationary, we can consider a linear autoregressive (AR) model of time series \( y_t \):

\[
y_t = \sum_{i=1}^{N} a_{11,i} y_{t-i} + \sum_{i=1}^{N} a_{12,i} x_{t-i} + E_t(y), \tag{2.5}
\]

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, and \( E_t(y) \) are 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 \( x \) G-causes \( y \), we assign as the weight of the link the value \( \text{LGC}_{xy} = 1 - p \)-value of the \( F \)-test. Values denoting the intensity of the causality range from 0 to 1.

Bradshaw and Orden (1990) uncovered an important LGC between the exchange rate and export sales, while the evidence on causality of the exchange rate on prices is
unclear. Rahman and Mustafa (1997) analyzed US equities and bonds. Their results attested that the causality from bonds to equities is much more robust than from equities to bonds. Abhyankar (1998) investigated causal relationships between futures contracts and cash markets. According to his results, futures contracts hold predictive information for the future states of the cash market. Dutta (2001) found that the causality from levels of telecommunications infrastructure to economic activity is stronger than that in the opposite direction. Foresti (2006) scrutinized the possibility of causal relationships between economic growth and stock market returns, concluding that the stock market drives economic growth. Wang et al (2007) tested for possible linkages between the euro and US, 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) found that crude oil prices have a statistically significant causal relationship to the prices of gold, but that the opposite was not supported. Billio et al (2012) analyzed time series data of hedge funds, banks, broker-dealers and insurance companies and found that banks exert the most causality on all the other time series they analyzed. Výrost et al (2015) uncovered an underlying mechanism of a preferential attachment between stock markets, ie, the probability of spillover effects between any given two markets increases with their degree of connectedness to other markets. Fiedor (2015) analyzed the relationships between companies listed on the 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 is its inability to capture nonlinearities. The latter drawback is avoided by 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 about another time series, a feat that LGC fails to accomplish. NGC was introduced by Hiemstra and Jones (1994), and further established by Péguin-Feissolle et al (2013). Following the definition by Péguin-Feissolle et al, we 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 define

\[
y_t = f_y(y_{t-1}, y_{t-p_1}, x_{t-1}, x_{t-q_1}; 1) + e_{1,t}.
\]  

(2.6)

This equation includes all combinations of 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 Péguin-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 the weight of the link the value $\text{NGC}_{xy} = 1 - p$-value of the Wald $F$-test. Values denoting the intensity of the causality range from 0 to 1.

Hiemstra and Jones (1994), having used the NGC between the equity returns of Dow Jones stocks and the volume rate of the NYSE, found statistically significant causality in both directions. Qiao and Lam (2011) sought causalities in East Asia stock markets. Despite the fact that LGC tests failed to detect statistically significant dependencies, its nonlinear relative, NGC, captured many causalities. Benhmad (2012) similarly analyzed oil prices and the US dollar exchange rate and found evidence of oil influencing the US dollar rate slightly more than the other way around. Zhou et al (2014) examined a data set of Chinese stock futures and spot markets. They claim to have found robust results in favor of futures influencing spot markets. Chu et al (2016) researched 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 on causality tools below, we deviate from the disciplines of statistics and econometrics and recall methodologies from information theory.

### 2.7 Shadow causality

The causality methods described above have several important weaknesses: they depend on requirements of stationarity (LICC, NICC, LCo, NCo, LGC, NGC), 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 two tools from information theory come into play: 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 and capture both linear and nonlinear causality. With a minor modification we were also able to make them distinguish between positive and negative causality. Following the “shadow correlation” of Granger and Lin (1994), and inspired by Schreiber (2000), who suggested that a lead/lag can be used in mutual information to include directionality in the calculations, we give the shadow causality formula as follows:

$$
\text{SC}_{x_t - \Delta t, y_t} = \text{sgn} \sqrt{1 - \exp(-2I(x_t - \Delta t, y_t))},
$$

(2.7)
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 \( \text{sgn} = +1 \) (homogeneous causality takes place when an increase in \( x \) causes an increase in \( y \) more often than a decrease in \( y \), while a decrease in \( x \) causes a decrease in \( y \) more often than an increase in \( y \)). If causality is heterogeneous, then \( \text{sgn} = -1 \) (heterogeneous causality takes place when an increase in \( x \) causes a decrease in \( y \) more often than an increase in \( y \), while a decrease in \( x \) causes an increase in \( y \) more often than a decrease in \( y \)). SC values denoting the intensity and type of the causality range from \(-1\) to \(1\) (negative values denote a heterogeneous relationship and positive values denote a homogeneous relationship).

Dionisio et al (2007) created a bundle of economic and financial indicators for Portugal and tested for possible dependencies between 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 between various municipalities in China. They found significant formations of groups between 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, such as LGC, they claim that MI provided more information regarding the underlying causalities in the stocks of their data set. Fiedor (2014a) investigated nonlinear relationships between companies listed in the NYSE and found that the mutual information rate produces different results than simple correlation. In the next section, we present our last causality tool, concluding our methodology section.

### 2.8 Hidden causality

Mutual information, which is the basis of shadow causality, needs a time lag to account for directionality and thus causality. Therefore, we can argue that it is not a natural tool of causality inference (much like LICC and NICC) but 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 only 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, \( y_{t+1} \). In a similar way to 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 Sandoval (2014). Our contribution lies only in mining the sign of positive or negative in a similar manner as we did for SC. The HC formula is given by

$$HC_{x_t \rightarrow y_t} = \text{sgn} \frac{\sum p(y_{t+1}, y_t, x_t) \log(p(y_{t+1}y_t, x_t) / p(y_{t+1}y_t))}{\sum p(y_t, x_t) \log_2(p(y_t, x_t) / p(x_t))}$$

where

$$\sum p(y_{t+1}, y_t, x_t) \log \frac{p(y_{t+1}y_t, x_t)}{p(y_{t+1}y_t)} = \text{TE}_{x_t \rightarrow y_t},$$

which is the TE of $x$ to $y$, and

$$\sum p(y_{t+1}, y_t) \log_2 \frac{p(y_{t+1}y_t)}{p(y_t)} = H_{y_{t+1}|y_t},$$

which is the conditional entropy of the future of $y$ on its past. For more technical details see Schreiber (2000) and Sandoval (2014). If causality is homogeneous, then $\text{sgn} = +1$ (homogeneous causality takes place when an increase in $x$ causes an increase in $y$ more often than a decrease in $y$, while a decrease in $x$ causes a decrease in $y$ more often than an increase in $y$). If causality is heterogeneous, then $\text{sgn} = -1$ (heterogeneous causality takes place when an increase in $x$ causes a decrease in $y$ more often than an increase in $y$, while a decrease in $x$ causes an increase in $y$ more often than a decrease in $y$). HC values denoting the intensity and type of causality range from $-1$ to $1$ (negative values denote a heterogeneous relationship and positive values denote a homogeneous relationship).

Baek et al (2005) analyzed via TE a data set consisting of equities from various industrial sectors, and found that energy-related equities such as oil, gas and electricity saturate the whole market. Kwon and Yang (2008) sought causal relationships in international stock market indexes and discovered that S&P 500 has the highest number of causal relationships with all the other indexes. Kim et al (2013) examined stock market indexes for most of the Group of Twenty. Their results stand in favor of the theory that western countries exert stronger causality on eastern countries than vice versa. Sandoval (2014) scrutinized the companies in the S&P 100. His results indicate that TE produces a network that creates much more realistic (in terms of industrial affinity) clusters than LICC. Sandoval et al (2015) analyzed the pairs of eighty-three stock market indexes in various countries and found that TE is an effective way to quantify the information flow between indexes. Yook et al (2016) studied a financial network, and found that the modular structure from LICC does not correctly reflect the known industrial classification and its hierarchy, unlike the transfer entropy method, which fits the market segmentation much better.

Table 1 briefly summarizes all the causality methods described in Section 2, and some of their basic properties.
TABLE 1  Causality methods: data.

<table>
<thead>
<tr>
<th>Causality method</th>
<th>Type of causality identification</th>
<th>Value range</th>
<th>Needs time series to be stationary</th>
</tr>
</thead>
<tbody>
<tr>
<td>LICC</td>
<td>Linear</td>
<td>[-1, 1]</td>
<td>Yes</td>
</tr>
<tr>
<td>NICC</td>
<td>Linear and nonlinear</td>
<td>[0, 1]</td>
<td>Yes</td>
</tr>
<tr>
<td>Linear cointegration</td>
<td>Linear</td>
<td>[-1, 1]</td>
<td>Yes</td>
</tr>
<tr>
<td>Nonlinear cointegration</td>
<td>Nonlinear</td>
<td>[-1, 1]</td>
<td>Yes</td>
</tr>
<tr>
<td>LGC</td>
<td>Linear</td>
<td>[0, 1]</td>
<td>Yes</td>
</tr>
<tr>
<td>NGC</td>
<td>Nonlinear</td>
<td>[0, 1]</td>
<td>Yes</td>
</tr>
<tr>
<td>Shadow causality</td>
<td>Linear and nonlinear</td>
<td>[-1, 1]</td>
<td>No</td>
</tr>
<tr>
<td>Hidden causality</td>
<td>Linear and nonlinear</td>
<td>[-1, 1]</td>
<td>No</td>
</tr>
</tbody>
</table>

LICC, linear intertemporal cross-correlation. NICC, nonlinear intertemporal cross-correlation. LGC, linear Granger causality. NGC, nonlinear Granger causality.

3 DATA AND FILTERING

For our analysis, we use weekly data for stock market indexes, sovereign bonds and oil from Thomson Reuters DataStream for the period from January 4, 2000 to February 12, 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 data set consists of the following (see Table 2).


- Fourteen bonds: two-year US bond; ten-year US bond; ten-year UK bond; two-year German bond; ten-year German bond; two-year Japanese bond; ten-year Japanese bond; two-year Australian bond; ten-year Australian bond; ten-year Swiss bond; two- to three-year Spanish bond; ten-year Greek bond; three-year Italian bond and ten-year Italian bond.

- Oil.

We use a rolling window of two years to construct the evolutionary financial network, which evolves week by week from January 4, 2000 until February 12, 2016 (a 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 of keeping a causal link is 95%. In order to negate nonstationarity we take the log returns of the time series and test with ADF for nonstationarity. No
TABLE 2  Data set details and asset numbering for Figures 9–16. [Table continues on next page.]

<table>
<thead>
<tr>
<th>#</th>
<th>Asset</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Shanghai</td>
<td>A stock market index of all stocks (A shares and B shares) traded at the Shanghai Stock Exchange</td>
</tr>
<tr>
<td>2</td>
<td>Bovespa</td>
<td>An index of about fifty stocks traded on the São Paulo Stock, Mercantile and Futures Exchange</td>
</tr>
<tr>
<td>3</td>
<td>Dow Jones</td>
<td>A stock market index, one of several created by <em>Wall Street Journal</em> editor and Dow Jones &amp; Company cofounder Charles Dow</td>
</tr>
<tr>
<td>4</td>
<td>S&amp;P 500</td>
<td>A US stock market index based on the market capitalizations of 500 large companies having common stock listed on the NYSE or Nasdaq</td>
</tr>
<tr>
<td>5</td>
<td>DAX 30</td>
<td>A blue chip stock market index consisting of the thirty major German companies trading on the Frankfurt Stock Exchange</td>
</tr>
<tr>
<td>6</td>
<td>Hang Seng</td>
<td>A free-float-adjusted market capitalization-weighted stock market index in Hong Kong, used to record and monitor daily changes in the largest companies on the Hong Kong stock market</td>
</tr>
<tr>
<td>7</td>
<td>CAC 40</td>
<td>A capitalization-weighted measure of the forty most significant values of the 100 highest market caps on the Euronext Paris</td>
</tr>
<tr>
<td>8</td>
<td>Nikkei 225</td>
<td>A price-weighted index of the Tokyo Stock Exchange, with components reviewed once a year; the Nikkei is the most widely quoted average of Japanese equities</td>
</tr>
<tr>
<td>9</td>
<td>ASX 200</td>
<td>A market-capitalization-weighted and float-adjusted stock market index of Australian stocks listed on the Australian Securities Exchange from S&amp;P</td>
</tr>
<tr>
<td>10</td>
<td>BSE</td>
<td>A free-float market-weighted stock market index of thirty well-established and financially sound companies listed on the Bombay Stock Exchange</td>
</tr>
</tbody>
</table>

time series in our data set is found to be nonstationary when log returns apply. After constructing $25 \times 25$ matrixes for each of the 738 weeks and each of the eight causality methods, we apply the filtering method of the maximum spanning tree to each matrix (Hu 1961). Thus, 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 applied to financial networks, such as the minimum spanning tree.
TABLE 2  Continued.

<table>
<thead>
<tr>
<th>#</th>
<th>Asset</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>2Y US bond</td>
<td>A two-years-to-maturity sovereign US bond</td>
</tr>
<tr>
<td>12</td>
<td>10Y US bond</td>
<td>A ten-years-to-maturity sovereign US bond</td>
</tr>
<tr>
<td>13</td>
<td>10Y UK bond</td>
<td>A ten-years-to-maturity sovereign UK bond</td>
</tr>
<tr>
<td>14</td>
<td>2Y German bond</td>
<td>A two-years-to-maturity sovereign German bond</td>
</tr>
<tr>
<td>15</td>
<td>10Y German bond</td>
<td>A ten-years-to-maturity sovereign German bond</td>
</tr>
<tr>
<td>16</td>
<td>2Y Japanese bond</td>
<td>A two-years-to-maturity sovereign Japanese bond</td>
</tr>
<tr>
<td>17</td>
<td>10Y Japanese bond</td>
<td>A ten-years-to-maturity sovereign Japanese bond</td>
</tr>
<tr>
<td>18</td>
<td>2Y Australian bond</td>
<td>A two-years-to-maturity sovereign Australian bond</td>
</tr>
<tr>
<td>19</td>
<td>10Y Australian bond</td>
<td>A ten-years-to-maturity sovereign Australian bond</td>
</tr>
<tr>
<td>20</td>
<td>10Y Swiss bond</td>
<td>A ten-years-to-maturity sovereign Swiss bond</td>
</tr>
<tr>
<td>21</td>
<td>2to3Y Spanish bond</td>
<td>A two- to three-years-to-maturity sovereign Spanish bond</td>
</tr>
<tr>
<td>22</td>
<td>10Y Greek bond</td>
<td>A ten-years-to-maturity sovereign Greek bond</td>
</tr>
<tr>
<td>23</td>
<td>3Y Italian bond</td>
<td>A three-years-to-maturity sovereign Italian bond</td>
</tr>
<tr>
<td>24</td>
<td>10Y Italian bond</td>
<td>A ten-years-to-maturity sovereign Italian bond</td>
</tr>
<tr>
<td>25</td>
<td>Oil</td>
<td>Crude oil as traded in the New York Mercantile Exchange</td>
</tr>
</tbody>
</table>

(MST), which has been thoroughly employed in the works of Mantegna (1999a,b), who was the first to introduce it in finance. The MST was also effectively used by Di Matteo et al (2010) and Aste and Di Matteo (2006), who also added their own flavor to filtering. Other filtering methods are the random matrix theory used by Iori et al (2007); Bonferroni statistical filtering, which was well presented by Iori et al (2015); and the 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, 2016a,b).

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 answers we examined the evolution of the average causality 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 bursting of the dot-com bubble in the early 2000s, the LICC in Figure 1 is on average 33% and displays a slightly upward trend as it peaks during the last gasp of the downturn (October 2002). Before the crisis it moves at an average of 27.42%; more specifically, it undergoes a marked downward slide throughout 2003, and then from 2004 to July 2007 it fluctuates, with a slight upward trend (Table 3). The global financial crisis period is characterized by a dramatic drop in LICC, with an average value of 24.29%. Then, in summer 2009, we observe a confident rising move as the echoes of the crisis die away.¹ The postcrisis period is characterized by a generic and fluctuating drop in 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 the NICC (see Figure 2) during the stock market downturn of the early 2000s, it is on average 29.18% and remains flat throughout that decade. During the precrisis period it moves at an average of 28.33%; more specifically the NICC moves slightly downward from 2004 to 2006, until it suddenly drops even more half a year before the “birth” of the global financial crisis (Table 3). The global financial crisis period is characterized by a dramatic increase in NICC, with an average value of 40.91%, but then in summer 2009 we observe a plunge until the crisis dies out. The postcrisis period is characterized by a marked

¹ Here and later, “summer” is the period from June to August in the northern hemisphere.
TABLE 3  Causalities: general statistics from the dot-com bubble burst until before the global financial crisis.

<table>
<thead>
<tr>
<th>Causality methods</th>
<th>Min</th>
<th>Avg</th>
<th>Max</th>
<th>SD</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>LICC</td>
<td>0.2666</td>
<td>0.3300</td>
<td>0.3620</td>
<td>0.0232</td>
<td>↑</td>
</tr>
<tr>
<td>NICC</td>
<td>0.2320</td>
<td>0.2918</td>
<td>0.3469</td>
<td>0.0188</td>
<td>→</td>
</tr>
<tr>
<td>LCo</td>
<td>0.1294</td>
<td>0.2034</td>
<td>0.2692</td>
<td>0.0339</td>
<td>↑</td>
</tr>
<tr>
<td>NCo</td>
<td>-0.1650</td>
<td>-0.0603</td>
<td>0.0348</td>
<td>0.0564</td>
<td>↑</td>
</tr>
<tr>
<td>LGC</td>
<td>0.7076</td>
<td>0.7752</td>
<td>0.8631</td>
<td>0.0333</td>
<td>→</td>
</tr>
<tr>
<td>NGC</td>
<td>0.6026</td>
<td>0.6881</td>
<td>0.8138</td>
<td>0.0562</td>
<td>↑</td>
</tr>
<tr>
<td>SC</td>
<td>0.1278</td>
<td>0.1877</td>
<td>0.2297</td>
<td>0.0281</td>
<td>↓</td>
</tr>
<tr>
<td>HC</td>
<td>0.0042</td>
<td>0.0548</td>
<td>0.0903</td>
<td>0.0179</td>
<td>↑</td>
</tr>
</tbody>
</table>

LICC, linear intertemporal cross-correlation. NICC, nonlinear intertemporal cross-correlation. LCo, linear cointegration. NCo, nonlinear cointegration. LGC, linear Granger causality. NGC, nonlinear Granger causality. SC, shadow causality. HC, hidden causality. Minimum, average, maximum and standard deviation (SD) are calculated in terms of the average causality of all financial assets throughout the time period declared. Trend symbols: ↑, upward trend; ↓, downward trend; →, flat. When two or more trend symbols are written in a row they symbolize consecutive trend changes.

increase in NICC, which is on average 49.09% (Table 4). The 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 Figure 3, during the dot-com bubble burst it is on average 20.34% and displays an upward trend throughout the downturn (October 2002). During the precrisis 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). The global financial crisis period is characterized by a smooth drop in LCo, with an average
### Table 4: Causalities: general statistics during and after the global financial crisis.

<table>
<thead>
<tr>
<th>Causality methods</th>
<th>Min</th>
<th>Avg</th>
<th>Max</th>
<th>SD</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>LICC</td>
<td>0.0425</td>
<td>0.2429</td>
<td>0.3632</td>
<td>0.0844</td>
<td>↓↑</td>
</tr>
<tr>
<td>NICC</td>
<td>0.0748</td>
<td>0.4091</td>
<td>0.5563</td>
<td>0.1053</td>
<td>↑↓</td>
</tr>
<tr>
<td>LCo</td>
<td>0.2336</td>
<td>0.3006</td>
<td>0.4065</td>
<td>0.0498</td>
<td>↓→</td>
</tr>
<tr>
<td>NCo</td>
<td>-0.2359</td>
<td>0.0771</td>
<td>0.3241</td>
<td>0.0900</td>
<td>↑↑↑</td>
</tr>
<tr>
<td>LGC</td>
<td>0.4861</td>
<td>0.7480</td>
<td>0.9192</td>
<td>0.0989</td>
<td>→↓→</td>
</tr>
<tr>
<td>NGC</td>
<td>0.4887</td>
<td>0.7314</td>
<td>0.9344</td>
<td>0.0752</td>
<td>↓↑→</td>
</tr>
<tr>
<td>SC</td>
<td>0.1545</td>
<td>0.2997</td>
<td>0.5327</td>
<td>0.1269</td>
<td>↓</td>
</tr>
<tr>
<td>HC</td>
<td>0.0310</td>
<td>0.1190</td>
<td>0.1996</td>
<td>0.0353</td>
<td>↓</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Causality methods</th>
<th>Min</th>
<th>Avg</th>
<th>Max</th>
<th>SD</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>LICC</td>
<td>0.0377</td>
<td>0.1895</td>
<td>0.3540</td>
<td>0.0903</td>
<td>↑↓↑</td>
</tr>
<tr>
<td>NICC</td>
<td>0.2379</td>
<td>0.3610</td>
<td>0.4909</td>
<td>0.0609</td>
<td>↑↓</td>
</tr>
<tr>
<td>LCo</td>
<td>-0.0134</td>
<td>0.2404</td>
<td>0.4281</td>
<td>0.1080</td>
<td>→↑↓</td>
</tr>
<tr>
<td>NCo</td>
<td>-0.1667</td>
<td>0.0679</td>
<td>0.2979</td>
<td>0.0890</td>
<td>↑→↓↑</td>
</tr>
<tr>
<td>LGC</td>
<td>0.4148</td>
<td>0.6462</td>
<td>0.8098</td>
<td>0.0952</td>
<td>↓</td>
</tr>
<tr>
<td>NGC</td>
<td>0.0441</td>
<td>0.5327</td>
<td>0.8754</td>
<td>0.2073</td>
<td>↓↑</td>
</tr>
<tr>
<td>SC</td>
<td>0.1717</td>
<td>0.2865</td>
<td>0.4037</td>
<td>0.0559</td>
<td>↑→↓→</td>
</tr>
<tr>
<td>HC</td>
<td>-0.0887</td>
<td>0.0534</td>
<td>0.1625</td>
<td>0.0649</td>
<td>↓↑↑</td>
</tr>
</tbody>
</table>

For notation see Table 3.

value of 30.06%, but then in summer 2009 it stops falling and moves on a marked support level around 25%. The postcrisis period is characterized by a continued move on the same resistance level as before until the end of 2011. Then LCo spikes around summer 2012, at 40%, and begins a marked 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 (Figure 4), during the stock market crash of the early 2000s it is on the negative side, averaging -6.03%, and displays a slightly upward trend as it peaks during the last gasp of the downturn (October 2002), nearing the zero level. During the precrisis period NCo moves at an average of 0.44%; more specifically, it displays an abrupt spike in the first half of 2003, hitting a ceiling of
TABLE 5  Causalities: general statistics during the Chinese stock market crash.

<table>
<thead>
<tr>
<th>Causality methods</th>
<th>Min</th>
<th>Avg</th>
<th>Max</th>
<th>SD</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>LICC</td>
<td>0.0187</td>
<td>0.1508</td>
<td>0.2298</td>
<td>0.0495</td>
<td>↑</td>
</tr>
<tr>
<td>NICC</td>
<td>0.0499</td>
<td>0.1938</td>
<td>0.2839</td>
<td>0.0564</td>
<td>↑</td>
</tr>
<tr>
<td>LCo</td>
<td>0.2074</td>
<td>0.0053</td>
<td>0.0782</td>
<td>0.0525</td>
<td>→</td>
</tr>
<tr>
<td>NCo</td>
<td>0.1452</td>
<td>0.0018</td>
<td>0.0881</td>
<td>0.0357</td>
<td>→</td>
</tr>
<tr>
<td>LGC</td>
<td>0.1763</td>
<td>0.5362</td>
<td>0.7201</td>
<td>0.1349</td>
<td>↑</td>
</tr>
<tr>
<td>NGC</td>
<td>0.3172</td>
<td>0.5941</td>
<td>0.7849</td>
<td>0.0998</td>
<td>↑</td>
</tr>
<tr>
<td>SC</td>
<td>0.2208</td>
<td>0.2831</td>
<td>0.3296</td>
<td>0.0220</td>
<td>→</td>
</tr>
<tr>
<td>HC</td>
<td>0.0535</td>
<td>0.0685</td>
<td>0.1730</td>
<td>0.0642</td>
<td>↓→↑</td>
</tr>
</tbody>
</table>

For notation see Table 3.

FIGURE 2  Average of NICC for all assets week by week, with a rolling window of two years.

20%, and then from 2004 to July 2007 it fluctuates with a marked downward trend, joining the negative side again as early as 2006. It bottoms out just before the breakout of the crisis at the lowest level ever, around −15% (Table 3). The global financial crisis period is characterized by a wild fluctuation in NCo around an average of 7.71%. The postcrisis 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
FIGURE 3  Average of LCo for all assets week by week, with a rolling window of two years.


FIGURE 4  Average of NCo for all assets week by week, with a rolling window of two years.


attractor around zero, being sometimes positive and sometimes negative but always averaging 0.18% (Table 5).

Next we focus on LGC (Figure 5), and note that during the downturn of the early 2000s it moves around a support level of 77.52%. During the precrisis 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 starts rolling somewhat downward (Table 3). The outbreak of the global financial crisis is characterized by a faintly diminishing LGC with an average value of 74.8%, but then, at the end of 2008, we observe a marked drop below 70%, reaching a new support level at the end of the global crisis. The postcrisis period is characterized by a generic and fluctuating increase in LGC, which is on average 64.62%, until summer 2012. 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 downturn in an upward trend; however, its levels are already as low as 53.62% (Table 5).

Concerning NGC (Figure 6), emerging from the dot-com burst it has a faintly upward trend, averaging 68.81%, becoming steeper as the downturn dies out in October 2002. During the precrisis period NGC plateaus at an average of 77.96%; this lasts until the end of 2004, when it suddenly drops to a support level of 60%. Then, in summer 2005 it bounces back up, continuing its rising trend until summer 2006, just one year before the outbreak of the crisis, when it reaches a resistance level of 88% and begins falling again (Table 3). On the eve of the global financial crisis NGC falls again, to the same support level as before (60%), while at the end of 2008 it bounces up to between 70% and 80%, moving at an average value of 73.14% until the end of the crisis. The postcrisis period is characterized by a historically unique drop in NGC, reaching a deep support level of just 20% and staying there from...
summer 2012 until summer 2013, when it starts to rise again in a volatile manner (Table 4). The late Chinese shock finds NGC still on the rise, at an average of 59.41% (Table 5).
Furthermore, the post-dot-com bubble burst is characterized by an SC (Figure 7), on average 18.77%, while its trend is downward. During the precrisis period SC enters a marked rising trend, averaging 32.16% even after the birth of the global crisis. Throughout the precrisis period SC more than doubles, from 20% in 2003 to 50% in summer 2007 (Table 3). The global financial crisis period is characterized by an extreme plunge in 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 plateaus at 20%; this continues into the postcrisis period. The postcrisis period is characterized by a marked increase in SC to a new support level of 30% between 2011 and 2012, and then in 2013 this support level becomes a resistance level, forcing the SC to stay beneath 30%, with an average of 28.65% (Table 4). The SC enters the financial crash of China in a faintly downward trend, and then plateaus at 28.31% (Table 5).

Ultimately, during the stock market downturn of the early 2000s, the HC (Figure 8) is on average 5.48% and displays a slightly upward trend as it peaks on the exhaustion of the downturn (October 2002). During the precrisis period it moves at an average of 14.19%; more specifically, the HC is governed by a steep increase from 2003 through summer 2004, when it hits the resistance level of 25% and then enters a prolonged fluctuation with a downward trend to the support level of 10% in summer 2006, almost one year before the global crisis (Table 3). The global financial crisis finds HC on the rise, with an average value of 11.90%, but then in summer 2008 we witness a marked diminishing trend as the global crisis enters its mature phase. The postcrisis period is characterized by an extension of the former downward trend, moving at
TABLE 6  Averaged similarity regarding the link structure after the MST filtering throughout the time period.

<table>
<thead>
<tr>
<th>Causality methods</th>
<th>LICC</th>
<th>NICC</th>
<th>LCo</th>
<th>NCo</th>
<th>LGC</th>
<th>NGC</th>
<th>SC</th>
<th>HC</th>
</tr>
</thead>
<tbody>
<tr>
<td>LICC</td>
<td>100.00</td>
<td>3.12</td>
<td>1.07</td>
<td>5.54</td>
<td>48.74</td>
<td>29.69</td>
<td>3.41</td>
<td>15.77</td>
</tr>
<tr>
<td>NICC</td>
<td>3.12</td>
<td>100.00</td>
<td>1.67</td>
<td>8.33</td>
<td>7.67</td>
<td>6.65</td>
<td>3.84</td>
<td>3.28</td>
</tr>
<tr>
<td>LCo</td>
<td>1.07</td>
<td>1.67</td>
<td>100.00</td>
<td>1.98</td>
<td>1.94</td>
<td>2.27</td>
<td>4.27</td>
<td>4.78</td>
</tr>
<tr>
<td>NCo</td>
<td>5.54</td>
<td>8.33</td>
<td>1.98</td>
<td>100.00</td>
<td>4.54</td>
<td>4.04</td>
<td>4.47</td>
<td>2.71</td>
</tr>
<tr>
<td>LGC</td>
<td>48.74</td>
<td>7.67</td>
<td>1.94</td>
<td>4.54</td>
<td>100.00</td>
<td>39.44</td>
<td>2.24</td>
<td>15.67</td>
</tr>
<tr>
<td>NGC</td>
<td>29.69</td>
<td>6.65</td>
<td>2.27</td>
<td>4.04</td>
<td>39.44</td>
<td>100.00</td>
<td>2.56</td>
<td>13.01</td>
</tr>
<tr>
<td>SC</td>
<td>3.41</td>
<td>3.84</td>
<td>4.27</td>
<td>4.47</td>
<td>2.24</td>
<td>2.56</td>
<td>100.00</td>
<td>4.36</td>
</tr>
<tr>
<td>HC</td>
<td>15.77</td>
<td>3.28</td>
<td>2.71</td>
<td>2.71</td>
<td>15.67</td>
<td>13.01</td>
<td>4.36</td>
<td>100.00</td>
</tr>
</tbody>
</table>

All values are given in percent. LICC, linear intertemporal cross-correlation. NICC, nonlinear intertemporal cross-correlation. LCo, linear cointegration. NCo, nonlinear cointegration. LGC, linear Granger causality. 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. The maximum spanning tree keeps only the strongest links of the network (in absolute values) but still keeps the network connected.

an average of 5.34%, until the start of 2012. Then we can see that the HC, having fallen to the negative side at around −5%, rallies upward by 15% at the end of 2012, and fluctuates above the support level of 5% until 2014, when it again makes a steep decline to subzero levels (Table 4). The 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).

4.2 The family of causalities: convergence or divergence?

Despite the fact that all the causality methods presented in this paper are normalized with values [−1, 1] or [0, 1], we cannot conduct a comparative analysis of 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 authenticate each individual method’s reaction and probable predictive capacity to events of the financial market. To further justify the incomparability of the eight causality methods we undertake a similarity analysis (calculation of the percentage of similar links) for each of the 738 weeks of our evolutionary network and then calculate the average similarity across all weeks for all possible combinations of the causality methods. The results of this comparison are presented succinctly in Table 6. The highest average similarity between any two causality tools is 48.74% of links, and occurs between LICC and LGC. The lowest average similarity between any two causality tools is 1.07% of links, and occurs 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 find some common ground on which to carry out some comparisons.

4.3 Causal linkages: time-tested relationships

Having studied the evolution of the eight causality metrics, and proved their lack of similarity, we move on to some distinct features, such as the most important links and assets. In Tables 7–11 we present the top ten links in terms of each causality separately, and the overall top thirty links in terms of all causalities together. As we can see from Table 7, in terms of LICC the most important causal relationship is 10Y US bond $\rightarrow$ 10Y German bond with LICC = 44.03%. However, in terms of NICC, the most causal pair is DAX 30 $\rightarrow$ CAC 40, with NICC = 72.49%. Furthermore, if we look at Table 8, we note 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 10Y UK bond $\rightarrow$ 2Y US bond, with NCo = −28.99%. In terms of LGC the most important relationship is 3Y Italian bond $\rightarrow$ 2to3Y Spanish bond, with LGC = 56.91%. However, in terms of NGC, the most important causal pair is 10Y Greek bond $\rightarrow$ 2to3Y Spanish bond, with NGC = 45.25% (Table 9). In terms of SC the most important causal relationship is DAX 30 $\rightarrow$ BSE with a score of 24.25%. Nevertheless, the most important causal relationship in terms of HC is 10Y US 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 10Y US bond $\rightarrow$ 2to3Y Spanish bond (Table 11).

4.4 Causal system: one attractor to pull them all

In order to rank the assets according to the causality they exert, we employ out-strength centrality, which we average over the period for every causality method. The complete rankings can be seen in Tables 12–14. As we can see, the most causal asset in terms of LICC is the 10Y US bond, while that in terms of NICC is the Hang Seng index. Moreover, in terms of LCo the most causal asset is the 2Y Japanese bond, while in terms of NCo it is the DAX 30 index. LGC coincides with LICC in crowning the 10Y US bond the most causal, which is also the leading causal asset in terms of NGC. However, the results in terms of SC and HC are different, giving the BSE index and the 2Y Japanese bond as the most causal assets, respectively. All in all, the most causal asset in terms of all causalities considered appears to be the 10Y US bond.

Furthermore, we note that, in agreement with Rahman and Mustafa (1997), LCo and HC unveil a “hidden” regime of causality occasionally monopolized by the bonds (see Tables 12 and 14). This result is astounding because LCo attests that those bonds exert the most powerful linear and profound long-term influence on the other assets.
### 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.

<table>
<thead>
<tr>
<th>Rank</th>
<th>LICC Score</th>
<th>NICC Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4403</td>
<td>0.7249</td>
</tr>
<tr>
<td>2</td>
<td>0.4105</td>
<td>0.6951</td>
</tr>
<tr>
<td>3</td>
<td>0.4092</td>
<td>0.5338</td>
</tr>
<tr>
<td>4</td>
<td>0.3956</td>
<td>0.4241</td>
</tr>
<tr>
<td>5</td>
<td>0.3834</td>
<td>0.4065</td>
</tr>
<tr>
<td>6</td>
<td>0.3766</td>
<td>0.4010</td>
</tr>
<tr>
<td>7</td>
<td>0.3509</td>
<td>0.3983</td>
</tr>
<tr>
<td>8</td>
<td>0.3265</td>
<td>0.3807</td>
</tr>
<tr>
<td>9</td>
<td>0.3075</td>
<td>0.3726</td>
</tr>
<tr>
<td>10</td>
<td>0.3021</td>
<td>0.3699</td>
</tr>
</tbody>
</table>

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 $x \rightarrow y$ 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 ascribed to each causal relationship is the average causal weight from $x$ to $y$ for the period January 4, 2000 to February 12, 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.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Linear cointegration</th>
<th>Score</th>
<th>Nonlinear cointegration</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10Y German bond → Bovespa</td>
<td>0.7940</td>
<td>10Y UK bond → 2Y US bond</td>
<td>-0.2899</td>
</tr>
<tr>
<td>2</td>
<td>10Y UK bond → Bovespa</td>
<td>0.7899</td>
<td>Hang Seng → Bovespa</td>
<td>0.2547</td>
</tr>
<tr>
<td>3</td>
<td>2Y Australian bond → Bovespa</td>
<td>0.7493</td>
<td>Dow Jones → 3Y Italian bond</td>
<td>0.2520</td>
</tr>
<tr>
<td>4</td>
<td>10Y Swiss bond → Bovespa</td>
<td>0.7249</td>
<td>Oil → Shanghai</td>
<td>0.2384</td>
</tr>
<tr>
<td>5</td>
<td>10Y Australian bond → Bovespa</td>
<td>0.7208</td>
<td>Nikkei 225 → 2Y US bond</td>
<td>-0.2384</td>
</tr>
<tr>
<td>6</td>
<td>10Y US bond → Bovespa</td>
<td>0.6937</td>
<td>10Y UK bond → 10Y US bond</td>
<td>-0.2303</td>
</tr>
<tr>
<td>7</td>
<td>2Y German bond → Bovespa</td>
<td>0.6924</td>
<td>Nikkei 225 → 2Y German bond</td>
<td>-0.2168</td>
</tr>
<tr>
<td>8</td>
<td>10Y Japanese bond → Nikkei 225</td>
<td>0.6815</td>
<td>10Y US bond → 2Y Japanese bond</td>
<td>0.2046</td>
</tr>
<tr>
<td>9</td>
<td>2Y US bond → Bovespa</td>
<td>0.6747</td>
<td>DAX 30 → 3Y Italian bond</td>
<td>0.2018</td>
</tr>
<tr>
<td>10</td>
<td>10Y Japanese bond → Bovespa</td>
<td>0.6667</td>
<td>10Y Swiss bond → 2to3Y Spanish bond</td>
<td>-0.1978</td>
</tr>
</tbody>
</table>

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 $x \rightarrow y$ 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 ascribed to each causal relationship is the average causal weight from $x$ to $y$ for the period January 4, 2000 to February 12, 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.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Linear Granger causality</th>
<th>Score</th>
<th>Nonlinear Granger causality</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3Y Italian bond → 2to3Y Spanish bond</td>
<td>0.7940</td>
<td>10Y Greek bond → 2to3Y Spanish bond</td>
<td>−0.2899</td>
</tr>
<tr>
<td>2</td>
<td>10Y US bond → 2to3Y Spanish bond</td>
<td>0.7899</td>
<td>3Y Italian bond → 2to3Y Spanish bond</td>
<td>0.2547</td>
</tr>
<tr>
<td>3</td>
<td>10Y Greek bond → 2to3Y Spanish bond</td>
<td>0.7493</td>
<td>10Y UK bond → 2to3Y Spanish bond</td>
<td>0.2520</td>
</tr>
<tr>
<td>4</td>
<td>2Y German bond → 2to3Y Spanish bond</td>
<td>0.7249</td>
<td>10Y US bond → 2to3Y Spanish bond</td>
<td>0.2384</td>
</tr>
<tr>
<td>5</td>
<td>10Y UK bond → 2to3Y Spanish bond</td>
<td>0.7208</td>
<td>10Y US bond → 10Y Australian bond</td>
<td>−0.2384</td>
</tr>
<tr>
<td>6</td>
<td>10Y Italian bond → 2to3Y Spanish bond</td>
<td>0.6937</td>
<td>10Y Italian bond → 2to3Y Spanish bond</td>
<td>−0.2303</td>
</tr>
<tr>
<td>7</td>
<td>10Y US bond → 10Y Australian bond</td>
<td>0.6924</td>
<td>2Y German bond → 2to3Y Spanish bond</td>
<td>−0.2168</td>
</tr>
<tr>
<td>8</td>
<td>2Y US bond → 2to3Y Spanish bond</td>
<td>0.6815</td>
<td>2Y US bond → 2to3Y Spanish bond</td>
<td>0.2046</td>
</tr>
<tr>
<td>9</td>
<td>Dow Jones → BSE</td>
<td>0.6747</td>
<td>10Y US bond → 10Y Japanese bond</td>
<td>0.2018</td>
</tr>
<tr>
<td>10</td>
<td>10Y Australian bond → 2to3Y Spanish bond</td>
<td>0.6667</td>
<td>10Y Greek bond → 10Y German bond</td>
<td>−0.1978</td>
</tr>
</tbody>
</table>

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 $x \leftarrow y$ 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 ascribed to each causal relationship is the average causal weight from $x$ to $y$ for the period January 4, 2000 to February 12, 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.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Shadow causality</th>
<th>Score</th>
<th>Hidden causality</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DAX 30 → BSE</td>
<td>0.7940</td>
<td>10Y US bond → 10Y German bond</td>
<td>−0.2899</td>
</tr>
<tr>
<td>2</td>
<td>BSE → Bovespa</td>
<td>0.7899</td>
<td>10Y US bond → 10Y Australian bond</td>
<td>0.2547</td>
</tr>
<tr>
<td>3</td>
<td>BSE → S&amp;P 500</td>
<td>0.7493</td>
<td>10Y Italian bond → 10Y German bond</td>
<td>0.2520</td>
</tr>
<tr>
<td>4</td>
<td>BSE → Oil</td>
<td>0.7249</td>
<td>2Y German bond → 2to3Y Spanish bond</td>
<td>0.2384</td>
</tr>
<tr>
<td>5</td>
<td>CAC 40 → BSE</td>
<td>0.7208</td>
<td>10Y UK bond → 10Y German bond</td>
<td>−0.2384</td>
</tr>
<tr>
<td>6</td>
<td>Hang Seng → BSE</td>
<td>0.6937</td>
<td>Dow Jones → S&amp;P 500</td>
<td>−0.2303</td>
</tr>
<tr>
<td>7</td>
<td>BSE → ASX200</td>
<td>0.6924</td>
<td>10Y Greek bond → 10Y Italian bond</td>
<td>−0.2168</td>
</tr>
<tr>
<td>8</td>
<td>Bovespa → BSE</td>
<td>0.6815</td>
<td>2Y Japanese bond → 3Y Italian bond</td>
<td>0.2046</td>
</tr>
<tr>
<td>9</td>
<td>BSE → Shanghai</td>
<td>0.6747</td>
<td>10Y UK bond → 10Y Swiss bond</td>
<td>0.2018</td>
</tr>
<tr>
<td>10</td>
<td>Dow Jones → BSE</td>
<td>0.6667</td>
<td>10Y German bond → 10Y Australian bond</td>
<td>−0.1978</td>
</tr>
</tbody>
</table>

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 $x \leftarrow y$ 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 ascribed to each causal relationship is the average causal weight from $x$ to $y$ for the period January 4, 2000 to February 12, 2016 for the specific causality method.
### TABLE 11  Top 30 out of 600 links in terms of average strength across all causalities.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Causal relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10Y US bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>2</td>
<td>10Y Greek bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>3</td>
<td>3Y Italian bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>4</td>
<td>10Y US bond → 10Y Australian bond</td>
</tr>
<tr>
<td>5</td>
<td>10Y UK bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>6</td>
<td>10Y Italian bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>7</td>
<td>2Y US bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>8</td>
<td>2Y German bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>9</td>
<td>10Y US bond → 10Y German bond</td>
</tr>
<tr>
<td>10</td>
<td>10Y US bond → 10Y Japanese bond</td>
</tr>
<tr>
<td>11</td>
<td>Dow Jones → BSE</td>
</tr>
<tr>
<td>12</td>
<td>S&amp;P 500 → Hang Seng</td>
</tr>
<tr>
<td>13</td>
<td>10Y US bond → 10Y Swiss bond</td>
</tr>
<tr>
<td>14</td>
<td>Dow Jones → Nikkei 225</td>
</tr>
<tr>
<td>15</td>
<td>10Y Greek bond → 10Y German bond</td>
</tr>
<tr>
<td>16</td>
<td>10Y Australian bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>17</td>
<td>Bovespa → BSE</td>
</tr>
<tr>
<td>18</td>
<td>2Y Australian bond → 2to3Y Spanish bond</td>
</tr>
<tr>
<td>19</td>
<td>S&amp;P 500 → Nikkei 225</td>
</tr>
<tr>
<td>20</td>
<td>Bovespa → Hang Seng</td>
</tr>
<tr>
<td>21</td>
<td>10Y German bond → Bovespa</td>
</tr>
<tr>
<td>22</td>
<td>10Y Swiss bond → Bovespa</td>
</tr>
<tr>
<td>23</td>
<td>Dow Jones → Hang Seng</td>
</tr>
<tr>
<td>24</td>
<td>DAX 30 → BSE</td>
</tr>
<tr>
<td>25</td>
<td>10Y UK bond → Bovespa</td>
</tr>
<tr>
<td>26</td>
<td>2Y Australian bond → Bovespa</td>
</tr>
<tr>
<td>27</td>
<td>2Y US bond → 10Y Swiss bond</td>
</tr>
<tr>
<td>28</td>
<td>2Y German bond → Bovespa</td>
</tr>
<tr>
<td>29</td>
<td>Bovespa → Shanghai</td>
</tr>
<tr>
<td>30</td>
<td>CAC 40 → BSE</td>
</tr>
</tbody>
</table>

Causality symbols: $x \rightarrow y$ denotes $x$ influences $y$ in the same direction, i.e., past $x$ increases cause future $y$ increases (similarly for decreases), while $x \rightarrow 
\neg y$ denotes $x$ influences $y$ in the opposite direction, i.e., past $x$ increases cause future $y$ decreases and vice versa. Causality score: the number ascribed to each causal relationship is the average causal weight from $x$ to $y$ for the period January 4, 2000 to February 12, 2016 for the specific causality method.

and HC further reveals an active and consistent short-term causality exercised by those bonds.

### 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.
### TABLE 12  Asset ranking in terms of out-strength centrality.

<table>
<thead>
<tr>
<th></th>
<th>LICC</th>
<th></th>
<th>NICC</th>
<th></th>
<th>LCo</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Asset</td>
<td>Strength</td>
<td>Asset</td>
<td>Strength</td>
<td>Asset</td>
<td>Strength</td>
<td></td>
</tr>
<tr>
<td>10Y US bond</td>
<td>1.075</td>
<td>Hang Seng</td>
<td>0.871</td>
<td>2Y Japanese bond</td>
<td>1.377</td>
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</tr>
<tr>
<td>Dow Jones</td>
<td>0.538</td>
<td>DAX 30</td>
<td>0.838</td>
<td>10Y Japanese bond</td>
<td>0.774</td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>0.501</td>
<td>10Y Greek bond</td>
<td>0.830</td>
<td>10Y Swiss bond</td>
<td>0.529</td>
<td></td>
</tr>
<tr>
<td>10Y UK bond</td>
<td>0.501</td>
<td>10Y German bond</td>
<td>0.761</td>
<td>10Y UK bond</td>
<td>0.479</td>
<td></td>
</tr>
<tr>
<td>2Y US bond</td>
<td>0.486</td>
<td>S&amp;P 500</td>
<td>0.713</td>
<td>10Y German bond</td>
<td>0.472</td>
<td></td>
</tr>
<tr>
<td>Bovespa</td>
<td>0.416</td>
<td>Nikkei 225</td>
<td>0.585</td>
<td>2Y German bond</td>
<td>0.464</td>
<td></td>
</tr>
<tr>
<td>10Y Greek bond</td>
<td>0.407</td>
<td>10Y Italian bond</td>
<td>0.521</td>
<td>10Y Greek bond</td>
<td>0.410</td>
<td></td>
</tr>
<tr>
<td>CAC 40</td>
<td>0.396</td>
<td>CAC 40</td>
<td>0.496</td>
<td>2Y Australian bond</td>
<td>0.393</td>
<td></td>
</tr>
<tr>
<td>DAX 30</td>
<td>0.391</td>
<td>10Y Swiss bond</td>
<td>0.383</td>
<td>10Y Australian bond</td>
<td>0.379</td>
<td></td>
</tr>
<tr>
<td>3Y Italian bond</td>
<td>0.223</td>
<td>2Y German bond</td>
<td>0.315</td>
<td>10Y US bond</td>
<td>0.377</td>
<td></td>
</tr>
<tr>
<td>2Y Australian bond</td>
<td>0.222</td>
<td>10Y US bond</td>
<td>0.302</td>
<td>10Y Italian bond</td>
<td>0.370</td>
<td></td>
</tr>
<tr>
<td>Oil</td>
<td>0.202</td>
<td>2to3Y Spanish bond</td>
<td>0.299</td>
<td>2Y US bond</td>
<td>0.314</td>
<td></td>
</tr>
<tr>
<td>10Y Japanese bond</td>
<td>0.185</td>
<td>10Y Australian bond</td>
<td>0.284</td>
<td>3Y Italian bond</td>
<td>0.311</td>
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<tr>
<td>10Y German bond</td>
<td>0.177</td>
<td>Dow Jones</td>
<td>0.282</td>
<td>2to3Y Spanish bond</td>
<td>0.163</td>
<td></td>
</tr>
<tr>
<td>BSE</td>
<td>0.170</td>
<td>BSE</td>
<td>0.282</td>
<td>Oil</td>
<td>0.021</td>
<td></td>
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<tr>
<td>2Y German bond</td>
<td>0.169</td>
<td>ASX 200</td>
<td>0.278</td>
<td>Shanghai</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.169</td>
<td>Bovespa</td>
<td>0.262</td>
<td>Bovespa</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>ASX 200</td>
<td>0.160</td>
<td>Oil</td>
<td>0.225</td>
<td>Dow Jones</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>10Y Swiss bond</td>
<td>0.145</td>
<td>2Y US bond</td>
<td>0.186</td>
<td>S&amp;P 500</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>10Y Italian bond</td>
<td>0.142</td>
<td>10Y Japanese bond</td>
<td>0.181</td>
<td>DAX 30</td>
<td>0.000</td>
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<tr>
<td>10Y Australian bond</td>
<td>0.137</td>
<td>3Y Italian bond</td>
<td>0.138</td>
<td>Hang Seng</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Hang Seng</td>
<td>0.122</td>
<td>Shanghai</td>
<td>0.096</td>
<td>CAC 40</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>2Y Japanese bond</td>
<td>0.105</td>
<td>10Y UK bond</td>
<td>0.077</td>
<td>Nikkei 225</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Nikkei 225</td>
<td>0.080</td>
<td>2Y Japanese bond</td>
<td>0.076</td>
<td>ASX 200</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>2to3Y Spanish bond</td>
<td>0.066</td>
<td>2Y Australian bond</td>
<td>0.059</td>
<td>BSE</td>
<td>0.000</td>
<td></td>
</tr>
</tbody>
</table>

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 January 4, 2000 to February 12, 2016 for the specific causality method.

To that end, we plot four phases of the network for every causality method (see Figures 9–16). The phases record

(a) 2002 during the post-dot-com 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.

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TABLE 13  Asset ranking in terms of out-strength centrality.

<table>
<thead>
<tr>
<th>Asset</th>
<th>NCo</th>
<th>LGC</th>
<th>NGC</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAX 30</td>
<td>0.637</td>
<td>10Y US bond</td>
<td>2.429</td>
</tr>
<tr>
<td>Nikkei 225</td>
<td>0.543</td>
<td>S&amp;P 500</td>
<td>1.352</td>
</tr>
<tr>
<td>10Y US bond</td>
<td>0.440</td>
<td>2Y US bond</td>
<td>1.267</td>
</tr>
<tr>
<td>10Y UK bond</td>
<td>0.440</td>
<td>Dow Jones</td>
<td>1.220</td>
</tr>
<tr>
<td>Oil</td>
<td>0.410</td>
<td>Hang Seng</td>
<td>1.146</td>
</tr>
<tr>
<td>3Y Italian bond</td>
<td>0.356</td>
<td>DAX 30</td>
<td>1.122</td>
</tr>
<tr>
<td>CAC 40</td>
<td>0.324</td>
<td>Bovespa</td>
<td>1.115</td>
</tr>
<tr>
<td>2Y Australian bond</td>
<td>0.322</td>
<td>10Y UK bond</td>
<td>1.115</td>
</tr>
<tr>
<td>2Y German bond</td>
<td>0.319</td>
<td>3Y Italian bond</td>
<td>1.047</td>
</tr>
<tr>
<td>Dow Jones</td>
<td>0.306</td>
<td>10Y Greek bond</td>
<td>1.024</td>
</tr>
<tr>
<td>2Y US bond</td>
<td>0.276</td>
<td>2Y German bond</td>
<td>0.835</td>
</tr>
<tr>
<td>BSE</td>
<td>0.273</td>
<td>CAC 40</td>
<td>0.823</td>
</tr>
<tr>
<td>Hang Seng</td>
<td>0.263</td>
<td>10Y Japanese bond</td>
<td>0.821</td>
</tr>
<tr>
<td>ASX 200</td>
<td>0.251</td>
<td>Shanghai</td>
<td>0.811</td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.249</td>
<td>2Y Australian bond</td>
<td>0.786</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>0.245</td>
<td>10Y Italian bond</td>
<td>0.771</td>
</tr>
<tr>
<td>10Y German bond</td>
<td>0.234</td>
<td>Oil</td>
<td>0.746</td>
</tr>
<tr>
<td>10Y Australian bond</td>
<td>0.229</td>
<td>BSE</td>
<td>0.729</td>
</tr>
<tr>
<td>10Y Greek bond</td>
<td>0.222</td>
<td>ASX 200</td>
<td>0.728</td>
</tr>
<tr>
<td>10Y Swiss bond</td>
<td>0.210</td>
<td>10Y Australian bond</td>
<td>0.700</td>
</tr>
<tr>
<td>10Y Japanese bond</td>
<td>0.200</td>
<td>10Y Swiss bond</td>
<td>0.650</td>
</tr>
<tr>
<td>10Y Italian bond</td>
<td>0.174</td>
<td>2Y Japanese bond</td>
<td>0.642</td>
</tr>
<tr>
<td>Bovespa</td>
<td>0.148</td>
<td>10Y German bond</td>
<td>0.512</td>
</tr>
<tr>
<td>2to3Y Spanish bond</td>
<td>0.110</td>
<td>Nikkei 225</td>
<td>0.488</td>
</tr>
<tr>
<td>2Y Japanese bond</td>
<td>0.107</td>
<td>2to3Y Spanish bond</td>
<td>0.460</td>
</tr>
</tbody>
</table>

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 January 4, 2000 to February 12, 2016 for the specific causality method.

On the onset of the LICC network (see Figure 9(a)), we can observe that the 2Y US bond is the predominant hub of causality, with the only competitive equity indexes being those of DAX 30 and CAC 40. During the global financial crisis, the 2Y US bond concedes its central role to the 10Y US bond, while the overall equity performance remained stable. Five years after the outbreak of the global crisis 10Y US bond still exerts the most causality on the network (see Figure 9(c)). However, its strength is diminished (see Figure 9(b)). As far as the equities are concerned, ASX 200 appears to be the most influential. Finally, during the Chinese stock market crisis it is really interesting to see that oil becomes a hub of causality.
TABLE 14  Asset ranking in terms of out-strength centrality.

<table>
<thead>
<tr>
<th>SC</th>
<th>Asset Strength</th>
<th>HC</th>
<th>Asset Strength</th>
<th>Total (mean)</th>
<th>Asset Strength</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSE</td>
<td>1.150 2Y Japanese bond</td>
<td>0.423 10Y US bond</td>
<td>0.904 10Y US bond</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.486 10Y US bond</td>
<td>0.346 10Y Greek bond</td>
<td>0.630 10Y Greek bond</td>
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<td></td>
</tr>
<tr>
<td>10Y Greek bond</td>
<td>0.458 2Y German bond</td>
<td>0.257 DAX 30</td>
<td>0.542 DAX 30</td>
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<td></td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>0.399 10Y UK bond</td>
<td>0.241 S&amp;P 500</td>
<td>0.540 S&amp;P 500</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dow Jones</td>
<td>0.342 2Y US bond</td>
<td>0.215 2Y US bond</td>
<td>0.516 2Y US bond</td>
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</tr>
<tr>
<td>2Y Japanese bond</td>
<td>0.323 10Y Greek bond</td>
<td>0.208 Dow Jones</td>
<td>0.507 Dow Jones</td>
<td></td>
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</tr>
<tr>
<td>Bovespa</td>
<td>0.307 Dow Jones</td>
<td>0.174 10Y UK bond</td>
<td>0.505 10Y UK bond</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASX 200</td>
<td>0.280 2Y Australian bond</td>
<td>0.156 2Y Japanese bond</td>
<td>0.468 2Y Japanese bond</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2Y German bond</td>
<td>0.262 10Y Australian bond</td>
<td>0.152 Hang Seng</td>
<td>0.458 Hang Seng</td>
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<td></td>
</tr>
<tr>
<td>CAC 40</td>
<td>0.259 10Y Italian bond</td>
<td>0.140 Bovespa</td>
<td>0.430 Bovespa</td>
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</tr>
<tr>
<td>10Y UK bond</td>
<td>0.234 S&amp;P 500</td>
<td>0.121 10Y Swiss bond</td>
<td>0.422 10Y Swiss bond</td>
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<td>DAX 30</td>
<td>0.225 10Y German bond</td>
<td>0.113 BSE</td>
<td>0.415 BSE</td>
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<td>10Y Italian bond</td>
<td>0.214 DAX 30</td>
<td>0.100 2Y German bond</td>
<td>0.415 2Y German bond</td>
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<td>Hang Seng</td>
<td>0.201 Bovespa</td>
<td>0.099 3Y Italian bond</td>
<td>0.409 3Y Italian bond</td>
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</tr>
<tr>
<td>Nikkei 225</td>
<td>0.200 Shanghai</td>
<td>0.074 10Y Italian bond</td>
<td>0.395 10Y Italian bond</td>
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<td></td>
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<tr>
<td>10Y Australian bond</td>
<td>0.200 3Y Italian bond</td>
<td>0.068 10Y Japanese bond</td>
<td>0.384 10Y Japanese bond</td>
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<tr>
<td>Oil</td>
<td>0.195 10Y Swiss bond</td>
<td>0.048 CAC 40</td>
<td>0.379 CAC 40</td>
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<tr>
<td>3Y Italian bond</td>
<td>0.190 BSE</td>
<td>0.040 10Y German bond</td>
<td>0.360 10Y German bond</td>
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<tr>
<td>2Y US bond</td>
<td>0.188 Nikkei 225</td>
<td>0.039 10Y Australian bond</td>
<td>0.345 10Y Australian bond</td>
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<tr>
<td>10Y German bond</td>
<td>0.184 Hang Seng</td>
<td>0.038 Oil</td>
<td>0.343 Oil</td>
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<td></td>
</tr>
<tr>
<td>2Y Australian bond</td>
<td>0.179 CAC 40</td>
<td>0.034 Nikkei 225</td>
<td>0.343 Nikkei 225</td>
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<td></td>
</tr>
<tr>
<td>10Y Japanese bond</td>
<td>0.176 ASX 200</td>
<td>0.031 2Y Australian bond</td>
<td>0.330 2Y Australian bond</td>
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<tr>
<td>10Y Swiss bond</td>
<td>0.173 10Y Japanese bond</td>
<td>0.028 Shanghai</td>
<td>0.321 Shanghai</td>
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<tr>
<td>2to3Y Spanish bond</td>
<td>0.173 Oil</td>
<td>0.024 ASX 200</td>
<td>0.318 ASX 200</td>
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<td></td>
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<td>10Y US bond</td>
<td>0.165 2to3Y Spanish bond</td>
<td>0.020 2to3Y Spanish bond</td>
<td>0.264 2to3Y Spanish bond</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

SC, shadow causality. HC, hidden causality. Score: out-strength centrality is calculated as the average for every node (asset) throughout the period January 4, 2000 to February 12, 2016 for the specific causality method.

Viewing the same financial network through the lens of NICC (see Figure 10), we witness a totally different situation: a disconnected network with substantially weaker relationships and no apparent hubs in all four phases. Unlike the LICC case, here we see little interaction between assets in different categories (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 produces more stable relationships than NICC. However, this does not necessarily mean that LICC is better; it could mean that LICC, being a linear method, overestimated the causality intensity, while NICC, being a more “explorative” nonlinear method, is stricter in assigning
higher scores. Investigation of the association between causality methods and their “meaning” is part of our future work.

We introduce LCo in Figure 11. Here we clearly see the reign of bonds throughout the four phases, with almost all of the linear long-term relationships being initiated
FIGURE 10  Nonlinear intertemporal cross-correlation network (a) during the post-dot-com bubble burst, (b) during the global financial crisis, (c) after the global financial crisis and (d) 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 us understand visually the dominant asset category in terms of the network area (light orange-red for equities, light yellow-green for bonds and gray for oil).

by the bonds. Clearly, the equities subgroup is totally broken, with the individual equities being strongly influenced by bonds. Note that the 2Y Japanese bond is the hub of the financial network, particularly in parts (a) and (c) of Figure 11, where it is obvious that it influences most equities.
FIGURE 11  Linear cointegration network (a) during the post-dot-com bubble burst, (b) during the global financial crisis, (c) after the global financial crisis and (d) 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 us understand visually the dominant asset category in terms of the network area (light orange-red for equities, light yellow-green for bonds and gray for oil).

In the nonlinear form of the cointegration network (NCo) bonds still have a greater presence than equities (see Figure 12). During the aftermath of the dot-com 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,
FIGURE 12 Nonlinear cointegration network (a) during the post-dot-com bubble burst, (b) during the global financial crisis, (c) after the global financial crisis and (d) 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 us understand visually the dominant asset category in terms of the network area (light orange-red for equities, light yellow-green for bonds and gray for oil).

and the 2Y US bond the most central bond. Going into the global crisis, the network appears slightly more structured, with the leading asset role of the equities being handed over to DAX 30, and the strength of the 2Y US bond somewhat undermined.
FIGURE 13  Linear Granger causality network (a) during the post-dot-com bubble burst, (b) during the global financial crisis, (c) after the global financial crisis and (d) 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 us understand visually the dominant asset category in terms of the network area (light orange-red for equities, light yellow-green for bonds and gray for oil).

After the crisis, the 2Y US 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
FIGURE 14 Nonlinear Granger causality network (a) during the post-dot-com bubble burst, (b) during the global financial crisis, (c) after the global financial crisis and (d) 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 us understand visually the dominant asset category in terms of the network area (light orange-red for equities, light yellow-green for bonds and gray for oil).

bonds is significantly more strongly connected than the subgroup of equities, which appear rather scattered.

LGC produces a financial network that, during the post-dot-com bubble burst (see Figure 13(a)), reveals a strong cluster of bonds and two broken groups of equities.
**FIGURE 15** Shadow causality network (a) during the post-dot-com bubble burst, (b) during the global financial crisis, (c) after the global financial crisis and (d) 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 us understand visually the dominant asset category in terms of the network area (light orange-red for equities, light yellow-green for bonds and gray for oil).

However, during the global financial crisis (see Figure 13(b)) the equities form a cluster and in fact outperform the group of disconnected bonds. Dow Jones, BSE and Bovespa exert the most causality during that period. After the global financial crisis we see a strong presence of bonds, with dominance of the 10Y UK bond and the 2Y
**FIGURE 16** Hidden causality network (a) during the post-dot-com bubble burst, (b) during the global financial crisis, (c) after the global financial crisis and (d) during the Chinese stock market crash.

US bond. As far as the equities are concerned, the Hang Seng 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 almost equally the causality in the network.
NGC appears to evolve in a parallel way (see Figure 14) to that of LGC: this is no surprise given that those processes are quite similar. The only significant difference seems to occur during the global financial crisis. Unlike 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 into three, with Dow Jones the strongest index. Again, oil rises in significance during the Chinese stock market crash (see Figure 14(d)).

The network as seen through SC is quite intriguing (see Figure 15). During the post-dot-com bubble burst we observe 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)) polarizes the financial network and renders the equities group 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 few, trivial interactions.

The last building block in our analysis (HC) further confirms the existence of a bonds regime (see Figure 16). In the post-dot-com bubble burst, the Shanghai index and a group of other equities are causally affected by the bonds cluster. The bonds cluster is mostly led by the 3Y Italian bond and the 10Y German bond (see Figure 16(a)). During the global financial crisis the group of equities seems further scattered, although the bonds seem to be connected with even stronger causal relationships (see Figure 16(b)). In the postmortem of the global financial crisis the 10Y and 2Y US bonds and the 10Y UK bond appear to concentrate most of the causal relationships. Ultimately, during the Chinese stock market crash we can see a network saturated absolutely by the bonds, with the 10Y German bond and the 10Y Greek bond being the undisputed hubs.

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 efficient market hypothesis (at least in its strong form) and opens up new horizons for analysis of market inefficiencies.

We tested the percentage of similarity of common links between all causality methods and found that the most similar pair of causality-induced networks is on average less than 50% similar throughout the time period examined. Thus, we consider it meaningless to try to compare the results of different causality methods: every method deserves an explanation of its own. However, to the best of our knowledge, our study is the first attempt to unify various causalities for the production and analysis of financial networks.
We ranked the causal links as produced by each causality method and found that the most intense and protracted relationship across all causality methods is that of 10Y US bond → (ie, causing the prices of) 2to3Y Spanish bond. Furthermore, we ranked the financial assets in terms of averaged causality emanation, and uncovered a hidden “bonds regime”, with the most causal asset being that of the 10Y US bond. Ultimately, we observed a recurring pattern of oil exerting increasing causality as the financial network entered the Chinese stock market crash. Causalities cannot be used for forecasting asset prices directly; rather they are tools to detect causal relationships, and to assist the model design process. Our future work will involve the use of causal networks as a basis for modeling and forecasting asset prices.

DECLARATION OF INTEREST

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REFERENCES


Causality networks of financial assets


Research Paper

Networks and lending conditions: empirical evidence from the Swiss franc money markets

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ABSTRACT

This paper provides an empirical analysis of the network characteristics of two interrelated interbank money markets and their effect on overall market conditions. Based on transaction data from the unsecured and secured Swiss franc money markets, the trading network structures are assessed before, during and after the financial market crisis. It can be shown that banks in the unsecured market are connected to a lower number of counterparties but rely heavily on reciprocal and clustered trading relationships. The corresponding network structure likely favored the exchange of liquidity prior to the financial market crisis but may have also led to a lower resilience of the unsecured market. There is empirical evidence that conditions in both sub-markets were significantly driven by the individual network position of banks. The network topology likely affected the shift observed from unsecured to secured lending and the increase in risk premiums for unsecured lending during the financial market crisis. This paper therefore provides further evidence of the functioning of interbank money markets, especially the impact of market participants’ interconnectedness.

Keywords: repo transaction; unsecured interbank money market; financial market turmoil; financial stability; Switzerland.
1 INTRODUCTION

Interbank money markets are a key factor in the efficient allocation of liquidity within the banking system. Broadly speaking, banks exchange central bank reserve balances through interbank money markets. That is, banks with excess liquidity transfer reserves to banks with a liquidity shortage (see, for example, Heider et al 2015; Mancini et al 2016). A failing interbank market can lead to an inefficient allocation of money and, consequently, impair the whole financial system as well as the real economy. If the liquidity is, for example, not where it can be used most efficiently, the financial intermediation to households and firms can be impaired (see, for example, Acharya and Merrouche 2010). Disruptions in the interbank money market can, at an extreme, even lead to bank runs (see, for example, Afonso et al 2011). Interbank money markets can therefore be seen as an important ingredient in the proper functioning of financial markets.

Banks typically exchange liquidity either on a secured basis (in the so-called secured or repurchase agreement (repo) market) or on an unsecured basis (in the so-called unsecured market). In the unsecured market, no collateral is involved, while in the secured market, liquidity is exchanged against high-quality securities as collateral. In contrast to secured transactions, unsecured money market transactions do not involve the opportunity cost for the cash taker of the securities involved. That is, the unsecured money market serves as an actual funding source for banks, as no initial endowment is required. However, an unsecured transaction is only concluded if the cash provider has faith in the cash taker that the liquidity will be returned. With increasing risk perception, the price for unsecured borrowing can rise. Secured transactions, in contrast, are considered safer, as the collateral obtained can be liquidated by the cash provider if the cash taker defaults. However, to conclude a repo transaction, the cash taker needs to be endowed with unencumbered securities.

It is of particular interest to understand how shocks in the interbank market evolve and whether the interbank market mitigates or amplifies shocks to individual banks or the banking sector as a whole. Likewise, it is important to gain a comprehensive understanding of the drivers of the ability and willingness of market participants to fund themselves in the unsecured or secured market. A comprehensive understanding of interbank money markets is crucial for central bankers, as a well-functioning money market is essential for the effectiveness of the monetary transmission mechanism.

During the financial market crisis of 2007–9, several interbank money markets across the global financial system were indeed impaired. At the height of the crisis, a strong increase in the risk premiums for unsecured loans and, in some jurisdictions, even a freeze in market activity was observed (see, for example,
Hördahl and King 2008). The US repo market experienced a so-called run on repo, which was characterized by heavily increasing haircuts on repo transactions and, accordingly, the inability to use certain asset classes as collateral (see, for example, Gorton and Metrick 2011). Turbulence in the Swiss franc money market was not as severe as in other money markets. However, a significant shift in market activity from the unsecured to the secured money market was observed; this was accompanied by increased risk premiums for unsecured money market transactions.

Presumably, the lack of trust in counterparties led to decreased market activity in the unsecured Swiss franc money market and increasing risk premiums for unsecured loans during the financial market crisis (Guggenheim et al 2011). The interconnectedness of market participants was apparently an important driver for the dispersion of such market tensions. If interconnectedness indeed plays an important role in lending conditions in money markets, the significance of a single market participant cannot be discerned solely by examining an institution in isolation. Instead, it is its position in a web of relationships that has to be considered, especially in times of high uncertainty and lack of counterparty confidence (Gabrieli 2012). An analysis of network characteristics, therefore, can entail important information on the functioning of relationship patterns within different markets, which in turn can provide information on the dispersion of shocks in the according markets.

The economic literature has shown that trading relationships and the interconnectedness of banks can influence the functioning of interbank money markets. Furfine (1999b), for example, finds that banking relationships affect the pricing of federal funds transactions, especially for small market participants. Cocco et al (2009) find evidence that in the Portuguese interbank money market, banks with large imbalances in liquidity reserves, small banks, banks with poor performance and banks with high volatility in liquidity shocks are more likely to borrow funds from banks with which they share a relationship. Further, Kraenzlin and von Scarpatetti (2011) find evidence for price differentiation in the Swiss franc repo market due to differences in the centrality scores and bargaining power of market participants as well as private information. Similarly, Bräuning and Fecht (2012) find that relationship lending can significantly affect the access to liquidity by improving private information about counterparties. Hence, failed relationships can lead to a loss of valuable information and thus hinder access to liquidity for borrowers. Allen et al (2012) find that market participants in the Canadian dollar market continued to support counterparties with high credit risk during the financial market crisis due to the tight interconnectedness of, and, hence, high contagion risk among, Canadian banks. Finally, Gabrieli (2012) examines the Italian unsecured interbank money market and finds evidence that measures
of interconnectedness can capture part of the cross-sectional variance in interbank rates.

The aim of this paper is to examine interconnectedness in two different interbank sub-markets. It thus adds to the literature by providing empirical evidence of the influence of market participants’ interconnectedness across sub-markets by conducting a thorough analysis of the networks in the two interrelated markets and estimating their effect on overall market conditions. In the first step, based on a comprehensive data set consisting of transactions of both the secured and unsecured Swiss franc money market, the network topology of two sub-markets that share a large number of market participants and common institutional features are simultaneously assessed and compared. The characteristics of the networks should tell us, how, according to the theoretical literature, shocks affect the market. In the second step, the impact of network characteristics on market activity and interest rates is analyzed. By running panel regression models, we can test whether network characteristics indeed affected the well-functioning of the money markets. Because the data set ranges from January 2005 to December 2012, the analysis is conducted before, during and after the financial market crisis and, therefore, also allows assessing the impact of the networks’ structures during various time periods. Moreover, a comprehensive data set from the Swiss payment system and individual bank bond yield spreads allows us to account for the liquidity position and credit risk of each market participant. Therefore, drivers of money market tensions, which previously had not been evaluated, can be assessed.

This analysis provides evidence that banks in the unsecured market are connected to a small share of potential market participants but rely heavily on a few clustered trading relationships. Through this type of trading relationship, market participants in the unsecured market may have been able to build a so-called social collateral that favored liquidity provision prior to the crisis. According to theoretical models, this type of link pattern can lead to a lower network resilience, as shocks can propagate easily. The econometric analysis reveals that the activity in the two sub-markets is driven by the individual network positions of market participants. The diversification of a bank, measured by its degree centrality, positively drove turnover and led to lower interest rates for unsecured lending and borrowing. Further, prior to the financial market crisis, the clustering of banks supported turnover in the interbank money markets and led to a reduction in interest rate premiums. The reduction in clustered trading relationships accompanied by the increasing credit risk of banks likely supported the shift in activity from an unsecured to a secured money market.

This paper is structured as follows. Section 2 introduces the institutional setup of the Swiss franc money market, provides information on its network topology and draws implications for funding conditions. In Section 3, the econometrical analysis is presented. Finally, Section 3 offers conclusions.
2 THE SWISS FRANC MONEY MARKETS

2.1 Setup

Repo transactions in Swiss francs are predominantly traded on an electronic trading platform. During the time period analyzed, these transactions were conducted on the Eurex Repo trading platform, which was also used by the Swiss National Bank (SNB) for the implementation of its monetary policy operations.¹ For the collateralization of cash, only high-quality securities are accepted. The automatic settlement of securities is performed in the Swiss security settlement system, SECOM, while the cash leg is simultaneously settled in the Swiss real-time gross settlement (RTGS) system, Swiss Interbank Clearing (SIC). For a detailed description of the Swiss franc repo market, see, for example, Fuhrer et al (2016).

In the unsecured market, transactions are traded on an over-the-counter (OTC) basis and are predominantly settled in the SIC system. For more information about the unsecured Swiss franc money market, see Guggenheim et al (2011).

The main motivation for a cash provider to trade cash against securities as collateral is to lend without counterparty risk. The cash taker, on the other hand, might take advantage of relatively low interest rates compared with unsecured transactions, but they may also require the availability of (high-quality) securities. Hence, only in the unsecured market can cash takers obtain liquidity without an initial endowment. This might also be a reason why the turnover in the unsecured Swiss franc money market was higher than in the secured market prior to the financial market crisis.

Between January 2005 and autumn 2007, the average daily turnover in the unsecured money market was approximately CHF 8 billion, whereas in the secured market it oscillated at approximately CHF 5 billion (see Figure 1 in the online appendix). With the outbreak of the financial market crisis, the turnover in the unsecured market decreased to a level of CHF 5 billion, while the secured market increased significantly. At the height of the crisis (autumn 2008), the activity in the unsecured market collapsed to a level below CHF 1 billion a day, while in the repo market the daily turnover reached a high of approximately CHF 15 billion. Thereafter, the activity in the repo market decreased again but remained at a level above CHF 5 billion, and thus far above the level in the unsecured market. Market activity in both markets only dropped significantly after autumn 2011 due to the substantial liquidity provision by the SNB. Overall, a shift in turnover can be observed from the unsecured to the secured interbank money market during the crisis (Guggenheim et al 2011).

In addition, a large increase in the spread between unsecured and secured interbank interest rates during the financial market crisis was observed (see Figure 2 in the online appendix).

¹ As of May 1, 2014 the SNB conducts its monetary policy operations on the SIX Repo trading platform. In addition, interbank money market transactions can be conducted on this new platform.
The spread reflects the risk premium for unsecured lending and can be seen as a measure for stress in the unsecured money market. This measure remained at a relatively low and constant level for a long time. However, it suddenly increased in August 2007 and reached a high in autumn 2008. After mid-2009, the spread reached low levels again but remained quite volatile. These facts indicate that, like unsecured money markets in other currencies, the unsecured money market for the Swiss franc exhibited significant stress during the height of the financial market crisis.

2.2 The data

The network structures in the Swiss franc money markets are estimated by analyzing transaction data that stems from two different sources. The first data set consists of repo transactions between commercial banks concluded on the Eurex Repo trading platform. Between January 2005 and December 2012, approximately 180,000 transactions from 161 banks were settled in the Swiss franc repo market. The second data set is based on the transaction data from the SIC system. Guggenheim et al (2011) introduced an augmented Furfine (1999a) algorithm to identify unsecured money market transactions from SIC data. The second data set contains this transformed data between January 2005 and December 2012 and approximately 365,000 transactions stemming from 241 market participants. In both data sets, information about the cash taker, the cash provider, the interest rate, the maturity and the cash volume is included. Because data from the unsecured market only contains transactions of a maturity of up to ninety days, both data sets are limited to transactions with a maturity of up to ninety days.2

The transaction data for the purpose of this analysis is favored over the data on interbank exposures collected by the SNB – which is used, for example, in Mueller (2006) – for several reasons. First, in contrast to data that provides balance sheet positions on specific days, the transaction data tracks every single transaction on every single business day and, therefore, allows a dynamic analysis of the network characteristics. Second, the transaction data provides information on the linkages among all market participants in the SIC system and, accordingly, in the Eurex Repo trading platform. Due to the open-access policy of the SNB, foreign banks, which do not need to report their exposure to the SNB, are included in the data set.3 Therefore,

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2 Robustness checks revealed that the algorithm only allows us to reliably estimate transactions with a maturity of up to ninety days.

3 In international terms, the access policy of the SNB is relatively liberal, such that foreign banks are also able to participate in SIC and, therefore, in the Swiss franc money markets (see Kraenzlin and Nellen 2015).
the coverage of the market is assumed to be much broader. Third, the data set allows us to study not only the exposure among banks but also the prevailing market prices.

Guggenheim et al (2011) highlight potential drawbacks of the algorithm when used to identify unsecured money market transactions. One important drawback is the missing identification of correspondent banking transactions, as only transactions settled on SIC can be identified by the algorithm. However, it can be shown that the misspecification of network measures due to correspondent banking is expected to be small, and that its negative influence on the analysis is limited (see the online appendix).

The average time to maturity of the relevant contracts in the two markets is roughly twenty-five days, ie, a contract will mature, on average, twenty-five days from today. Hence, on average, the relationships a bank has formed during the past twenty-five days decide whether it is able to renew a contract. In other words, it is reasonable to presume that a bank’s network position is determined within the next twenty-five days before a contract expires and might have to be renewed. To analyze the network structures of the two markets, daily networks, each consisting of transactions from the past twenty-five days, are computed. Compared with networks that only contain transactions from a single day, network statistics are less volatile, and more banks can be related to the different network statistics. Further, it seems reasonable that the network position of a bank is not as volatile as networks based on a single day would suggest.

2.3 Network topology

In the following, the network characteristics of the Swiss franc money markets are illustrated by making use of network theory (also called graph theory in the mathematical literature). Some basic concepts and the measures used in the analysis are explained in the online appendix. In addition to the graphs based on actual data (actual networks), so-called random networks are computed that are determined by the densities, ie, the unconditional probabilities that two nodes in a network are connected, and the number of nodes of the actual networks.4 The random networks serve as a basis for comparison, as the number of banks, the degree and the density are identical to the actual network, but links are formed randomly. The difference from the random network illustrates the special aspect of the actual networks, which can be explained by the formation of trading relationships. The network characteristics of the actual networks and their random counterparts can be illustrated by the distribution of individual measures at certain points in time as well as by the development

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4 For each day and market, the overall network statistics of the random networks are determined by the mean of one hundred random networks.
FIGURE 1  Network characteristics of Swiss franc money markets, January 2005 to December 2012.

(a) Number of banks. (b) Average degree. (c) Density. (d) Average path length. (e) Diameter (fifteen-day moving average). The illustrations show the development of selected network characteristics of the unsecured and secured Swiss franc money markets as well as their random counterparts. The network measures are computed on a daily basis. Random networks are computed based on the number of nodes and the density of the actual networks. For each day and market, the network statistics of the random networks are determined by the mean of one hundred random networks.

of overall network measures over time. Figures 1 and 2 illustrate the overall network statistics of the unsecured and secured money markets and their random counterparts for the period from January 2005 to December 2012. Additionally, Figures 5 to 8 in the online appendix show particular distributions of individual network measures for selected days and months.

(a) Number of disconnected banks (fifteen-day moving average). (b) Average clustering coefficient. (c) Reciprocity. (d) Average maximum borrowing preference index. (e) Average maximum lending preference index. The illustrations show the development of selected network characteristics of the unsecured and secured Swiss franc money markets as well as their random counterparts. The network measures are computed on a daily basis. Random networks are computed based on the number of nodes and the density of the actual networks. For each day and market, the network statistics of the random networks are determined by the mean of one hundred random networks.

Stylized facts

There are several network measures indicating that banks in the unsecured market are not as well connected to each other as those in the repo market. First, although there are more participating banks in the unsecured market, the average degree (ie, average
number of counterparties) in the repo market is significantly higher. Accordingly, the density in the repo market is much higher, i.e., banks in the repo market trade with a larger share of potential counterparties. Before the collapse of Lehman Brothers, approximately 20% of the possible links are used in the repo market, whereas only approximately 5% are used in the unsecured market. Although the density in the repo market decreases at the end of 2008 to a level of roughly 10%, it remains significantly above the level of that in the unsecured market of 5%. The degree distributions for selected months also reveal that the market participants’ degrees in the repo market are much more uniformly distributed. In the unsecured market, we can observe a large mass at very low levels and a few outliers with a very high degree. Thus, a large proportion of the market participants in the unsecured market trade with very few counterparties.

Second, in absolute terms, market participants in the repo market are closer to each other. The average path length in the secured market is approximately half of a link shorter than in the unsecured market. However, this is also due to the higher number of market participants in the unsecured market. Between mid-2006 and autumn 2009, the unsecured market even shows a lower average path length than its random counterpart, indicating a short average path length relative to the size of the network. The repo market, on the other hand, exhibits a higher average path length than the random network. Further, the diameter, i.e., the path in the graph that connects the two most distant nodes, is approximately two links longer in the unsecured market. The diameter in the repo market only increases at the end of the observation period, when the market activity in the repo market decreases. Hence, figuratively speaking, market participants in the repo market are more closely connected to each other through links to other banks.

Third, the number of disconnected banks, i.e., banks not connected to the giant component, is very low in both markets until the end of 2008. Afterwards, the average number of disconnected banks in the unsecured market increases greatly, to a level far above that in its random counterpart. The number of disconnected banks in the repo market, on the other hand, remains at a level slightly above zero until autumn 2011. Thus, after 2008, an increasing number of banks in the unsecured market cannot be linked, by transactions, to a large part of the network.

There is evidence that in the unsecured market, in contrast to the repo market, trading relationships with specific counterparties matter greatly. First, banks in the unsecured market rely heavily on clustered trading relationships. The average clustering coefficient (i.e., the probability that two market participants with a common neighbor share a link as well) in the unsecured market lies far above that in its random counterpart, at least until mid-2010. Clustering in the repo market is at a very low level compared with the level in its random network. The levels remain constant in the repo market until the end of 2008, whereas in the unsecured market they decrease
heavily after August 2007. Moreover, the clustering in the unsecured market is very pronounced at banks with low degrees. Clustering coefficients in the repo market are distributed much more uniformly over the degree. Thus, until August 2007 (and, to a lesser extent, until mid-2010) it is quite common in the unsecured market for two trading partners to have a trading relationship with a mutual trading partner. Further, many of these market participants only rely on a few specific counterparties.

Second, reciprocity is much higher in the unsecured market than in the repo market. Whereas the share of reciprocal lending in the repo market corresponds to the random network, in the unsecured market it is ten times as high as in the random equivalent. Thus, for trading on an unsecured basis, market participants more often rely on reciprocal trading relationships. In the unsecured market, 20–30% of the transactions are based on reciprocal lending; however, in the secured market, only 5–10% are based on reciprocal transactions. Moreover, reciprocal borrowing and lending become more important with the evolvement of the financial market crisis. After 2009, banks in the unsecured market increase reciprocal lending and borrowing from roughly 20% to 30%.

Third, banks in the unsecured market depend more heavily on just a few trading partners. The average maximum borrower preference index lies at almost 70%, ie, banks, on average, borrow 70% of their funds from the same counterparty. In the repo market, this share lies at around 40% before the start of the crisis, declining to approximately 30% afterwards. In both markets, the indexes are much higher than in the random counterparts.

Overall, the illustrations reveal that the networks in the repo and unsecured markets significantly differ from their equivalent random networks and are thus determined by the formation of specific trading relationships. While network measures such as clustering and reciprocity in the unsecured market lie far above the measures of the random network, the respective measures in the repo market do not reach the levels in the random network. This further highlights the importance of the establishment of specific trading relationships in the unsecured market compared with the repo market.

**Implications**

*Market participants in the unsecured market make use of so-called social collateral in order to increase trust and thus facilitate access to liquidity.* In contrast to the secured market, in the unsecured money market no physical collateral is involved to reduce counterparty risk. Thus, trust must be an important factor for the conclusion of transactions, which in turn can be ameliorated by the maintenance of trading relationships. According to the theoretical literature, the establishment of reciprocal and clustered trading relationships can increase trust and thus facilitate access to liquidity. Mobius and Szeidl (2007) and Karlan *et al* (2009) propose a game-theoretic model in
which a valuable friendship can secure a transaction in a manner similar to physical collateral. They find that “the level of trust equals the sum of the weakest link values over all disjoint paths connecting borrower and lender”; thus, it positively depends on the number of common friends of two agents, or, put differently, on the clustering coefficient. In other words, the network position may serve as social collateral for tomorrow’s borrowing and lending activities. The model further reveals that a change in the network structure or social collateral today may affect the lending conditions of subsequent periods. Because the dissolution of a trading relationship today can lead to the breakup of additional relationships tomorrow, a small variation in today’s network might have a significant impact on conditions tomorrow. The illustrations of the network characteristics above underline the important role social collateral can play in the unsecured market. Market participants in the unsecured market do not trade with many different trading partners; instead, they rely on relationships with specific counterparties as well as clustered and reciprocal trading relationships. This may in turn foster trust between market participants and thus foster the exchange of liquidity in the unsecured market. Because the maintenance of such trading relationships is likely to be costly, market participants may optimize the number of links and therefore only trade with a few counterparties.

In the repo market, market participants do not need to rely as heavily on specific counterparties, as trust plays a minor role due to the inclusion of physical collateral. In contrast to the unsecured market, the diversification of repo market participants is much higher.

The resulting network structure makes the unsecured market more prone to shocks than the secured market. The related literature suggests that a network structure such as that found in the unsecured market, characterized by the importance of specific trading relationships and low diversification, makes a market less resilient. Relative to the total number of market participants, banks are relatively close to each other in the unsecured market, which, according to Cohen-Cole et al (2012), favors a fast spread of shocks. The network of the unsecured market, with its low density, high local clustering and short average path length, resembles a so-called small-world network, as introduced by Watts (1999). According to Georg (2011) and Haldane (2009), such networks are relatively prone to contagion. Also, Allen and Gale (2000) find that financial contagion is favored by chains of overlapping liabilities that allow the losses to move through the network. Consequently, the impact of a liquidity shock is strongest in an incomplete but connected market with a high degree of interconnectedness.5

5 For descriptions of this, see the online appendix. Both secured and unsecured markets can be classified as incomplete but connected.
Consequently, there are reasons to presume that the network in the unsecured market exhibits a lower resilience to shocks than the secured market. A typical market participant in the unsecured market has a very low degree and a high clustering coefficient, and it usually trades the majority of its liquidity with a few counterparties on a reciprocal basis. These facts indicate a risk for such banks in the sense that shocks can easily flow through overlapping liabilities (high clustering), but the risk of being hit cannot be diversified (low degree). A shock, such as banks starting to hoard liquidity, can spread rapidly within a cluster of banks. Because these banks are not diversified, they are unable to obtain liquidity elsewhere in the network. Clustering is not as evident in the repo market as in the unsecured market, and market participants are diversified to a higher degree. Thus, repo market participants are more likely to be able to connect with alternative trading partners in case a shock hits them. Therefore, due to their network structures, one would expect the repo market to be more resilient to shocks than the unsecured market.

The related literature finds that a tipping point can be reached such that the network structure no longer supports access to liquidity but rather favors the dispersion of shocks. Georg (2011) finds that a high degree of interconnectedness in a financial network can amplify access to liquidity in normal times but may intensify shocks and destabilize the system in times of high market stress. Haldane (2009) calls this the “robust-yet-fragile” or “knife-edge” property of financial networks. The network can thus serve as a shock absorber up to a certain tipping point, but afterwards it tends to support the spread of shocks.

The combination of the important role of social collateral and the low resilience of the network structure could have rapidly exacerbated lending conditions in the unsecured market. Due to the existing network structure in the unsecured market, a shock, such as evolving mistrust in other participants, could have spread rapidly through the market after the emergence of critical events at the beginning of the financial market crisis. Accordingly, increasing mistrust may have led to a lower willingness of market participants to lend on an unsecured basis. This in turn likely induced a decline in the level of social collateral, which, according to Karlan et al. (2009), again worsened subsequent lending conditions. Therefore, the unsecured Swiss franc money market might have exhibited the robust-yet-fragile or knife-edge property, according to Haldane (2009), favoring a stable exchange of liquidity

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6 Note that shocks do not need to be equated with the default of a market participant. As Cohen-Cole et al (2012) show, uncertainty, risk or specific behavior can also spread through a network, even without a default.
7 As proposed by Karlan et al (2009), a change in today’s social collateral can have a significant effect on conditions tomorrow, as a reduction in trading relationships can induce a negative effect on others’ social collateral and the dissolution of further trading relationships.
in normal times but also a sudden deterioration in lending conditions in times of stress.

Thus, aside from the fact that unsecured lending is riskier due to the absence of physical collateral, the network structure of the unsecured market tends to be less resilient. Overall, one can expect that shocks in the unsecured market instead have a more contagious effect than would be the case in the repo market.

3 ECONOMETRIC ANALYSIS

The econometric analysis aims at assessing whether network characteristics can affect the conditions in the Swiss franc money market. The market turmoil during the financial market crisis provides the opportunity to evaluate the impact of the network characteristics on the activity in the market in times of market stress. Because a comprehensive data set of transactions in the secured and unsecured money market is available, the network position of each market participant can be assessed. Therefore, it can be tested whether the individual network position affected the individual market activity as well as the interest rates paid before, during and after the market turmoil took place. To test for the impact of network characteristics on conditions in the money market, an econometric analysis is conducted. In the following paragraphs, the choice of potential determinants (i.e., variables) is motivated, the models are specified and the regression results are stated.

3.1 Determinants of money market conditions

Network variables

The individual network measures that presumably had a major impact on lending conditions, as mentioned above, are taken into account to determine their effect on money market conditions.

The degree centrality, defined as the degree of a market participant divided by the total number of market participants in the network, is included in the regressions to account for the relative importance of the number of counterparties of a cash taker and a cash provider. As already noted, if a market participant has a higher degree centrality, it is connected to a larger share of the network, is better diversified and is thus able to conduct a money market transaction in case a shock hits the market. The degree centrality should therefore have a positive effect on money market conditions. Hence, the degree centrality is expected to have a positive effect on turnover in the money markets. Moreover, a better-diversified market participant should be able to receive a larger set of offers, place its price quotations at more banks and, therefore, pay or receive an advantageous interest rate. Thus, the degree centrality should have a negative effect on the interest rates paid in the money markets. As seen above, market
participants in the secured market seem to be better diversified. Hence, the effect is expected to be more pronounced in the secured market.

The clustering coefficient, defined as the probability that two trading partners of a market participant are connected to each other as well, is included in the regression to account for the interconnectedness of a market participant. As argued above, clustering, or having a common “friend”, can increase trust between two market participants. As in the unsecured money market, no collateral is involved. A certain level of trust may even be essential so that a transaction takes place between two market participants. Clustering is therefore expected to have a positive effect on funding conditions. Hence, a cash provider with a high clustering coefficient is more willing to provide cash, or a cash taker with a high clustering coefficient is more able to take cash. The same argument holds for the interest rates. A market participant with a high clustering coefficient is able to establish social collateral with trading partners and is therefore able to receive or is willing to provide better interest rates. The effect of clustering should be more pronounced in the unsecured market due to the lack of physical collateral. As shown above, clustering, that is, having a common trading partner, can serve as social collateral and foster trust between market participants. In contrast, due to the involvement of physical collateral, trust should play a minor role in the secured market.

Reciprocity, defined as the number of reciprocal links divided by the total number of links established by a market participant, is included in the regression to account for the impact of reciprocal trading relationships on money market conditions. Reciprocity tends to increase trust between two market participants and, thus, to foster a trade relationship. Therefore, specifically in the unsecured market, reciprocity should have a positive effect on funding conditions. Hence, cash providers with many reciprocal trading relationships are expected to be more willing to provide cash or more able to take cash. Analogously, interest rates offered or received by a market participant with a high reciprocity level should be lower than average. Due to the missing physical collateral, the effect of reciprocity should be more pronounced in the unsecured market than in the repo market.

Strength, defined as the net flow of transactions of a market participant, ie, the value lent net the value borrowed, is included in the regressions to account for the importance of a cash provider and cash taker in the money market during the past observation period. On the one hand, a high measure of strength indicates that a market participant has conducted a large number of money market transactions as a cash provider. It can be assumed that a strong market participant is generally cash long and a typical cash lender. However, a low (negative) strength value indicates that a market participant has conducted a large number of money market transactions as cash taker. Strength is thus expected to have a positive effect on cash provision and a negative effect on borrowing.
Control variables

It has been widely recognized in the literature that increasing credit and liquidity risk can lead to disruptions and thus drive the funding conditions in interbank money markets. Several theoretical models suggest that increasing liquidity risk and liquidity hoarding can lead to lending disruptions (see, for example, Allen et al 2009; Caballero and Krishnamurthy 2008; Diamond and Rajan 2009; Eisenschmidt and Tapking 2009). Therefore, three variables are incorporated to control for the liquidity risk of market participants. First, the net excess reserves according to Fecht et al (2011) are used. This variable accounts for the balances at the central bank relative to the minimum reserve requirements of a bank and is a measure of the liquidity position of bank $i$ at time $t$ (at the beginning of the settlement day).\(^8\) Excess reserves have increased since the global financial market crisis due to the SNB’s unconventional monetary policy (see above). A bank with higher excess reserves in general has a lower need to obtain liquidity in the interbank money market. Therefore, the overall need for the redistribution of liquidity in the system may have been decreasing due to the higher liquidity available in the system. It can further be seen as a proxy variable for the size of a market participant. Second, current transactions in the Swiss RTGS system (SIC) are considered as a proxy for current liquidity shocks by including the net value (incoming minus outgoing transactions, excluding money market transactions) of bank $i$ on settlement day $t$. The variable indicates the size of the liquidity shocks that banks have on a specific settlement day. For both liquidity variables, it holds that the higher the value, the better the liquidity position of a participant. Third, the overall value of balances at the central bank is included in the interest rate regressions as a variable for the market liquidity.\(^9\) According to Schwarz (2010), the overall level of liquidity in the market significantly influences the prices in the market.

Moreover, several models emphasize asymmetric information and the increasing level of credit risk. In such a situation, market participants are unable to distinguish between banks with low and high credit risk, and banks start to ration cash provision (see, for example, Freixas and Jorge 2008; Heider et al 2015). A measure to control for credit risk is included in the regression analysis. Because CDS spreads are only available for a fraction of the participants in the Swiss franc money markets, bond yield spreads are used as a proxy variable for the credit risk of a bank.\(^{10}\) Bond yield

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\(^8\) Banks domiciled outside Switzerland do not need to hold minimum reserves at the SNB. Therefore, a value of zero is assumed for their lower bounds.

\(^9\) The variable is not included in the turnover regression due to the potential endogeneity problem.

\(^{10}\) Special thanks goes to Adrian Bruhin and the Financial Stability division of the SNB, who provided the codes in R for the calculation of the bond yield spreads.
spreads are defined by the volume-weighted yield spread between a set of bonds denominated in Swiss franc with a time to maturity of between two and five years and the according yield for Swiss confederation bonds, which is assumed to be risk free. The related literature suggests the bond yield and CDS spreads move together in the long run (see Eisenschmidt and Tapking 2009; Zhu 2004). The premium on a specific bond compared with the risk-free bond can therefore be seen as a proxy for the credit risk of the according issuer. Data on bonds denominated in Swiss francs are available for approximately sixty-five banks, allowing their yield spreads to be computed. They account for approximately 85% of the turnover and outstanding volume in the market. In addition, bond spreads for different groups belonging to the same geographical regions and types of bank are computed. Banks without an individual bond spread are assigned to these artificial group bond spreads.

As Eisenschmidt and Tapking (2009) argue, the credit risk of both lender and borrower determines the risk premium. Consequently, in the interest rate regression, the credit risks of both the cash taker and cash provider are included. The collateral basket is included in the interest rate regression.

3.2 Models

To examine the effect of network characteristics on funding conditions in the Swiss franc money markets, two regression models are applied. First, variables accounting for the activity of cash takers and cash providers in the unsecured and secured Swiss franc money markets are regressed on a set of variables considering the individual network measures as well as individual liquidity risk and credit risk (turnover regression). Second, variables accounting for interest rate premiums in the money markets are regressed on the same set of variable rates (interest rate regression). To account for the unobservable individual specific characteristics of the banks, panel and least-square dummy variable (LSDV) regression models are applied.

Turnover regression

In the turnover regression, the determinants of the difference between the individual turnover in the unsecured and secured markets are evaluated, and thereby the relative

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11 The following groups are computed: Swiss cantonal banks, Swiss insurances, small banks from Switzerland and banks from Liechtenstein, Belgium, France, Luxembourg, the Netherlands, Great Britain, Scandinavia, Austria, Germany, southern Europe, eastern Europe/Russia, Asia and North America. The majority of banks without an individual bond spread are small, domestic-private and regional banks as well as small, private and regional banks from neighboring countries such as Austria, Germany and Liechtenstein. The bond spreads of these groups are also computed based on bonds of rather small private or regional banks. Therefore, it can be argued that the risk profile of these banks should approximately correspond to the credit risk based on the group bond spreads.
importance of the secured and unsecured markets is assessed. The following fixed effects model is estimated:

\[ y_{it} = X'_{it} \beta + \alpha_i + \varepsilon_{it}, \quad (3.1) \]

with

\[ X'_{it} \beta = \sum_{n=1}^{N} \beta_n NW^n_{it-1} + \sum_{l=1}^{L} \gamma_l LR^l_{it} + \sum_{c=1}^{C} \delta_c CR^c_{it}, \quad (3.2) \]

where \( NW^n_{it-1} \) denotes the network measure \( n \) at date \( t-1 \), \( LR^l_{it} \) are the liquidity risk variables \( l \) and \( CR^c_{it} \) is the credit risk component \( c \) of market participant \( i \) at day \( t \).

In the baseline regression, the dependent variable \( y_{it} \) is defined as the spread between the log value (in million CHF) of the turnover in the unsecured market \( TU_{it} \) and the log value (in million CHF) of the turnover in the secured market \( TS_{it} \) of cash provider \( i \) on day \( t \):

\[ y_{it} = \log(\max\{1, TU_{it}\}) - \log(\max\{1, TS_{it}\}). \quad (3.3) \]

Regressing the ratio of unsecured and secured turnover on the potential drivers will provide information as to whether market participants are traded in the unsecured or secured market due to their network position. The turnovers of market participants as lenders and borrowers are both assessed, and therefore \( TU \) (TS) can be denoted as either the amount of liquidity lending or borrowing of market participant \( i \) at time \( t \) in the unsecured (secured) market. Hence, the relative importance of lending as well as borrowing in the unsecured and secured markets is analyzed. Note that the very few transactions with a value between zero and CHF 1 million are replaced by a value of zero.\(^{12}\)

As a robustness check, further assessments will be made as to whether the potential drivers affected the turnover in the two sub-markets. Therefore, the individual turnover of market participants – as lender and borrower – in the two sub-markets are regressed on the same set of variables:

\[ y_{it} = \log(\max\{1, TU_{it}\}), \quad (3.4) \]

\[ y_{it} = \log(\max\{1, TS_{it}\}). \quad (3.5) \]

\(^{12}\) Specifically, 0.1% of the transactions worth 0.001% of the total turnover in the unsecured market, and none in the secured market.
The determinants of the interest rate premiums in the unsecured money market are evaluated by means of an LSDV regression. The interest rate regression is given by:

\[
\hat{r}_{i,t} = \sum_{n=1}^{N} \beta_n NW^n_{CTUnsec,i,t-1} + \sum_{n=1}^{N} \gamma_n NW^n_{CPSec,i,t-1} \\
+ \sum_{n=1}^{N} \eta_n NW^n_{CTSec,i,t-1} + \sum_{n=1}^{N} \theta_n NW^n_{CPSec,i,t-1} \\
+ \sum_{l=1}^{L} \delta_l LR^l_{CT,i,t} + \sum_{l=1}^{L} \kappa_l LR^l_{CP,i,t} \\
+ \sum_{c=1}^{C} \zeta_c CR^c_{CT,i,t} + \sum_{c=1}^{C} \lambda_c CR^c_{CP,i,t} \\
+ \sum_{d=2}^{D} \mu_d CT_i,t + \sum_{s=2}^{S} \nu_s CP_{i,t} + \alpha_i + \varepsilon_i, \quad (3.6)
\]

where \(\hat{r}_{i,t}\) denotes the difference between the interest rate of the unsecured transaction \(i u_i\) and the Swiss Average Rate for secured contracts \(S_t\) in basis points (bps). The regressions are run separately for transactions with maturities of one day (ON), one week (1W), one month (1M) and three months (3M). \(NW^n_{CT(CP)Unsec(Sec),i,t-1}\) denotes the network characteristic \(n\) of the cash taker (or provider) of transaction \(i\) in the unsecured (secured) market at \(t-1\). \(LR^l_{CT(CP),i,t}\) stands for the liquidity risk measure \(l\) of the cash taker (provider) and \(CR^c_{CT(CP),i,t}\) stands for the credit risk component \(c\) of the cash taker (provider) of transaction \(i\) on day \(t\). In addition, the indicator variables \(CT(CP)_{i,t}\), which equal one if the cash taker (provider) \(d(s)\) was involved in transaction \(i\), are included. To account for the direct reciprocal relationship of the two market participants involved, an indicator variable \(RP(D)\) is included; this is equal to one if the two participants conducted a transaction within the past twenty-five days in the opposite direction.

13 Standard panel models cannot be applied due to the highly unbalanced data set. In contrast to turnover regression, missing values cannot be replaced by zeros. Due to the low number of observations for longer maturities, only overnight transactions are considered.

14 Swiss Average Rates are based on the transactions and quotes concluded or posted on the Eurex Repo trading platform.
3.3 Data issues

As outlined in Section 2, the levels of interest rate premiums and turnover change significantly during the observation period 2005–12. To account for different time periods and levels in turnover and interest rates, the sample is split into four sub-periods. The first period starts in 2005 and lasts until August 8, 2007, when market turmoil first occurred and unsecured interest rates started to hike.\footnote{On August 8, 2007 BNP Paribas had to suspend three funds exposed to the US subprime mortgage market. This event is seen by many economists as the outbreak of the financial market crisis (see, for example, Acharya et al 2009).} The subsequent period lasts from August 9, 2007 until September 14, 2008: the day before the investment bank Lehman Brothers collapsed. The third period ranges from September 15, 2008 until April 22, 2010, when the European sovereign debt crisis started to emerge.\footnote{During April 2010, Greek government bond yields increased heavily, which revealed the unsustainability of Greek fiscal policy. In May 2010, European countries had to agree on the provision of bilateral loans totalling €80 billion (Minka and de Haan 2013).} The subsequent and final period lasts from April 23, 2010 until August 2, 2011. Afterwards, SNB began a major increase in liquidity provision, and activity in both markets nearly came to a halt.

Transactions concluded on the last working day of a minimum reserve requirement period and on the last working day of a month are excluded due to the high volatility in interest rates on such days, as proposed by Kraenzlin (2009) and Mancini et al (2016). Table 1 in the online appendix provides summary statistics for the dependent variables for different time periods.

In the panel regressions, only banks participating in both markets are included. Overall, there are 113 banks participating in both markets between January 2005 and December 2012. However, a number of banks do not participate, either on a daily basis or during the whole sample period, which leads to attrition and, consequently, to a potential bias of the estimates in panel regression models (see, for example, Baltagi 2005). Nevertheless, it can be argued that attrition should not lead to a self-selection problem and should not bias the results. In the specifications stated above, the goal is actually to evaluate the difference in total turnover in the unsecured and repo markets, which by definition is only determined by actual transactions. Moreover, missing values can be replaced by zeros, which leads to a perfectly balanced panel data set.

To measure the market activity, the turnover or the outstanding volume in the according market could be measured. As mentioned above, the goal of the regressions is to determine the drivers for funding conditions on a specific day by accounting for individual network positions as well as liquidity and credit risk characteristics. Therefore, turnover is favored over the outstanding volume of market participant $i$ at
time \( t \), as its turnover reveals the ability to conclude a new transaction on a specific day. When using the outstanding volume, concluded transactions in the past are considered as well. Depending on the maturities of the trades a market participant has completed, the conclusion of trades a long time ago can influence the outstanding volume. Hence, there can be situations in which the model would try to explain activity in the money markets a long time ago based on the current network position of a market participant. Moreover, an endogeneity problem may arise, as simultaneity in the outstanding volume and past network measures may occur through past transactions.

As independent variables, the lagged individual network measures are used, which are based on the network positions between \( t - 26 \) and \( t - 1 \). The dependent variable is based on the current market situation, i.e., the turnover at time \( t \). By regressing current turnover values on past network measures, simultaneity in the dependent and independent variables, and therefore endogeneity, can be ruled out, as proposed in Cocco et al (2009).

The daily network measures are partially correlated. Specifically, the strength and degree centrality show a relatively high correlation exceeding 0.5. To avoid multicollinearity, the degree centrality (DC) in the secured (unsecured) market is orthogonalized with respect to the strength (ST) in the secured (unsecured) market:

\[
DC_{i,t} = \beta_1 + \beta_1 ST_{i,t} + v_{i,t}. \tag{3.8}
\]

Thus, the variation in the degree centrality, which is not driven by the strength \( v_{i,t} \), is used as an independent variable in the regression model. Due to the orthogonalization of the two variables, the correlation between the degree centrality and the reciprocity can be reduced as well.

Several panel regression tests are computed. Tests for spatial (cross-sectional) and serial correlation are conducted. Höchle (2007) introduces a panel data model with standard errors according to Discroll and Kraay (1989) that are robust to serial and spatial correlation, specifically for panels with a large number of \( T \). If the tests cannot be rejected, these robust standard errors are used. Moreover, a Hausman test is computed to check for random effects. These, however, can always be rejected. Finally, in the LSDV regression, heteroscedasticity-robust standard errors are applied.

### 3.4 Results: turnover regression

The turnover regressions show the impact of a market participant’s network position on its market activity in the unsecured and secured markets while controlling for its liquidity and credit risk. The regression results can be found in Tables 1 to 3. In the baseline regression, a positive sign indicates a positive effect on unsecured lending and a negative effect on secured lending, and vice versa. Coefficients in the robustness check regressions with the dependent variables specified in (3.4) and (3.5) can be
interpreted one-to-one, ie, a positive sign indicates a positive effect on the turnover in the market in question.

The majority of the coefficients are consistent for different specifications, ie, the signs of the coefficients on the robustness check regression are in line with those in the baseline regressions. The regressions show a goodness-of-fit of between 0.12 and 0.60. The robustness check regressions as well as the regressions with the cash provision as a dependent variable generally show a higher goodness-of-fit. The majority of the coefficients are statistically significant at least at the 5% level. Hausman tests all indicate fixed effects. Therefore, the results of the fixed effects regressions are reported. Serial and cross-sectional correlation cannot be rejected in all cases. For this reason, robust standard errors according to Höchle (2007) are used in such cases.

The hypothesis regarding the degree centrality stated above can be confirmed: the degree centrality, which is measured by the network position during the previous twenty-five business days, has a statistically and economically significant positive effect on borrowing and lending in the unsecured and secured Swiss franc money markets. The baseline regression reveals that the degree centrality in the secured market positively affects turnover in the secured market. Turnover in the unsecured market is affected to a much lower extent. For instance, lending in the unsecured market is only positively influenced by the degree centrality in the unsecured market in the first and last periods. It is likely that diversification in the unsecured market was not high enough to ensure stable market activity. Robustness check regression reveals that the coefficients for the degree centrality are significantly positive in almost all cases. Note that diversification seems to be a more important factor for borrowers than for lenders. Also, the effect on the activity in the secured market is more pronounced.

The hypothesis regarding the clustering of market participants can only partly be confirmed. The baseline regression reveals that the lender’s willingness to provide cash is increasing in the clustering coefficients of the corresponding market. The impact tends to decrease over time, especially in the unsecured market. The effect in the secured market is economically stronger and remains significant until the last period. Robustness checks confirm the results from the baseline regression, but they also reveal that clustering entails a (economically lower) negative effect on borrowing, especially in the repo market. Only in the third period does clustering in the repo market show a slightly positive effect on cash taking in the unsecured market. Thus, the establishment of clustered trading relationships apparently leads to a higher probability of cash lending, whereas it reduces the probability for cash borrowing. These results lead to the conjecture that typical lenders, ie, cash-long market participants, often maintain clustered trading relationships, which might help them increase trust in the counterparties. For typical borrowers, ie, cash-short market participants, trust is less important, as they typically do not rely on clustered trading relationships.
### TABLE 1  Turnover regression ($y_{it}$ based on (3.3)).

<table>
<thead>
<tr>
<th></th>
<th>Lending</th>
<th></th>
<th></th>
<th>Borrowing</th>
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<td>P4</td>
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<td>DC</td>
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<td>0.04</td>
<td>0.11*</td>
<td>0.035</td>
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<td>−0.15***</td>
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<tr>
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<td>−0.061***</td>
<td>−0.072***</td>
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<td>0.13***</td>
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<tr>
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</tr>
<tr>
<td>BS</td>
<td>0.041***</td>
<td>−0.031**</td>
<td>0.0014</td>
<td>0.028*</td>
<td>0.023***</td>
<td>−0.065***</td>
<td>−0.026**</td>
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<tr>
<td>Const.</td>
<td>0.21***</td>
<td>0.068</td>
<td>−0.090***</td>
<td>−0.18***</td>
<td>−0.026</td>
<td>−0.11**</td>
<td>−0.18***</td>
</tr>
<tr>
<td>$R^2$</td>
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<td>0.35</td>
<td>0.35</td>
<td>0.36</td>
<td>0.22</td>
<td>0.33</td>
<td>0.15</td>
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<td>35 482</td>
<td>67 687</td>
<td>30 510</td>
<td>44 183</td>
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</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001; coefficients are standardized. DC, degree centrality; CL, clustering coefficient; RP, reciprocity; ST, strength; NE, net excess reserves; PS, liquidity position payment system; BS, bond spreads; No. obs., number of observations; P1 = 3/1/05–8/7/07; P2 = 8/8/07–9/15/08; P3 = 9/16/08–4/22/10; P4 = 4/23/10–7/31/11.
### TABLE 2  Turnover regression unsecured market ($y_{it}$ based on (3.4)).

<table>
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<td>P1</td>
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<td></td>
</tr>
<tr>
<td>DC</td>
<td>0.30***</td>
<td>0.093*</td>
<td>0.22***</td>
<td>0.23***</td>
<td>0.33***</td>
<td>0.28***</td>
<td>0.18***</td>
<td>0.28***</td>
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<tr>
<td>CL</td>
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<td>0.056***</td>
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<td>-0.038***</td>
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<td>-0.027***</td>
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<tr>
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<td>0.0036</td>
<td>-0.003</td>
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<td>-0.016</td>
</tr>
<tr>
<td>ST</td>
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<td>-0.062***</td>
<td>-0.097***</td>
<td>0.41***</td>
<td>0.36***</td>
<td>0.12***</td>
<td>0.033**</td>
</tr>
<tr>
<td><strong>NW secured market</strong></td>
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</tr>
<tr>
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<td>0.067*</td>
<td>0.050*</td>
<td>0.16***</td>
<td>0.21***</td>
<td>0.12***</td>
<td>-0.038*</td>
<td>0.19***</td>
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<tr>
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<td>0.014</td>
<td>0.0038</td>
<td>0.011</td>
<td>-0.010*</td>
<td>-0.016**</td>
<td>0.012***</td>
<td>-0.0091*</td>
</tr>
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<td>-0.0089</td>
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<td>-0.013*</td>
<td>-0.016*</td>
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<tr>
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<td>-0.011</td>
<td>0.038***</td>
<td>0.094***</td>
<td>-0.029***</td>
<td>0.011*</td>
<td>0.017*</td>
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<td>-0.17***</td>
<td>-0.027***</td>
<td>-0.033***</td>
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<tr>
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<td>0.060***</td>
<td>0.068***</td>
<td>-0.11***</td>
<td>-0.13***</td>
<td>-0.095***</td>
<td>-0.11***</td>
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<td>-0.0032</td>
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<td>0.0068</td>
<td>-0.028**</td>
<td>-0.035***</td>
<td>-0.024**</td>
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<tr>
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<td>0.26***</td>
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<td>0.36***</td>
<td>0.32***</td>
<td>0.21***</td>
<td>0.26***</td>
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<tr>
<td><strong>R^2</strong></td>
<td>0.45</td>
<td>0.12</td>
<td>0.39</td>
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<td>0.60</td>
<td>0.47</td>
<td>0.54</td>
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<td>67 687</td>
<td>30 510</td>
<td>44 183</td>
<td>35 482</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001; coefficients are standardized. DC, degree centrality; CL, clustering coefficient; RP, reciprocity; ST, strength; NE, net excess reserves; PS, liquidity position payment system; BS, bond spreads; No. obs., number of observations; P1 = 3/1/05–8/7/07; P2 = 8/8/07–9/15/08; P3 = 9/16/08–4/22/10; P4 = 4/23/10–7/31/11.
TABLE 3  Turnover regression secured market (y_{it} based on (3.5)).

<table>
<thead>
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<th>Borrowing</th>
<th>Lending</th>
<th>Borrowing</th>
</tr>
</thead>
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<td>P3</td>
<td>P4</td>
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<tr>
<td><strong>NW unsecured</strong></td>
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</tr>
<tr>
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<td>0.00085</td>
<td>0.01</td>
<td>0.024*</td>
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<tr>
<td>RP</td>
<td>0.013**</td>
<td>0.014***</td>
<td>0.018***</td>
<td>0.017*</td>
</tr>
<tr>
<td>ST</td>
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<td>-0.029</td>
<td>0.041*</td>
<td>-0.0071</td>
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<td><strong>NW secured market</strong></td>
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</tr>
<tr>
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<td>0.11**</td>
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<td>0.29***</td>
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<tr>
<td>CL</td>
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<td>0.15***</td>
<td>0.15***</td>
<td>0.066***</td>
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<td>0.0069</td>
<td>-0.006</td>
<td>-0.012</td>
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<tr>
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<td>-0.082***</td>
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<td>-0.22***</td>
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<tr>
<td><strong>LR</strong></td>
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</tr>
<tr>
<td>NE</td>
<td>0.13***</td>
<td>0.17***</td>
<td>0.023**</td>
<td>-0.00015</td>
</tr>
<tr>
<td>PS</td>
<td>0.13***</td>
<td>0.13***</td>
<td>0.060***</td>
<td>0.068***</td>
</tr>
<tr>
<td><strong>CR</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BS</td>
<td>-0.027***</td>
<td>0.026***</td>
<td>-0.004</td>
<td>-0.028*</td>
</tr>
<tr>
<td>Const.</td>
<td>0.40***</td>
<td>0.42***</td>
<td>0.35***</td>
<td>0.38***</td>
</tr>
<tr>
<td><strong>R^2</strong></td>
<td>0.54</td>
<td>0.48</td>
<td>0.53</td>
<td>0.43</td>
</tr>
<tr>
<td>No. obs.</td>
<td>67 687</td>
<td>30 510</td>
<td>44 183</td>
<td>35 482</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001; coefficients are standardized. DC, degree centrality; CL, clustering coefficient; RP, reciprocity; ST, strength; NE, net excess reserves; PS, liquidity position payment system; BS, bond spreads; No. obs., number of observations; P1 = 3/1/05–8/7/07; P2 = 8/8/07–9/15/08; P3 = 9/16/08–4/22/10; P4 = 4/23/10–7/31/11.
Reciprocity hardly exhibits any effect in the baseline regression. The hypothesis, however, cannot be rejected, because in the robustness check regressions, the coefficients reveal a statistically significant, although economically weak, effect. In the unsecured market, a statistically significant effect on both cash provision and cash taking in the third period can be observed. In addition, reciprocity in the unsecured market exhibits a positive effect on secured borrowing in the third period. Hence, at the height of the crisis, market participants in the unsecured market seem increasingly to have maintained reciprocal trading relationships to conclude money market transactions. Therefore, in addition to maintaining clustered trading relationships, reciprocity may have supported the access to liquidity by fostering trading relationships.

The strength of a market participant, especially in the unsecured market, significantly influenced the borrowing in the secured and unsecured market. Secured borrowing is increasing in the strength of the market participants in the unsecured market. That is, net cash lenders in the unsecured market also borrow funds in the secured market. The coefficients are statistically and economically significant in the first two periods. The effect diminishes afterwards. Further, the borrowing in the secured market is increasingly influenced by the strength of the repo market in the third and fourth periods. Hence, market participants seem to have borrowed cash on a secured basis and lent it on an unsecured basis in the first two periods, which is potentially associated with earning a spread. With the evolvement of the crisis, these trade patterns changed, and market participants instead traded as cash takers and providers only within the repo market. Thus, there is evidence that market making across the two sub-markets was reduced by strong market participants.

The effects of the control variables are in line with expectations. On the one hand, banks experiencing positive cash shocks preferably provide cash on a secured basis. On the other hand, banks with a negative liquidity shock are more able to obtain liquidity in the secured market. The credit risk has an ambiguous effect on turnover in the two markets. Market participants with a higher credit risk are more likely to lend and borrow cash in the unsecured market at the beginning of the sample period. After the first period, however, market activity in the unsecured market is significantly decreasing in the credit risk. Further, in the second period, the market activity in the secured market is significantly increasing in the credit risk. This switch can be ascribed to the fact that market participants with a high credit risk were able to borrow on a secured basis, and cash providers became more risk averse due to precautionary reasons and lent cash in the secured market.

### 3.5 Results: interest rate regressions

The interest rate regression shows the impact of a market participant’s network position on the interest rate premiums paid in the unsecured money market, while
controlling for its liquidity and credit risk. A positive sign indicates a positive effect on the premiums or an increasing unsecured rate. Put differently, a positive sign indicates that a cash taker is worse off and a cash provider is better off than average.

Most coefficients, including those for bank-specific dummy variables, are statistically significant at least at the 5% level. The goodness-of-fit varies between 0.14 and 0.48 and is the highest in the third period, when the interest rate premiums increased heavily. The regression results for overnight transactions can be found in Table 4. The rest of the tables can be found in the online appendix.

As in the turnover regression, the economic impact of the degree centrality is the highest among all regressors. The degree centrality seems to be the most important driver of price differentiations, as the economic and statistical significance is the highest among all independent variables. The hypothesis regarding the degree centrality can partly be confirmed. Interest rate premiums generally decrease with the degree centrality of cash takers and cash providers. In some instances during the second and third periods, interest rate spreads increase in the degree centrality of cash takers. Moreover, during the second and third periods (especially in the overnight and one-week segment), cash providers with a high degree centrality were able to take advantage of higher interest rates. Therefore, with a few exceptions during the financial market crisis, diversification seems to have reduced the risk premiums in the unsecured market.

The hypothesis regarding the clustering of market participants cannot be rejected either. The interest rate premiums in the unsecured market are in most cases decreasing in the clustering coefficients of market participants. However, compared with the degree centrality, the economic effect is less pronounced. Generally speaking, interest rate premiums are decreasing in the clustering coefficient of cash takers. Moreover, there is evidence that cash providers who established clustered trading relationships granted rebates in the overnight market during the second and third periods. Thus, cash providers with a high clustering coefficient in the unsecured market not only provided more liquidity but also offered better interest rates to their counterparties.

The hypothesis regarding the impact of reciprocity only holds during the second period. Hence, reciprocity entails a significant negative impact on the interest rate premiums in the overnight unsecured market during the crisis. So, reciprocal relationships can lead to a reduction in interest rate premiums in times when market participants increasingly rely on trust to conclude a transaction. Note, however, that the results also reveal that interest rates are often increasing in the reciprocity of market participants. This may be for two reasons. First, cash takers with high reciprocity rely heavily on a specific counterparty, which may increase the bargaining power of the cash provider. Moreover, if the counterparty is unable to provide funds, it may be more difficult to find an alternative counterparty to conclude a transaction.
The strength of a market participant has an ambiguous effect on interest rate premiums. Interest rates increase in proportion to the strength of the cash provider. This is likely due to the fact that strong cash providers (i.e., net lenders) have a higher
bargaining power and can thus demand higher interest rates. On the other hand, interest rates are also increasing in the strength of cash takers, especially after the first period and in short-term contracts. Strong cash takers had previously provided a relatively large amount of liquidity, making them sensitive to unexpected liquidity shocks. In the case of such shocks, they would have to fund themselves again in the interbank market, which is likely to be done on a short-term basis. As they may be in immediate need of cash, their interest rates are likely to increase. The regression results indicate that such unexpected shocks with a price impact likely occurred with the evolvement of the financial market crisis.

The effect of liquidity risk is ambiguous and, in most cases, has low economic explanatory power. Credit risk, however, exhibits a statistically and especially economically significant positive impact on interest rate premiums in the second and third periods. While even in the first period a slight negative effect is observed, during the financial market crisis premiums are increasing in the credit risk of both cash takers and cash providers. Moreover, the positive effect increases with the maturity of the contract. This finding is in line with the reasoning of Eisenschmidt and Tapking (2009), who argue that the credit risk of cash providers negatively affects unsecured lending due to high uncertainty with regard to refunding conditions.

4 CONCLUSION

The network topology of the secured and unsecured Swiss franc money markets significantly differs from so-called random graphs and is thus determined by the formation of specific trading relationships. The network topology reveals that market participants in the unsecured market are less diversified but locally more interconnected than in the secured market, ie, banks trade with only a small fraction of potential counterparties and rely heavily on a few reciprocal and clustered trading relationships. There is an indication that market participants in the unsecured market establish social collateral in order to increase trust and facilitate the exchange of liquidity.

The regression results indicate that the interconnectedness or network position of market participants influences their ability to obtain and their willingness to provide liquidity in the interbank market. Further, interest rates are affected by individual network positions. It can be shown that the turnover in the interbank markets is increasing in the degree centrality, especially in the repo market, where diversification by market participants is much higher. The degree centrality accordingly reduces interest rate premiums. Clustering fosters the trading relationship of two banks and can thus support – to an economically lesser extent than the degree centrality – the exchange of liquidity and the reduction of interest rate premiums. Although clustering in the secured market is lower than in the unsecured market, the effect on turnover is more pronounced in the former, especially after the first period. However, this may also be
due to a reduction in the number of clustered trading relationships in the unsecured market during the crisis. Instead, market participants in the unsecured market seem to have increasingly maintained reciprocal trading relationships to conclude money market transactions at reduced risk premiums. This, in turn, may have reduced the social collateral between market participants and increased dependency on specific counterparties. In contrast, in the repo market, the effect of the network position remained quite stable and seems to have continued supporting the exchange of liquidity. Finally, regression results indicate that strong market participants reduced cross-market market making, which may have reduced turnover in the unsecured market.

Another important finding of the regressions is that the network positions in both sub-markets influenced the conditions. This result can certainly be ascribed to the fact that the markets are closely related. It nonetheless gives rise to the interpretation that even the interconnectedness of market participants in other market segments can affect market functioning.

In addition to network characteristics, credit risk affected money market conditions. After the outbreak of the financial crisis, turnover in the unsecured market was decreasing and interest rate premiums were increasing in the credit risk of market participants. The increasing credit risk likely contributed to the shift of turnover toward the secured market and the increased risk premiums for unsecured lending at the height of the crisis.

Network theory has proven to be a useful tool for analyzing the effects of interconnectedness in financial markets. This network analysis reveals that interconnectedness in unsecured money markets can be accentuated by heavy local clustering and reciprocity, which supports access to liquidity through social collateral. By their nature, markets such as the unsecured money market have to rely on trust or on social collateral. Ordinarily, such behavior is certainly favorable, both for an individual bank and for the system as a whole, as it supports access to liquidity. In times of high market stress, it turns out that the resulting network structure can make the market prone to shocks, which may lead to reduced market activity and increased interest rate premiums.

Although the perception of credit risk has decreased during the last couple of years, activity in the unsecured market has not yet picked up. This is certainly also due to the vast liquidity available in the market, which makes a redistribution of liquidity less necessary. Moreover, with the new regulatory initiatives, it is doubtful whether the market activity in the unsecured Swiss franc money market will start to increase again in times of lower overall liquidity in the system. Finally, it may also be uncertain whether a network structure that allows for a stable level of market activity in the unsecured Swiss franc money market can be reached again. In this respect, a nearly nonexistent unsecured money market may be a probable scenario in the future.
this might mean for the well-functioning of the financial system will be left for further research.

DECLARATION OF INTEREST

The views expressed in this paper are those of the author and do not necessarily represent those of the Swiss National Bank.

ACKNOWLEDGEMENTS

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REFERENCES


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