Systemic Risk: a Network Approach

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Abstract

We propose a new measure of systemic risk based on interconnectedness, defined as the level of direct and indirect links between financial institutions in a correlation-based network. Deriving interconnectedness in terms of risk, we empirically show that within a financial network, indirect links are strengthened during systemic events. The relevance of our measure is illustrated at both local and global levels. Our framework offers policymakers a useful toolbox for exploring the real-time topology of the complex structure of dependencies in financial systems and for measuring the consequences of regulatory decisions.

Keywords: Financial networks, Interconnectedness, Systemic risk, Spillover.

JEL Classification: G01, G15, G21

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1. Introduction

The past decade has demonstrated an increased need to better understand risks leading to systemic crises. The increasingly complex and interconnected structure of interbank markets played a crucial role in spillover mechanisms during the global financial crisis (Haldane, 2009). Consequently, the relationship between systemic risk and the architecture of the banking system has become a central issue for policymakers. Following the recent survey of Benoit et al. (2017), systemic risk can be broadly defined as the likelihood that an entire financial system could be severely affected by banks' large and common exposures or by an amplification or contagion mechanism initiated by one or several individual extreme losses. According to conventional wisdom, the highly interconnected structure of banking systems is caused by financial integration, and, as conjectured by Cechetti (2012), financial integration has a dual impact on systemic risk. Lane and Milesi-Ferretti (2008) introduced the idea of a nonlinear relationship between financial integration and economic growth, and Candelon et al. (2020) empirically showed that financial integration had a positive effect on growth while exposing the economy to a negative impact during banking or stock market crises. In the same way that financial integration is both a blessing and a threat to financial stability, the architecture of the interbank market is *"robust yet fragile"*.

Accordingly, the structure of the financial system and its impact on systemic risk has become a major concern of regulators. The dependence structure that emerges from market integration determines financial networks, regardless of whether the links between nodes are interbank loans or correlations in banks' portfolios. From this network perspective, mapping an interlinked banking system facilitates the visualization of direct and indirect interdependencies and enables both local and global analyses. Moreover, the process thus calls for the use of graph theory as a toolbox for a better understanding of systemic risk related to a given financial architecture. Among the topological approaches to systemic risk, exploring the interaction structure between network nodes, defined as interconnectedness, has emerged a way of studying the spillover mechanisms related to the structure of banking networks. Several slightly different definitions and measures of interconnectedness can be found in the literature. Broadly, interconnectedness refers to the degree of interactions between financial institutions, portfolios or assets. Links between nodes model interdependencies arising from interbank loans or exposure similarities due to overlapping positions across banks. From a supervisory perspective, interconnectedness is considered to be a characteristic of financial stability due to its impact on potential contagion (Yellen, 2013).

According to the seminal works of Allen and Gale (2000) and Freixas et al. (2000), a high level of interconnectedness in banking networks has two components: on the one hand, it enables diversification of counterparty risks and reduces uncertainty while providing liquidity; on the other hand, it amplifies market friction and information asymmetry, especially during financial turmoil. These negative externalities can potentially amplify coordination problems (Diamond and Dybvig, 1983) or shocks and can lead to a spillover of bankruptcies (Caballero and Simsek, 2013). As discussed in Yellen (2013), the potential role of the structure of the banking network in spillover and amplification mechanisms leads to questions about the relationship between the rising interconnectedness of the banking system and its potential consequences for systemic risk.

This paper proposes a new measure of systemic risk developed from a network perspective. Rather than studying interconnectedness as a global measure that proxies systemic risk, we investigate the complex architecture of such systems built from direct and indirect interdependencies. Focusing on the dichotomy between direct and indirect links, we follow our intuition that systemic risk is related to the relative strength of indirect links in financial systems. The economic rationale behind our intuition about the role of indirect links is straightforward. In financial networks, interconnectedness measures are based on the topology of links between banks, insurers and financial services companies. Focusing on correlation-based networks, pairwise interactions between these financial institutions can be related to the level of similarity between their holdings, and their common sensitivity to the economic and financial environment or the level of risk concentration among them (Billio et al., 2012). However, pairwise correlations between financial institutions can be impacted by both direct and indirect paths. From an economic point of view, such indirect paths can be related to indirect asset and liability links between two financial institutions through one or several other institutions. These indirect paths can also be related to indirect cross-holdings or a common sensitivity to the economic environment due to similar geographical locations. Disentangling the roles of direct and indirect links is crucial, as interconnectedness can be affected by one or the other. We empirically measure systemic risk by analyzing the European financial system and verify our measure's adequacy, following the methodology described in Benoit et al. (2017). Our measure is easy to implement and can be used to survey systemic risk at both local and system levels. This measure could also help policymakers, as our framework enables real-time analysis of a financial system's architecture.

The rest of this paper is organized as follows. In Section 2, we present a review of the literature on systemic risk and the structure of financial networks. In Section 3, we introduce a topological framework to define our new measure of systemic risk based on interconnectedness in a correlation-based network. Moreover, this framework includes a proposed methodological extension of the literature on correlation-based networks' analysis. In Section 4, we discuss the empirical results obtained for our measure of systemic risk and its relationship with interconnectedness. Finally, we summarize the usefulness of our new measure of systemic risk for regulators and highlight policy implications with respect to the role of direct and indirect links in the architecture of financial systems.

2. Literature

2.1. Measuring systemic risk

In the aftermath of the global financial crisis, systemic risk has become a crucial topic for policymakers. Specifically, the quest for an ideal measure of systemic risk has fueled research. Facing the difficulty of defining systemic risk, scholars have paid particular attention to the mechanisms leading to systemic crises. Indeed, the identification of the sources and mechanisms leading to a crisis enables the construction of measures of systemic risk, which is at the core of financial regulatory control. According to Benoit et al. (2017), systemic risk measures can be classified into two main categories: those derived from specific sources of systemic risk and those derived from the global approach to a given financial system. In the early literature on systemic risk, studies focusing on specific sources of systemic crises, such as spillover and amplification mechanisms, or systemic risk-taking mechanisms have laid the groundwork for systemic risk measurement.

However, these systemic risk measures are specific to a given channel of transmission. Regulators have advocated for global measures of systemic risk, favoring a multichannel approach. Moreover, regulatory supervision requires real-time measures to ensure adequate monitoring of financial stability. As stated by Billio et al. (2012), the economic rationale behind the use of financial institutions' stock returns for building econometric systemic risk measures lies in the well-established fact that *"the likelihood of major financial dislocation is related to the degree of correlation among the holdings of financial institutions, how sensitive they are to changes in market prices and economic conditions [...], how concentrated the risks are among those financial institutions, and how closely linked they are with each other and the rest of the economy"*. Popular measures such as the marginal expected shortfall (MES) and systemic expected shortfall (SES) of Acharya et al. (2010), $SRISK$ of Acharya, Engle, and Richardson (2012), and $\Delta CoVaR$ of Adrian and Brunnermeier (2016) and correlation-based network measures have roots in these linkages. Measure MES (resp., SES) corresponds to the marginal (resp., systemic) expected shortfall (i.e., the risk contribution of a given bank to the whole banking system). $SRISK$ extends MES by adding another dimension to systemic risk to account for both the interconnections and sizes of banks. $\Delta CoVaR$ focuses on the risk contribution in terms of value at risk rather than expected shortfall. Broadly, these authors build global measures of systemic risk via a statistical approach, estimating the loss probability distribution of a given institution conditioned on the occurrence of an extreme event in the financial system. These measures are based on the size and probability of default of institutions as well as on pairwise correlations between financial companies. Due to the multivariate nature of systemic risk, these models share a common weakness: correlation matrices are related only to direct links between each pair of financial companies' stock returns.

Another strand of the literature has emphasized the network approach (Allen and Gale, 2009). Considering the multivariate nature of systemic risk, models based on the structural properties of financial systems have received particular attention in the literature. The network approach used to model financial systems is grounded in the increasing level of interconnectedness and complexity among institutions. In addition to the advantages of being a multivariate approach, this framework is the most intuitive way to model the architecture of interlinked banking systems. Indeed, a network is a collection of vertices (nodes) and edges (links) between vertices. This representation focuses on the high-dimensional structure of interactions. Hence, the network approach provides holistic analysis and visualization tools for policymakers and market participants. Furthermore, graph theory offers a valuable toolbox for studying the topological properties of such complex systems.

Two types of financial networks coexist in the literature on systemic risk: accounting and correlation-based networks. Accounting networks, based on interbank lending transactions or cross-holdings of assets, describe the structure of the financial system from the perspective of banks or insurers' balance sheets. Correlation-based networks emerge from market price dependencies, and links can be related to Granger causality (Billio et al., 2012; Diebold and Yilmaz, 2014) or to pairwise correlations between returns (Chi et al., 2010; Tumminello et al., 2010). As discussed by Brunetti et al. (2015), these two types of network architecture lead to different results in terms of the role of interconnections during the global financial crisis. The level of interconnectedness decreases in accounting networks during times of poor financial performance but increases in correlation-based networks. Giudici et al. (2017) investigate this feature by comparing the topology of an accounting network derived from the BIS data and its related correlation-based network. The authors identify the different roles of direct and common exposures in financial networks. The network perspective enables the interconnectedness in financial systems to be measured, considering both direct and indirect links that form interconnections. Hence, the network approach provides an excellent framework for studying the multivariate nature of systemic risk.

2.2. Interconnectedness and stability in financial networks

The debate about the dual impact of financial integration on financial stability has enhanced the structural dimension of systemic risk and, therefore, the network approach. In the wake of the global financial crisis, Haldane (2009) and Shin (2009) emphasize that the increasing numbers of cross-border transactions and interconnections have enriched the structure of financial markets. Moreover, both researchers note that innovation has increased the number and types of financial transactions, contributing to a more complex and integrated financial system. To this extent, Cecchetti (2012) argues that financial globalization benefits the economy up to a point and that high levels of integration could weaken the financial system. Measuring financial integration, Lane and Milesi-Ferretti (2008) describe a nonlinear relationship between financial integration and economic growth. Recently, Candelon et al. (2020) go further: they empirically show that financial integration has a positive effect on growth while exposing the economy to a negative impact during banking or stock market crises. On the one hand, financial integration is related to a high level of interconnectedness and exhibits the advantage of enabling a more efficient allocation of capital. On the other hand, higher levels of integration could weaken the financial system. From this perspective, Lagarde (2013) and Yellen (2013) address the global issue of interconnectedness in banking systems, asking if it could have a dark side related to its role in spillover mechanisms and systemic risk consequences.

From a regulatory perspective, interconnectedness has a dual impact on financial stability, as does financial integration on economic growth. The pioneering works of Allen and Gale (2000) and Freixas et al. (2000) have initiated the economic debate about the *"robust yet fragile"* nature of banking systems. Interconnectedness has emerged as a way of measuring levels of interactions in financial networks. Accordingly, the recent literature has drawn considerable attention to interconnectedness that describes the architecture of financial networks. Several measures of systemic risk based on interconnectedness exist and can be categorized based on the source of systemic risk. Blei and Ergashev (2014) and Cai et al. (2014) measure similarities between banks' portfolio assets to track systemic risk-taking. Focusing on contagion mechanisms, Markose et al. (2012) use eigenvector centrality to identify banks that are *"too interconnected to fail"*.[1] More recently, Constantin et al. (2016) estimate network linkages using the multivariate extreme value theory and show that interconnectedness in equity-based tail-dependent networks is linked to systemic risk. Following this multivariate perspective, Giudici et al. (2017) capture systemic risk via interconnectedness while considering direct and common exposures. Among studies considering these interconnectedness-based measures of systemic risk, some rely on proprietary data (balance sheet positions, cross-holdings of assets or interbank transactions) and others are based on public market data (bank stock returns or CDS). The choice of data sources is an important issue for regulatory supervision,

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[1]See also Amini, Cont and Minca (2013) and Barucca et al. (2016) for a mathematical approach to contagion mechanisms.

as their different properties (high/low frequency, real-time/lagged series, proprietary/public data) affect the measurement and forecasting models of systemic risk. The literature on systemic risk can be divided into two strands in terms of source datasets. The use of market data exhibits some valuable advantages, enabling real-time analysis of the financial system for regulators and relying on public data that are available to all market participants. Even if using accounting data from banks collected by regulators has some benefits, these datasets are disclosed with a lag, which makes structural breaks in systemic risk difficult to anticipate, thereby making forecasting impossible. Therefore, modeling financial networks based on time-varying dependencies between stock returns opens broad prospects. In his seminal work, Mantegna (1999) introduced the use of correlation-based graphs in finance to study the topology of stock markets. This strand of literature applying Mantegna's methodology to studying financial network topology has since been growing. Correlation-based networks can consider the multivariate features of the structure of dependencies in complex financial systems. Stock markets have been the first field of empirical application of this approach. Onnela et al. (2003) and Bonanno et al. (2004) explore stock markets using clustering techniques. Chi et al. (2010) and Tumminello et al. (2010) investigate the structure of correlation matrices using filtering procedures. More recently, Peralta and Zareei (2016) link network theory and Markowitz's framework and show that the topology of a correlation-based network can be used to improve portfolio selection. Constantin et al. (2016) and Giudici et al. (2017) improve multivariate analysis enabled by correlation-based networks and develop a measure of systemic risk based on both direct and common exposures. However, van de Leur et al. (2017) empirically show that the value added by correlation-based networks is attributable mainly to pairwise cross-sectional heterogeneity. Furthermore, the researchers argue that systemic risk is driven by direct rather than indirect dependencies between bank stock returns. In the recent literature, the main difference between these results on interconnectedness is related to the methodology developed to transform time-varying correlations into dynamic networks.

This ongoing debate about the role of indirect links in financial networks is a key issue in the analysis of interconnectedness of such networks. Different results for the importance of indirect links arise from some of the issues pertaining to different methodologies implemented to build correlation-based networks.

3. Modeling framework

Our contribution is part of the debate about the role of indirect links in financial networks. Such networks can be built from different types of links between financial institutions (e.g., banks, insurers, brokers or asset managers). Specifically, correlation, vector autoregression (VAR) and Granger causality models can be used to model links between each pair of institutions. In his seminal work, Mantegna (1999) introduced correlation-based networks for modeling financial systems as networks. This framework is intuitive and flexible, and its only drawback is that directionality of links disappears. As stated by Billio et al. (2012), Granger causality measures of interconnectedness are useful indicators of systemic risk. Indeed, Granger causality tests are used to determine the directionality of correlations among financial institutions. However, spurious causalities can arise from indirect contagion effects (Hué, Lucotte and Tokpavi, 2019). Alternatively, the dynamics of financial spillover effects can also be captured with time-varying VAR models (Geraci and Gnabo, 2018). However, using VAR models prevents multidimensional analysis that would allow disentangling the roles of direct and indirect dynamic links at both local and global levels. Ultimately, correlation-based networks are the most appropriate framework for investigating the time-varying role of direct and indirect links in dynamic financial networks. Revisiting Mantegna's framework, we propose a new topological framework for measuring interconnectedness.

3.1. Estimating time-varying correlations

In the recent literature on financial networks, authors have studied time-varying correlation using sample splitting (Tumminello et al., 2010 ; Tse et al., 2010 ; Anufriev and Panchenko, 2015 ; Giudici et al., 2017), rolling window (Diebold and Yilmaz, 2014; Peralta and Zareei, 2016; van de Leur et al. (2017); Wang et al., 2017; Demirer et al., 2018) or DCC-GARCH (Hasse, 2016; Yin et al., 2017) approaches. In this paper, we focus on realized correlations to avoid any assumptions about the dynamic structure of correlations (i.e., temporal dependencies).[2] Moreover, measuring variance over nonoverlapping samples avoids issues with autocorrelation. Finally, this model-free approach is potentially more accurate than others, as it increases the frequency of observations.

The first step of our approach is to empirically estimate realized correlation matrices. We measure realized variances over each month (with M_T trading days over month T) using daily returns. We denote by σ^2_{iT} the realized variance of returns of equity i at time T with B as the number of banks and $i \in \{1, ..., B\}$:

$$\sigma^2_{iT} = \frac{1}{M_T} \times \sum_{t=1}^{M_T} (r_{i,t} - \overline{r_{i,T}})^2, \tag{1}$$

where $r_{i,t}$ is the return of equity i on day t, $t \in \{1, ..., M_T\}$, and M_T is the number of observations in month T. Term $\overline{r_{i,T}}$ is the average return of equity i over month T, where $T \in \{1, ..., M\}$.

Then, we compute $B \times B$ monthly realized covariance matrices $Cov_T(i, j)$ for month T and $i, j \in \{1, ..., B\}$ as

$$Cov_T(i, j) = \frac{1}{M_T} \times \sum_{t=1}^{M_T} ((r_{i,t} - \overline{r_{i,T}}) \times (r_{j,t} - \overline{r_{j,T}})). \tag{2}$$

Finally, we compute $B \times B$ monthly realized correlation matrices $Corr_T(i, j)$ from (1) and (2) as

$$Corr_T(i, j) = \frac{Cov_T(i, j)}{\sigma_{iT} \times \sigma_{jT}}, \tag{3}$$

where σ_{iT} and σ_{jT} are the realized standard deviations of equities i and j, respectively, for month T.

[2]The results appear to be robust to the use of other models to model the time-varying correlation.

As stated by Barndorff-Nielsen and Shephard (2004), such realized correlation matrices are unlikely to be positive semidefinite. In the next two subsections, for brevity, we will assume that $Corr_T(i,j)$ are positive semidefinite. However, in the empirical part, we will deal with this statistical issue by using the eigenvalue method of Rousseeuw and Molenberghs (1993) to transform initial realized correlation matrices.

3.2. Building financial networks

The second part of the modeling framework concerns the methodology used to transform the correlation matrices into financial networks. We present a rigorous analytical framework for transforming a set of M realized correlation matrices obtained in (3) into M distance matrices. First, we have to properly define the set of realized correlation matrices.

Definition 1. Let $S_B(\mathbb{R})$ denote the set of real $B \times B$ symmetric matrices. Let $S_B^+(\mathbb{R})$ denote the set of real $B \times B$ positive semidefinite (PSD) matrices. A $B \times B$ real symmetric matrix with positive eigenvalues is called a *positive semidefinite* matrix, i.e.,

$$S_B^+(\mathbb{R}) := \{X \in S_B(\mathbb{R}) \quad | \quad \forall i = \{1, ..., B\}, \lambda_i(X) \geq 0\}, \tag{4}$$

where $\lambda_i(X)$ is the i^{th} eigenvalue of X.

Definition 2. Let $\mathcal{S}^{B\times B}$ denote the set of $B \times B$ correlation matrices. A positive semidefinite matrix with diagonal entries equal to 1 is called a *correlation matrix*, i.e.,

$$\mathcal{S}^{B\times B} := \{C \in S_B^+(\mathbb{R}) \quad | \quad \forall i = \{1, ..., B\}, c_{ii} = 1\}. \tag{5}$$

From these definitions, the first step of our methodology is to transform the correlation matrices into financial networks. To do so, we need to define a distance function that maps M realized correlation matrices (each defined in $\mathcal{S}^{B\times B}$) onto M distance matrices. In other words, we need to transform correlation coefficients defined in $[-1;1]^B$ onto path lengths defined in $[0;\infty]^B$. In the financial literature, the most widely used transformation function is $d(i,j) = \sqrt{2(1 - c_{ij})}$, where c_{ij} are the correlation coefficients of a given correlation matrix C. This transformation is introduced in the seminal work of Mantegna (1999), who chose $d(i,j)$ as the distance function used to map the correlation coefficients onto the Euclidean space (see Appendix).

Remark. In Mantegna (1999), $d(i,j)$ is a monotonically decreasing distance function that enables the definition of an ultrametric space and induces a topological space (Gower, 1966; Gower and Legendre, 1986).

The use of this transformation provides a shortcut that enables the application of filtering procedures such as the minimum spanning tree (MST) (Chi et al., 2010; Peralta and Zareei, 2016) and the planar maximally filtered graph (PMFG) (Tuminello et al., 2010). This transformation function is also used by Giudici et al. (2017) and Cai et al. (2018) with some rearrangements to build financial networks defined within the Euclidean space. Although this transformation exhibits several advantages, it also has a crucial drawback: this distance function is not neutral with respect to the structure of the network. Indeed, the third axiom of the Euclidean distance (Minkowski's inequality) forbids indirect links to be shorter than direct links. In other words, the Euclidean space is a restricted topological space in which indirect paths must be longer than direct paths. Such a restriction is irrelevant in our work, as we aim to disentangle indirect and direct links and to assess the relative strength of indirect links.

Therefore, we need to introduce an additional step in network analysis. The second step of our methodology is to transform the correlation matrix C into a nonmetric distance matrix.

Definition 3. Let C be a $B \times B$ correlation matrix, and A be a $B \times B$ hollow matrix with positive off-diagonal elements. For every i and j in $\{1, ..., B\}$ and $i \neq j$, we define the elementwise distance function ψ with respect to C:

$$\psi : [-1; 1] \mapsto \mathbb{R}^+$$
$$a_{ij} = \psi(c_{ij}) = -ln(c_{ij}^2), \tag{6}$$

where $a_{ii} = 0$, and A is a nonmetric distance matrix.

Remark. The purpose of distance function $\psi(.)$ is to model a correlation matrix as a nonmetric distance matrix. Stronger (resp., weaker) absolute correlations between stock returns induce shorter (resp., longer) path lengths. Among the possible transformations (we could have chosen $\frac{1}{|c_{ij}|}$ instead, following Newman (2001), who chose $\frac{1}{c_{ij}}$ as the transformation function), $\psi(.)$ offers a crucial advantage and moreover reduces the shortest-path problem. This property will be useful in the following.

The third step consists of highlighting the role of indirect links in interconnectedness of financial networks. Specifically, we compare the lengths of direct and indirect paths between each pair of vertices to identify the most important links. The structure of the topological space in which A is defined allows the use of the *geodesic* as a nonmetric distance. The *geodesic* of a pair of nodes is the minimum of the sums of weights on the shortest paths joining these two nodes. We can now introduce mapping function $\phi(.)$.

Definition 4. Let A be a $B \times B$ nonmetric distance matrix. We define mapping function $\phi(.)$ with respect to A:

$$\phi : [0; \infty]^{B\times B} \mapsto [0; \infty]^{B\times B}$$
$$A^* = \phi(A) = geodesic(A), \tag{7}$$

where nodes V_i and V_j represent financial institutions i and j, *geodesic* is the shortest path between V_i and V_j, $a^*_{ij} = \phi(a_{ij}) = geodesic(V_i, V_j)$ and A^* is a Euclidean distance matrix.

The structure of the topological space in which A is defined enables the application of Dijkstra's algorithm to identify the shortest paths in distance matrix A^*. By construction, there is only a single path between each pair of nodes, and no self-path, as $a_{ii} = 0$. Moreover, this mapping function has an interesting property that $\phi(.)$ maps A, which is defined in a nonmetric space, onto a Euclidean space.

3.3. A measure of systemic risk

This methodology allows us to identify cases where indirect paths are shorter (i.e., links are stronger) than direct paths between two given nodes of the network. From this point, the network effect emerges: interconnectedness depends on both direct and indirect links between financial institutions. What is the impact of such indirect links in terms of systemic risk? We return from distance to correlation matrices to estimate the impact of interconnectedness on systemic risk.

Definition 5. Let A and A^* be two $B \times B$ distance matrices. We define the elementwise mapping function $\psi^{-1}(.)$ with respect to A and A^*:

$$\begin{aligned} \psi^{-1} &: \mathbb{R}^+ \mapsto \mathbb{R}^+ \\ c_{m,ij} &= \psi^{-1}(a_{ij}) = \sqrt{e^{-a_{ij}}}, \\ c^*_{m,ij} &= \psi^{-1}(a^*_{ij}) = \sqrt{e^{-a^*_{ij}}}, \end{aligned} \tag{8}$$

where C_m and C^*_m are $B \times B$ real symmetric matrices.

Before proceeding, we have to verify that C_m and C^*_m are correlation matrices (i.e., C_m and $C^*_m \in \mathcal{S}^{B\times B}$).[3]

Proposition 1. Let $S_B(\mathbb{R}^+)$ and $S^+_B(\mathbb{R}^+)$ be the sets of $B \times B$ positive symmetric matrices and PSD matrices, respectively. Consider matrix $M \in S_B(\mathbb{R}^+)$ with $m_{ii} = 0$ and $\psi^{-1}(m_{ij}) =$

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[3]We denote by C_m the matrix that has gone through the process of transformations from the initial correlation matrix C: $\psi \circ \psi^{-1}$. We denote by C^*_m matrix C_m that has been through the whole process: $\psi \circ \phi \circ \psi^{-1}$ (i.e., the process that silences direct links that are weaker than indirect links and replaces them by the latter).

$\sqrt{e^{-m_{ij}}}$; then,

$$\psi^{-1} : S_B(\mathbb{R}^+) \mapsto S_B^+(\mathbb{R}^+). \tag{9}$$

Proof. First, we note that $M \in S_B(\mathbb{R})$ induces $\psi^{-1}(M) \in S_B(\mathbb{R}^+)$. Indeed, $\psi^{-1}(M)^\top = \sqrt{e^{-M}}^\top = \sqrt{e^{-M^\top}} = \psi^{-1}(M^\top) = \psi^{-1}(M)$. Second, according to the spectral theorem, M can be diagonalized on an orthonormal basis as:

$$M = Pdiag(\lambda_1, ..., \lambda_B)P^{-1},$$

where $P \in O_B(\mathbb{R}^+)$, and $\lambda_1, ..., \lambda_B$ are real eigenvalues. We then obtain:

$$\psi^{-1}(M) = Pdiag(\sqrt{e^{-\lambda_1}}, ..., \sqrt{e^{-\lambda_B}})P^{-1}.$$

The term $\psi^{-1}(M)$ has positive eigenvalues, so $\psi^{-1}(M) \in S_B^+(\mathbb{R}^+)$. □

Proposition 2. Let A and A^* be $B \times B$ distance matrices. If $c_{m,ij} = \psi^{-1}(a_{ij})$ and $c^*_{m,ij} = \psi^{-1}(a^*_{ij})$, then

$$C_m \text{ and } C^*_m \in \mathcal{S}^{B\times B}. \tag{10}$$

Proof. As A and A^* are distance matrices, we have $a_{ii} = a^*_{ii} = 0$. Next, $\psi^{-1}(0) = \sqrt{e^{-0}} = 1$, so $c_{m,ii} = c^*_{m,ii} = 1$. Finally, as $\psi^{-1}(A)$ and $\psi^{-1}(A^*)$ are both defined on $S_B^+(\mathbb{R}^+)$, C_m and C^*_m are correlation matrices. □

Theorem 1. Let σ_P^{2*} and σ_P^2 be the variance and the corrected variance of two given portfolios of B equities P^* and P, respectively. Let w_i be the weight of equity i in P and let σ_i be its standard deviation. Let $c_{m,ij}$ and $c^*_{m,ij}$ be the modified realized correlation and the modified corrected realized correlation, respectively, between equities i and j. We compute the variance and the corrected variance of the portfolio as follows:

$$\begin{cases} \sigma_P^2 = \sum_{i=1}^{B}\sum_{j=1}^{B} w_i w_j \sigma_i \sigma_j c_{m,ij}, \\ \sigma_P^{2*} = \sum_{i=1}^{B}\sum_{j=1}^{B} w_i w_j \sigma_i \sigma_j c^*_{m,ij}, \end{cases} \tag{11}$$

$\sigma^2_{systemic}$ is a measure of systemic risk that represents the risk induced by interconnectedness (i.e., the risk driven by the network effect from indirect links) as follows:

$$\sigma^2_{systemic} = \sigma^{2*}_P - \sigma^2_P. \tag{12}$$

Proof. By definition, $a^*_{ij} = \phi(a_{ij})$, so $a^*_{ij} \leq a_{ij}$. As $\psi^{-1}(.) = \sqrt{e^{-.}}$ is a monotonically decreasing function, we have $\psi^{-1}(a^*_{ij}) \geq \psi^{-1}(a_{ij})$. As C^*_m and C_m are defined in $S^+_B(\mathbb{R}^+)$, we can write $c^*_{m,ij} \geq c_{m,ij}$ and $\sigma^{2*}_P \geq \sigma^2_P$. We note that $\sigma^{2*}_P - \sigma^2_P \geq 0$, and the difference between these modified variances of the same portfolio is related to the network effect driven by indirect links only. $\square$

In this section, we develop a new framework based on Mantegna's approach to study both direct and indirect dependencies in financial networks. Furthermore, this framework enables us to compare the roles of these two types of links at both the local and global levels. Based on Markowitz's framework, we derive their respective strengths in terms of risk, and we analytically demonstrate that indirect links have no impact on systematic risk but are related to systemic risk.

4. Data and summary statistics

In this section, we present the database and show the motivation for our choices of the variables of interest, the financial institution samples and the nature of their interrelationships.

4.1. Data

The financial networks that we build are based on market data to ensure that we develop a systemic risk measure that is operationalized, easily replicable and amenable to real-time analysis. Among the available market data, we use stock returns of banks, insurance companies and other financial institutions to build correlation-based networks, following Billio et al. (2012). Our empirical work focuses on the European financial system because of several features related to systemic risk. First, Europe was subject to two major systemic crises during the past decade: the 2007-2008 financial crisis and the 2010-2011 sovereign debt crisis. Moreover, the European financial system is a heterogeneous yet integrated financial system composed of a large number of financial institutions from 38 countries. This interlinked system of numerous heterogeneous elements can be intuitively modeled as a complex financial network. As we aim to track indirect links between financial returns to identify sources of systemic risk, we focus on 72 major financial institutions in Europe.

4.2. Summary statistics

Our dataset covers 72 large European financial institutions in 18 different countries. It includes 29 banks, 23 insurance companies and 20 other financial companies from the STOXX Europe 600 index. Our final sample of 72 financial companies covers more than 80% of the market capitalization of the STOXX Europe 600 Financial Services Index. According to the Consolidated Banking Data provided by the European Central Bank,[4] our sample of 29

[4] ECB website's direct URL: `https://www.ecb.europa.eu/press/pr/date/2017/html/ecb.pr170628.en.html`

Table 1: Financial companies in the sample

Name	Ticker on Bloomberg	GICS	Country	Mean	Std. Dev.
3i Group PLC	III LN Equity	Diversified Financials	United Kingdom	2.79E-04	2.22E-02
Ackermans & van Haaren NV	ACKB BB Equity	Diversified Financials	Belgium	4.26E-04	1.61E-02
Aegon NV	AGN NA Equity	Insurance	The Netherlands	-6.72E-05	2.81E-02
Ageas	AGS BB Equity	Insurance	Belgium	1.26E-04	2.83E-02
AIB Group PLC	AIBG ID Equity	Banks	Ireland	-3.61E-04	4.34E-02
Allianz SE	ALV GY Equity	Insurance	Germany	1.76E-04	2.17E-02
Assicurazioni Generali SpA	G IM Equity	Insurance	Italy	4.21E-05	1.69E-02
Aviva PLC	AV/ LN Equity	Insurance	United Kingdom	1.34E-04	2.41E-02
AXA SA	CS FP Equity	Insurance	France	2.60E-04	2.53E-02
Baloise Holding AG	BALN SE Equity	Insurance	Switzerland	2.45E-04	1.84E-02
Banco Bilbao Vizcaya Argentaria SA	BBVA SQ Equity	Banks	Spain	9.55E-06	0.02E+00
Banco Santander SA	SAN SQ Equity	Banks	Spain	4.24E-05	2.15E-02
Bank of Ireland Group PLC	BIRG ID Equity	Banks	Ireland	8.79E-05	0.03E+00
Bankinter SA	BKT SQ Equity	Banks	Spain	2.17E-04	2.06E-02
Barclays PLC	BARC LN Equity	Banks	United Kingdom	2.25E-04	2.88E-02
BNP Paribas SA	BNP FP Equity	Banks	France	2.57E-04	2.32E-02
BPER Banca	BPE IM Equity	Banks	Italy	6.47E-06	2.27E-02
Close Brothers Group PLC	CBG LN Equity	Diversified Financials	United Kingdom	2.49E-04	1.95E-02
CNP Assurances	CNP FP Equity	Insurance	France	3.08E-04	0.01E+00
Commerzbank AG	CBK GY Equity	Banks	Germany	-2.99E-04	2.84E-02
Credit Suisse Group AG	CSGN SE Equity	Diversified Financials	Switzerland	-5.30E-05	2.41E-02
Danske Bank A/S	DANSKE DC Equity	Banks	Denmark	2.52E-04	1.95E-02
Deutsche Bank AG	DBK GY Equity	Diversified Financials	Germany	-1.15E-04	2.52E-02
DNB ASA	DNB NO Equity	Banks	Norway	5.52E-04	2.14E-02
Erste Group Bank AG	EBS AV Equity	Banks	Austria	5.29E-04	2.50E-02
Eurazeo SA	RF FP Equity	Diversified Financials	France	3,67E-04	1,92E-02
Groupe Bruxelles Lambert SA	GBLB BB Equity	Diversified Financials	Belgium	2.48E-04	1.38E-02
Hannover Rueck SE	HNR1 GY Equity	Insurance	Germany	5.46E-04	2.02E-02
Helvetia Holding AG	HELN SE Equity	Insurance	Switzerland	3.44E-04	0.01E+00
Hiscox Ltd	HSX LN Equity	Insurance	United Kingdom	6.38E-04	1.96E-02
HSBC Holdings PLC	HSBA LN Equity	Banks	United Kingdom	1.19E-04	1.63E-02
Industrivarden AB	INDUA SS Equity	Diversified Financials	Sweden	3.42E-04	1.89E-02
ING Groep NV	INGA NA Equity	Banks	The Netherlands	2.36E-04	2.83E-02
Intermediate Capital Group PLC	ICP LN Equity	Diversified Financials	United Kingdom	5.68E-04	2.14E-02
Intesa Sanpaolo SpA	ISP IM Equity	Banks	Italy	1.93E-04	2.49E-02
Investor AB	INVEB SS Equity	Diversified Financials	Sweden	4.02E-04	1.66E-02
Jyske Bank A/S	JYSK DC Equity	Banks	Denmark	3.85E-04	1.75E-02
KBC Group NV	KBC BB Equity	Banks	Belgium	4.34E-04	2.89E-02
Kinnevik AB	KINVB SS Equity	Diversified Financials	Sweden	4.61E-04	2.22E-02
Komercni banka as	KOMB CK Equity	Banks	Czech Republic	5.81E-04	1.97E-02
L E Lundbergforetagen AB	LUNDB SS Equity	Diversified Financials	Sweden	5.97E-04	1.40E-02
Legal & General Group PLC	LGEN LN Equity	Insurance	United Kingdom	3.88E-04	2.33E-02
Lloyds Banking Group PLC	LLOY LN Equity	Banks	United Kingdom	3.05E-05	2.81E-02
Man Group PLC	EMG LN Equity	Diversified Financials	United Kingdom	4.78E-04	2.53E-02
Mapfre SA	MAP SQ Equity	Insurance	Spain	4.03E-04	2.06E-02
Mediobanca Banca di Credito Finanziario	MB IM Equity	Banks	Italy	2.10E-04	2.04E-02
Munich Re	MUV2 GY Equity	Insurance	Germany	1.80E-04	1.91E-02
Natixis SA	KN FP Equity	Diversified Financials	France	2.81E-04	2.61E-02
NEX Group PLC	NXG LN Equity	Diversified Financials	United Kingdom	8.85E-04	2.20E-02
Nordea Bank AB	NDA SS Equity	Banks	Denmark	3.01E-04	2.03E-02
Old Mutual PLC	OML LN Equity	Insurance	United Kingdom	3.20E-04	2.40E-02
Pargesa Holding SA	PARG SE Equity	Diversified Financials	Switzerland	2.14E-04	0.01E+00
Prudential PLC	PRU LN Equity	Insurance	United Kingdom	3.99E-04	2.49E-02
Royal Bank of Scotland Group PLC	RBS LN Equity	Banks	United Kingdom	-1.28E-05	3.01E-02
RSA Insurance Group PLC	RSA LN Equity	Insurance	United Kingdom	3.84E-05	2.17E-02
Sampo Oyj	SAMPO FH Equity	Insurance	Finland	4.91E-04	0.01E+00
Schroders PLC	SDR LN Equity	Diversified Financials	United Kingdom	4.44E-04	2.30E-02
SCOR SE	SCR FP Equity	Insurance	France	6.15E-05	2.36E-02
Skandinaviska Enskilda Banken AB	SEBA SS Equity	Banks	Sweden	4.14E-04	2.32E-02
Societe Generale SA	GLE FP Equity	Banks	France	1.83E-04	2.60E-02
St James's Place PLC	STJ LN Equity	Diversified Financials	United Kingdom	5.84E-04	0.02E+00
Standard Chartered PLC	STAN LN Equity	Banks	United Kingdom	2.56E-04	2.32E-02
Storebrand ASA	STB NO Equity	Insurance	Norway	3.97E-04	2.70E-02
Svenska Handelsbanken AB	SHBA SS Equity	Banks	Sweden	3.37E-04	1.75E-02
Swedbank AB	SWEDA SS Equity	Banks	Sweden	2.88E-04	0.02E+00
Swiss Life Holding AG	SLHN SE Equity	Insurance	Switzerland	2.23E-04	2.25E-02
Swiss Re AG	SREN SE Equity	Insurance	Switzerland	1.35E-04	2.14E-02
Sydbank A/S	SYDB DC Equity	Banks	Denmark	4.13E-04	1.69E-02
UBS Group AG	UBSG SE Equity	Diversified Financials	Switzerland	6.59E-05	2.25E-02
UniCredit SpA	UCG IM Equity	Banks	Italy	-1.28E-04	2.65E-02
Wendel SA	MF FP Equity	Diversified Financials	France	4.43E-04	2.30-02
Zurich Insurance Group AG	ZURN SE Equity	Insurance	Switzerland	9.29E-05	2.11E-02

banks represents more than 82% of the European banking system's total assets.

5. Network approach: local and global measures of systemic risk

In this section, we empirically show that our measure of systemic risk is relevant at both the local and global levels in Europe. Although there is no accepted definition of systemic risk, one consensual assertion is that systemic risk arises in complex and interconnected financial systems (Yellen, 2013). We use this relationship to build a topological measure of systemic risk; our dynamic measure of systemic risk is associated with the time-varying level of interconnectedness between financial institutions. Specifically, our measure of interconnectedness is based on the role of indirect links. Following the recommendations of Benoit et al. (2017), we analytically and empirically verify that our measure of interconnectedness is related to systemic risk and not to systematic risk. Then, we empirically test whether high levels of our systemic risk measure are associated with future recessions, as in Giglio, Kelly, and Pruitt (2016). Specifically, we test if our systemic risk measure is positively and significantly associated with recessions in the Early Warning System (EWS) framework developed by Candelon et al. (2012; 2014). Finally, results indicate that our measure of systemic risk is relevant and exhibits features similar to those of other common measures of systemic risk.

5.1. Building dynamic financial networks

The time-varying dependence structure that emerges from the realized correlations of returns of European banks, insurers and other financial companies defines the dynamic financial network in Europe. Consequently, our empirical study begins with the estimation of time-varying correlations between each pair of returns of financial institutions to capture the pairwise relationships between them. First, the realized variances of equity returns are computed for each month of daily returns. Then, monthly realized correlations are computed from the previously estimated realized variances. By construction, such correlation matrices are unlikely to be positive semidefinite (see Barndorff-Nielsen and Shephard (2006)). To deal with this statistical issue, we transform these initial correlation matrices, following the eigenvalue method of Rousseeuw and Molenberghs (1993).[5] Following the methodology developed in Section 3, we transform the correlation matrices into dependence networks for each month.

5.2. Systemic risk at a local level

Following the framework introduced in Section 3, we track indirect links between financial institutions, especially those that are stronger than direct links. Moreover, our methodology enables the identification of entities that are most affected by these strong indirect links. On the one hand, a comparison of distance matrix A and Euclidean distance matrix A^* can be used to identify indirect links that are stronger than direct links in the network for a given period T. On the other hand, we can establish a ranking of financial institutions as a function of their involvement with indirect links that are stronger than direct links.

Interconnectedness in financial networks is time-varying. Figures 1 and 2 illustrate the dynamics of indirect links in the European financial network at two different times: June 2006 and June 2007. These two graphs represent filtered networks, where only the strongest (the last decile) indirect links are plotted for clarity. Colors of nodes represent GICS sectors: gray (banks), blue (insurers) and white (financial services companies). These figures highlight another feature: the distribution of indirect links is heterogeneous, and the strength of indirect links is not constant over time, motivating the application of a dynamic approach. Focusing on the financial network in June 2007, we identify the Royal Bank of Scotland (RBS) as the node with the greatest concern with strong indirect links among the entire European network.

Furthermore, a comparison of strengths of direct and indirect links indicates eleven indirect links of paths between the RBS and the whole network that are shorter than pairwise

[5]The correlation matrices' transformation is computed using R package "highfrequency" by Boudt and Cornelissen (2018).

Figure 1: Financial network - June 2006

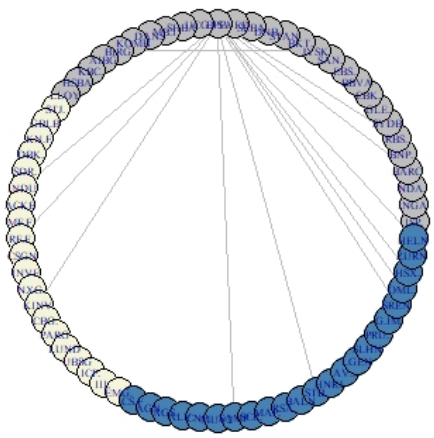
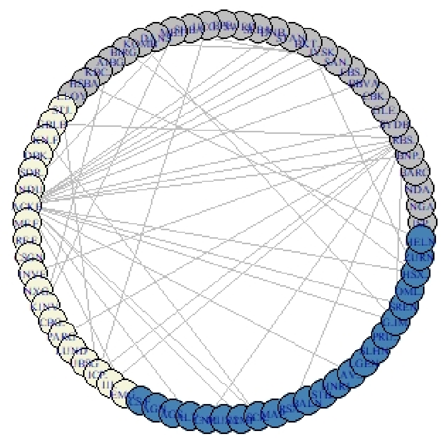


Figure 2: Financial network - June 2007



Notes: These figures show filtered networks for two different periods around the global financial crisis. Only the 10% strongest indirect links between financial institutions are plotted. Colors of nodes represent GICS sectors: gray (banks), blue (insurers) and white (financial services companies). These figures highlight that (i) the role of indirect links is time-varying and (ii) the strongest indirect links are not uniformly distributed among sectors and companies.

paths. Table 2 reports this comparison and the relative difference in length between these direct and indirect paths. For example, the relative differences between direct and indirect path lengths indicate that the RBS is more strongly connected to Groupe Bruxelles Lambert SA via indirect links than via direct links. Then, most of these indirect links involve financial institutions in countries other than the UK: Belgium, France, Switzerland, Italy, Sweden and Denmark. More interestingly, Table 2 reports that indirect links involve financial sectors other than banks: the financial services sector indicates the greatest concern with indirect links.

Following this firm-level analysis based on our methodology, we can go further to identify how the RBS is indirectly linked to the eleven financial companies identified above. Table 3 reports six companies with indirect links that bypass direct links from the RBS to these eleven companies.

Table 2: Comparison of direct and indirect links at a local level: Focusing on the RBS in June 2007

Institution	GICS	Country	Relative difference
Groupe Bruxelles Lambert SA	Diversified Financials	Belgium	89.99%
Intermediate Capital Group PLC	Diversified Financials	United Kingdom	14.58%
Ackermans & van Haaren NV	Diversified Financials	Belgium	12.08%
CNP Assurances	Insurance	France	10.41%
Hiscox Ltd	Insurance	United Kingdom	8.33%
RSA Insurance Group PLC	Insurance	United Kingdom	6.15%
Investor AB	Diversified Financials	Sweden	6.14%
Sydbank A/S	Banks	Denmark	5.24%
Assicurazioni Generali SpA	Insurance	Italy	5.11%
Pargesa Holding SA	Diversified Financials	Switzerland	4.29%
3i Group PLC	Diversified Financials	United Kingdom	3.41%

Notes: This table reports the relative difference of path lengths between RBS and eleven other financial institutions. The results represent the relative difference between lengths of paths following direct and indirect links. This is an illustration of the impact of indirect links for a given bank (RBS) and a given period (June 2007). Here, we identify within the network 11 financial institutions among 72 for which indirect links are stronger than direct links. This example illustrates the role of indirect links and, interestingly, shows that the RBS (UK) is more connected to these 11 European financial institutions than expected.

Table 3: Identification of indirect paths at a local level: Focusing on the RBS in June 2007

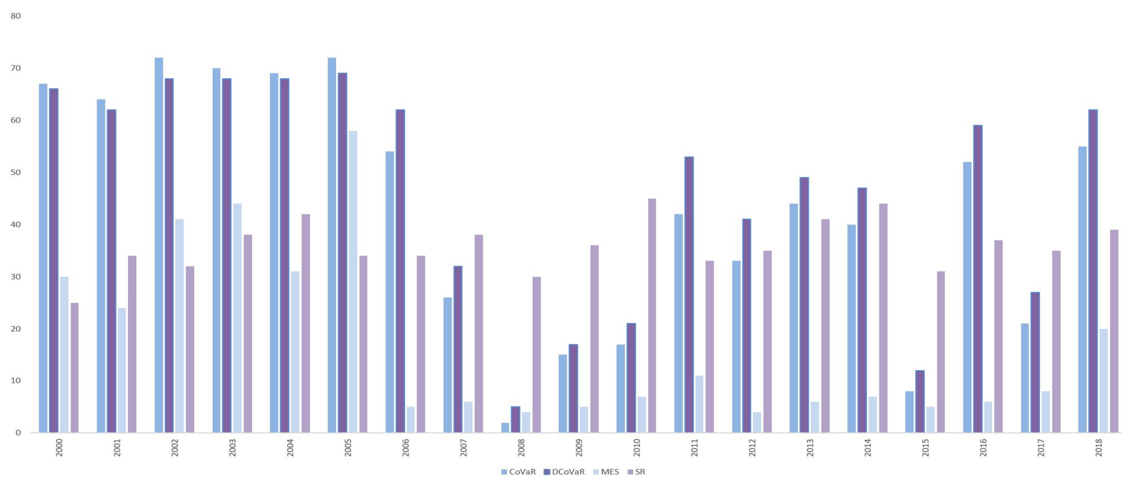
Identified Indirect Link	Identified Indirect Path	Countries Involved
RBS - Groupe Bruxelles Lambert SA	Lloyds Banking Group PLC	UK - UK - Belgium
RBS - Intermediate Capital Group PLC	DNB ASA	UK - Norway - Sweden
RBS - Ackermans & van Haaren NV	Storebrand ASA	UK - Norway - Denmark
RBS - CNP Assurances	DNB ASA	UK - Norway - France
RBS - Hiscox Ltd	Lloyds Banking Group PLC	UK - UK - UK
RBS - RSA Insurance Group PLC	Aviva PLC	UK - UK - UK
RBS - Investor AB	L E Lundbergforetagen AB	UK - Sweden - Sweden
RBS - Sydbank A/S	DNB ASA	UK - Norway - Denmark
RBS - Assicurazioni Generali SpA	Aviva PLC	UK - UK - Italy
RBS - Pargesa Holding SA	Erste Group Bank AG	UK - Austria - Switzerland
RBS - 3i Group PLC	Aviva PLC	UK - UK - UK

Notes: This table reports the identification of indirect paths from the RBS to eleven other financial services companies. These last results complete those in Table 1: after tracking indirect links that are stronger than direct links between a given company and the rest of the network, we identify companies that are part of such indirect links. Here, we observe that the Lloyds Banking Group PLC (UK) and Aviva PLC (UK) both have significant roles in indirect links between the RBS and the rest of the financial network.

Interestingly, the six financial companies that could be described as short circuits in this interaction are not only banks but also insurers and financial services companies. These results show that the indirect relationship between the RBS (UK) and the eleven financial institutions involves not only the UK but also three other European countries: Austria, Norway and Sweden. Incidentally, extending this local-level analysis to other geographical regions could facilitate a better description of indirect links with origins outside of Europe. However, such an extension would not improve our results at the local level. In our framework, focusing on the Eurozone does not limit our analysis by geographical boundaries. Indeed, financial integration induces interconnections of financial systems. For instance, Lehman Brothers is not included in our sample, but its bankruptcy had an impact on the European financial system. At the local level, we cannot trace indirect links originating from this American bank, but its impact on European bank stock prices was notable.

The important role of indirect links at the local level can also be illustrated by systemic risk rankings. Figure 4 focuses on the RBS rank in terms of $CoVaR$, $\Delta CoVaR$, MES and SR (i.e., interconnectedness) among all other institutions in the sample from 2000 to 2018. For each year, ranks with and without indirect links are computed. On the one hand, these results show that the difference between these four ranks is time-varying and that during systemic events (specifically, 2008-2009 and 2011-2012), the systemic ranking of the RBS was dramatically impacted. On the other hand, the SR ranking exhibits some differences. This ranking appears to be unrelated to the three other rankings and varies little year-on-year. Specifically, using indirect links leads to a more stable ranking.

Figure 3: Systemic risk rankings and indirect links.



Notes: Focusing on a financial institution, namely, the Royal Bank of Scotland, this figure presents a comparison of several systemic risk rankings ($CoVaR$, $\Delta CoVaR$, and MES) with a ranking based on interconnectedness (SR) that takes into account indirect links only.

In summary, indirect links significantly modify the structure of dependence between financial companies at the local level. The methodology that we introduce in Section 3 enables exploration of the local time-varying topology of the system and the role of each institution with respect to its neighbors. Compared to other measures of connectedness, such as closeness or betweenness centrality, the study of the length of direct and indirect paths allows the nodes that create such indirect links to be identified. Furthermore, a microanalysis of the complex structure of dependencies can be used to enrich systemic risk rankings.

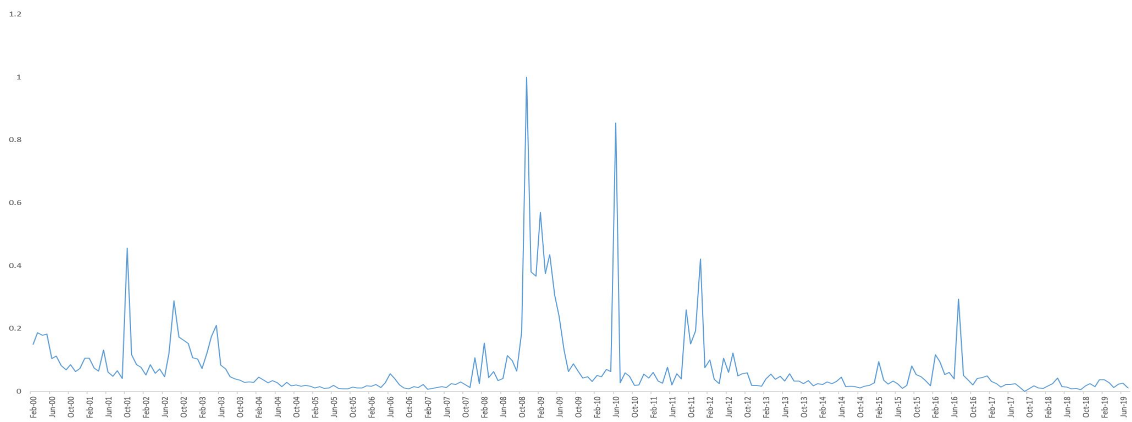
5.3. Systemic risk at the system level

A system-level analysis of interconnectedness is based on the aggregation of direct and indirect path lengths. In contrast to the previous firm-level analysis where path lengths can be compared to study a given financial institution's neighborhood in the network, the estimation of interconnectedness in the whole financial network requires an additional step. Indeed, the process of correcting the correlation matrix described in Section 3 does not enable us to directly compare C_m^* to C_m. However, we can use C_m^* to re-estimate volatility σ_p^* of portfolio p of financial companies' stocks.

Transitioning from correlation matrices C_m and C_m^* to volatilities σ_p and σ_p^* of portfolio p, we can compare the two risk estimates of the portfolio of financial equities. By construction, the difference between these two measures of volatility is driven only by indirect links, which we label the "network effect" hereafter. This methodological trick enables us to assess the impact of indirect links on interconnectedness and to interpret this network effect in terms of risk. The difference $\sigma_p^* - \sigma_p$ represents the risk of portfolio p driven by the network effect in the financial network, which we identify as systemic risk.

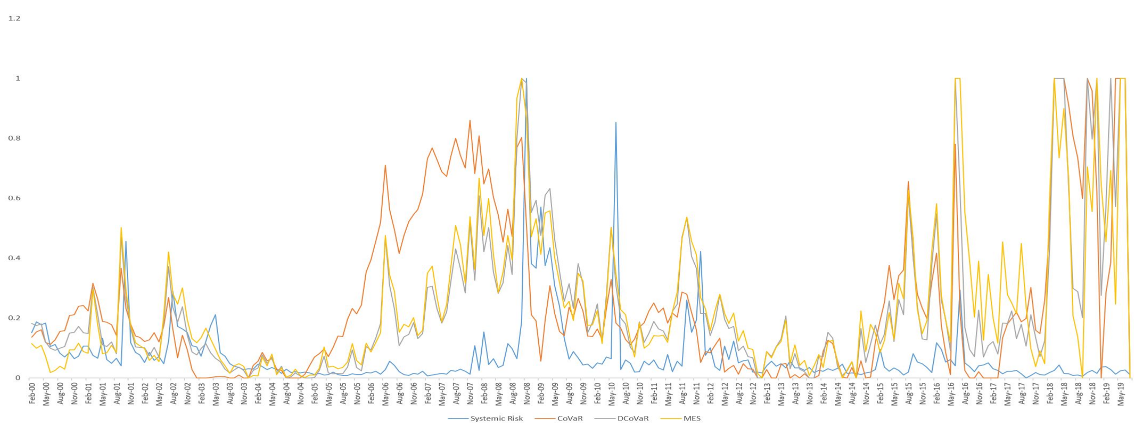
Figure 4 illustrates our time-varying measure of systemic risk on the global sample. Several observations can be made from this figure: the highest levels of our gauge of systemic

Figure 4: Systemic risk measure - European financial system.



Notes: This figure shows the time-varying systemic risk measure in Europe. The blue line represents the systemic risk estimated from the difference between the volatility and the corrected volatility of the portfolio of financial companies. Systemic risk is normalized by rescaling values to the range between 0 and 1. The results are computed using R version 3.6.0 (R Core Team, 2020) and package *SystemicR* (*v0.1.0*; Hasse, 2020). This figure highlights periods of high systemic risk: the subprime crisis and the European sovereign debt crisis.

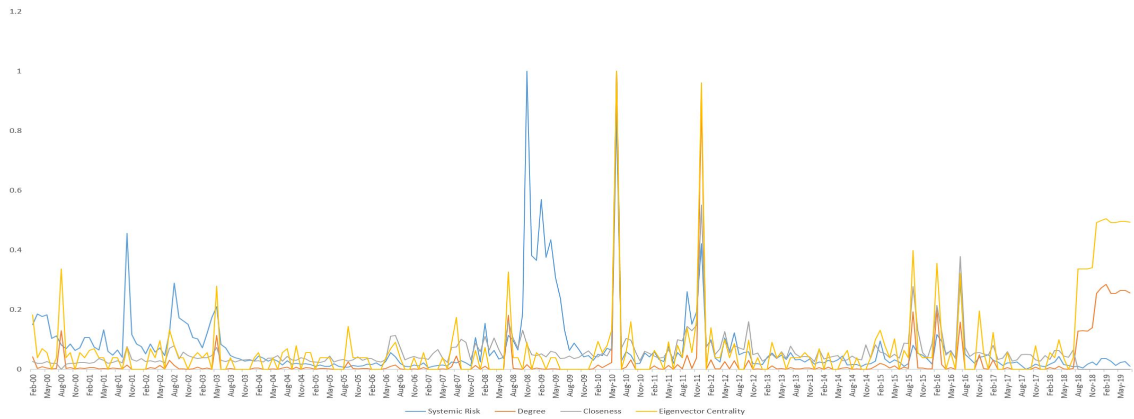
Figure 5: Comparison of systemic risk measures I - European financial system.



Notes: This figure shows four time-varying systemic risk measures in Europe: $CoVaR$, $\Delta CoVaR$, MES and SR (our systemic risk measure based on indirect links). These different measures are normalized by rescaling values to the range between 0 and 1. The results are computed using R version 3.6.0 (R Core Team, 2020) and package *SystemicR* (*v0.1.0*; Hasse, 2020). This figure highlights periods of high systemic risk: the subprime crisis and the European sovereign debt crisis.

risk are observed during the global financial crisis and to a lesser extent during the European sovereign debt crisis. Our methodology also results in a consistent measure of systemic risk. Figures 5 and 6 illustrate the differences between our systemic risk measure and six other measures used by scholars and practitioners (namely, $CoVaR$, $\Delta CoVaR$, MES, *degree*, *closeness* and *eigenvector centrality*). The comparison highlights that our measure is similar to other network-based measures and better identifies the 2007-2008 financial crisis. These two illustrations show that our measure of systemic risk, as with other network-based measures, appears to be more procyclical than $CoVaR$, $\Delta CoVaR$ and MES. In addition, our

Figure 6: Comparison of systemic risk measures II - European financial system.



Notes: This figure shows four time-varying systemic risk measures in Europe: *degree*, *closeness*, *eigenvector centrality* and SR (our systemic risk measure based on indirect links). These different measures are normalized by rescaling values to the range between 0 and 1. The results are computed using R version 3.6.0 (R Core Team, 2020) and package *SystemicR* (*v0.1.0*; Hasse, 2020). This figure highlights periods of high systemic risk: the subprime crisis and the European sovereign debt crisis.

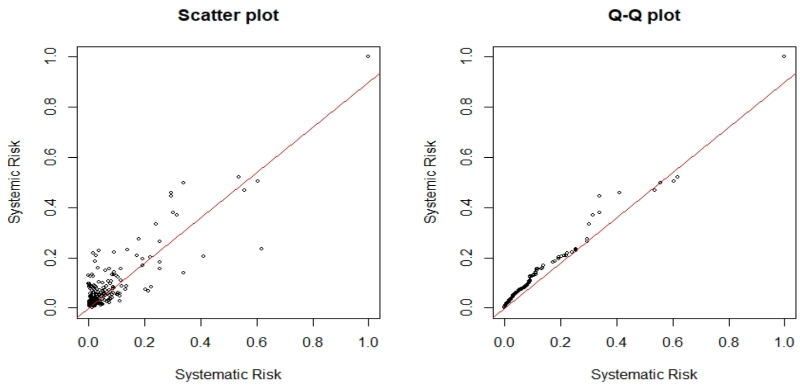
measure fails to capture systemic risk that has arisen from Italy's banking sector since 2018. These two points call for an empirical validation and assessment. The two next sections empirically verify that our measure of systemic risk is not related to market risk and that our measure clearly identifies systemic risk crises.

5.4. Empirical validation: systemic or systematic?

As noted by Benoit et al. (2017) in the survey on systemic risk, a common issue in measuring systemic risk is the empirical relationship between systemic and systematic risk. Although these two measures differ by construction, the relevance of a given measure of systemic risk is related to the additional information provided from a simple beta analysis. Therefore, we empirically examine the relationship between the volatility of the portfolio of financial equities and our measure of systemic risk. As our measure is derived from the impact of interconnectedness, it should not be correlated with systematic risk. Indeed, the connectedness of each institution in the network is related to direct links and indirect links, with the latter being unreachable through the correlation matrix defining systematic risk.

Figure 7 provides empirical evidence of the independence of systemic and systematic risk

Figure 7: Systemic or Systematic?



Notes: The scatter plot and the quantile-quantile (Q-Q) plot show no cross-sectional link between the time series of systemic risk estimated for the financial system (y-axis) and its systematic risk (i.e., beta) (x-axis). Each point represents the portfolio of equities at a given time t. The estimation period is from January 2000 to June 2019.

(i.e., beta). As expected, the risk driven by indirect links is not correlated with the risk driven by pairwise correlations. According to our theoretical demonstration, we empirically confirm that our systemic risk measure is not an artifact.

5.5. Empirical assessment

Finally, the quality of our measure of systemic risk is related to its usefulness for policymakers. By its very nature, our methodology is easily replicable and allows real-time analysis because it is based on public market data. Furthermore, the methodology that we develop offers a useful visualization tool for policymakers to monitor the complex structures of dependencies. To empirically validate our new measure of systemic risk, we verify that our measure is informative and/or predictive of major systemic events.

The purpose of this subsection is to empirically show that our new systemic risk measure delivers real added value for policymakers. Our measure is derived from the time-varying interconnectedness in the European financial network and is computed relative to the direct and indirect risk exposures of a set of financial institutions. In the preceding subsection, we empirically checked that our systemic risk measure was not dependent on the systematic risk of the portfolio of financial equities. Here, we consider whether our systemic risk measure has added value compared with information contained in systematic risk. Specifically, we empirically test if our measure has explanatory power with respect to macroeconomic downturns.

According to the recent work of Giglio et al. (2016), the equity volatility of the financial sector is highly informative of future macroeconomic shocks. Following these authors, we estimate the explanatory power of both systematic and systemic risk in modeling business cycles. This model can be interpreted as an Early Warning System (EWS), where the volatility of the portfolio of European financial companies and the associated systemic risk could predict future recessions. EWSs have become a useful tool for both policymakers and academics. Candelon et al. (2014) give a proper definition of an EWS based on its purpose *"to detect accurately the occurrence of a crisis, which is represented by a binary variable which takes the value of one when the event occurs, and the value of zero otherwise"*. Following the evaluation methodology proposed by Candelon et al. (2012), we choose to implement the exact maximum likelihood estimation method introduced by Kauppi and Saikkonen (2008). In the first experiment (Table 4), we compare estimates obtained from static and dynamic logit models (1)-(2) at the monthly and quarterly frequencies (a)-(b).[6] The results based on the Akaike information criterion (AIC) indicate that the best specification is the dynamic logit model. Similarly, quarterly data are more appropriate for forecasting recessions.

Table 4 provides evidence of the explanatory power of our measure of systemic risk as a model for recession. Indeed, our EWS relies on logit regression, in which the dependent variable is a dummy of recession, and the independent lagged variables are systemic and systematic risk. The estimates of systemic risk are highly significant, and systematic and systemic risk coefficients are both positive. Moreover, our systemic risk measure could be

[6]Considering the low ratio of instances of 1 to instances of 0 exhibited by the recession dummy, logit models are preferable to probit models. See Ben Naceur, Candelon and Lajaunie (2019).

Table 4: Estimation results of logit models – Monthly and quarterly frequency – 2000-2019

Model	(1a)	(2a)	(1b)	(2b)
Intercept	-1.293***	-0.947***	-0.928**	-1.180**
	(0.330)	(0.224)	(0.421)	(0.575)
$Index_{t-1}$		0.317***		-0.172
		(0.103)		(0.298)
β_{t-1}	6.848326	5.286*	-1.690	-5.825
	(4.652)	(3.075)	(4.914)	(6.175)
SR_{t-1}	4.907	3.612	8.955	15.764*
	(4.478)	(3.091)	(5.680)	(8.661)
		Relevant Statistics		
AIC	273.8	272.2	100.5	99.0
		Data		
Frequency	Monthly	Monthly	Quarterly	Quarterly
No. Observations	234	234	78	78

Notes: This table reports the estimates obtained from static and dynamic logit models (1)-(2) for data covering the period from February 2000 to June 2019 at the monthly and quarterly frequencies (a)-(b) with one lag. The dependent variable is the recession dummy. The independent variables are the volatility of the portfolio of financial equities and our systemic risk measure. The results are computed using R version 3.6.0 (R Core Team, 2020) and package *ews* (*v0.1.0*; Hasse and Lajaunie, 2020). The full reproducible code is available on CRAN. We report values of the Akaike information criterion (AIC) for each specification. Standard errors are reported in parentheses below the estimates. Labels $***$, $**$ and $*$ indicate significance at 99%, 95% and 90% levels, respectively.

Table 5: Early warning signal: an application of the systemic risk measure

Model	(1)	(2)	(3)	(4)
Intercept	-7.137***	-6.480***	-6.556	-7.518***
	(2.297)	(1.858)	(9.290)	(2.045)
$Index_{t-1}$	0.685***	0.886***	0.906***	0.596***
	(0.017)	(0.007)	(0.037)	(0.037)
β_{t-1}	-3.339*	-11.404***	-15.956	-9.793**
	(1.815)	(4.242)	(24.267)	(3.947)
		Systemic risk measures		
$CoVaR_{t-1}$	0.651			
	(0.960)			
$\Delta CoVaR_{t-1}$		4.917**		
		(2.371)		
MES_{t-1}			7.897	
			(10.694)	
SR_{t-1}				9.482**
				(4.091)
		Macro-control variables		
$CRESPR_{t-1}$	0.286***	0.212***	0.152	0.320***
	(0.099)	(0.078)	(0.125)	(0.085)
$LIQSPR_{t-1}$	1.120***	0.955***	0.926	1.096***
	(0.370)	(0.297)	(1.570)	(2.763)
$YIESPR_{t-1}$	0.634**	0.869**	1.203	0.470
	(0.278)	(0.379)	(2.533)	(0.298)
		Data		
Frequency	Quarterly	Quarterly	Quarterly	Quarterly
Observations	78	78	78	78

Notes: This table reports the estimates obtained from dynamic logit models (1) to (4). The dependent variable and macro-control variables are extracted from the FRED St. Louis and OECD databases, respectively, for the period from 2000 Q1 to 2019 Q2. Results are computed using R version 3.6.0 (R Core Team, 2020) and package *ews* (*v0.1.0*; Hasse and Lajaunie, 2020). The full reproducible code is available on CRAN. We report values of the Akaike information criterion (AIC) for each specification. Standard errors are reported in parentheses below the estimates. Labels $***$, $**$ and $*$ indicate significance at 99%, 95% and 90% levels, respectively.

used as an early warning signal that is positively and significantly associated with future macroeconomic downturns.

In the second experiment (Table 5), we enrich the model by introducing several macro-control variables and systemic risk measures from the literature. Following Hasse and Lajaunie (2020), we introduce three macro-control variables: credit spread ($CRESPR$), liquidity spread ($LIQSPR$) and yield spread ($YIESPR$).[7] In addition, we introduce three systemic risk measures: $CoVaR$, $\Delta CoVaR$ and MES. The purpose is twofold: to obtain more robust estimates and to compare our systemic risk measures with other measures.

Table 5 confirms previous results (see Table 4), providing evidence of the usefulness of our systemic risk measure. Our empirical evidence is robust to the introduction of macro-control variables, and our measure of systemic risk exhibits interesting results compared to other measures. Indeed, all systemic risk estimates are positive, but only $\Delta CoVaR_{t-1}$ and SR_{t-1} coefficients are significant. We note that results for macro-control variables are similar in models (1)-(2). In model (3), MES contains more information about the macroeconomic stance than the other measures, as macro-control variables are not significant. In model (4), the coefficient of macro-control variable $YIESPR_{t-1}$ is positive, weaker than in models (1) and (2) and not significant. Therefore, our systemic risk measure contains more information about yield spread than $CoVaR_{t-1}$ and $\Delta CoVaR_{t-1}$.

[7] $CRESPR$, $LIQSPR$ and $YIESPR$ are defined as the change in the credit spread (the BAA corporate bond rate minus the 10Y treasury bond rate), the change in the liquidity spread (the 3M treasury bill rate minus the ECB refinancing rate) and the change in the yield spread (the 10Y treasury bond rate minus the 3M treasury bond rate).

5.6. Policy implications

From a policy perspective, our framework offers a useful toolbox for systemic risk supervision and financial regulation. Because our correlation-based network model relies on public market data, the model is easily replicable and allows real-time analysis of a complex financial system at both the local and global levels.

At the firm level, the network approach we developed could be useful in building systemic risk rankings that consider the multivariate nature of systemic risk. In line with Giudici et al. (2017), our multidimensional approach has the advantage of accounting for both direct and indirect links in financial networks. Disentangling the role of each link is crucial to assessing the level of risk diversification. As stated by Battiston et al. (2012), managing systemic risk requires an assessment of the resilience of the financial system that depends on a complex network topology. Moreover, the rigorous topological framework that we introduce in this paper allows us to better capture indirect links, increasing the added value of interconnectedness compared to other measures such as scores from the G-SIB assessment methodology in the framework of the Basel Committee on Banking Supervision (BCBS).[8] Indeed, BCBS's interconnectedness concept is limited, as it focuses for a given bank on its direct counterparts, while our framework enables a multidimensional approach to interconnectedness. In line with the recent methodology published by the Bank of International Settlements (BIS, 2013), we advocate for a global approach to financial institutions' contributions to systemic risk. Our framework enables supervisors to build robust and accurate rankings to identify the systemically important financial institutions (labeled "SIFIs" by the Financial Stability Board). Consequently, regulators could better target the financial institutions that should

[8]Interconnectedness is one of the five systemic risk categories used by the Basel Committee in its scoring approach to identify and regulate SIFIs since 2011. See Benoit, Hurlin and Pérignon (2019) for an overview of this framework.

be subjected to higher capital requirements or systemic risk tax. Future financial regulation should also be oriented toward a multidimensional analysis of financial institutions' risks, and the network approach should be used to better capture the multivariate nature of systemic risk. Indeed, the relevance of capital surcharges for G-SIBs (Poledna, Bochmann and Thurner, 2017) or firebreaks (Elliott, Georg and Hazell, 2018) depends on the topology of the financial network (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015). The banking and insurance sectors have been regulated to reach lower systemic risk. However, future financial regulations should also consider other financial sectors. Asset managers, brokers and other agents of the financial sector have direct and indirect links with the banking and insurance sector. Hence, they could have a role in spillover effects during a systemic risk crisis.

At a system level, our systemic risk measure provides additional information compared to that provided by market-based measures such as $CoVaR$, $\Delta CoVaR$ and MES. Indeed, these statistical approaches are based on pairwise relationships between financial companies, whereas the network perspective allows us to account for both direct and indirect links in a financial network. Moreover, our measure of systemic risk has an advantage over other network-based measures such as *degree*, *closeness* and *eigenvector centrality*. Indeed, our approach enables us to take into account n-dimensional indirect links. Hence, our measure adds information about systemic risk at the global level, which is related to the overall interconnectedness in the network. Our systemic risk measure should be used by policymakers to complement other measures and especially to disentangle the direct and indirect exposures of banks, insurers and other financial companies, which combined could become a strong transmission channel. In line with Bicu and Candelon (2013), who study the importance of direct and indirect exposures in the Eurozone, we find that indirect links play a central role in complex financial networks. As indirect links become an additional transmission channel during systemic events, such links have a significant impact on financial stability. Our work also leads to practical policy implications for surveying financial systems and allocating systemic risk. During systemic crises, deleveraging strategies focused on SIFIs will not be able to optimally reduce risk if financial companies' indirect exposures are not considered. Considering the complex interrelationships in financial networks, policymakers should not analyze firm-specific exposures independently but rather should study financial companies' systemic risk at the system level.

6. Conclusions

In this paper, we study systemic risk from a network perspective. We focus on interconnectedness, modeling the structure of dependencies between equity returns as a correlation-based network of banks, insurers and other financial companies. The topological framework that we develop introduces a useful visualization tool for the dynamic architecture of such financial systems. Moreover, this framework enables interconnectedness to be studied via direct and indirect connections between financial companies at both the local and global levels. We derive the impact of interconnectedness in terms of risk, and build portfolios of financial companies' stocks to assess the risk driven by indirect connections. We empirically validate the relevance of our methodology on a sample of European banks, insurers and financial companies in two steps. First, we compare our measure of systemic risk with the volatility of a portfolio of financial firms during systemic events and find evidence that our measure differs from systematic risk. Then, we show that our measure of systemic risk can be used as an early warning signal of macroeconomic shocks.

Several innovations emerge from this work. First, the topological framework we develop allows us to study interconnectedness in a correlation-based network. Furthermore, this framework enables a microanalysis of interconnectedness through direct and indirect links. In contrast to other network topology measures, such as closeness and betweenness centrality, our method allows us to study the role of each link that contributes to these aggregated measures. A new measure of systemic risk is derived from this framework and allows interconnectedness to be studied at both the local and global levels. Because the measure is based on market data, it can be replicated easily and allows real-time analysis of the dynamic structure of dependence in a financial network.

From the regulatory perspective, our framework enables a measurement of systemic risk through interconnectedness and provides a relevant visualization tool that allows real-time analysis of the architecture of dependencies among banks, insurers and financial companies. The analysis of the role of indirect dependencies among financial firms could help policymakers identify the most interconnected companies at the local level as well as the companies that are involved in these indirect dependencies. Additionally, this extended exploration of financial firms' neighborhoods could help policymakers measure the negative externalities imposed by systemically important financial institutions. At the global level, the roles of direct and indirect dependencies between firms are translated into risk exposure used to properly measure the aggregate risk driven by the network effect. A new measure of systemic risk emerges from such an analysis of the financial system modeled as a network. In summary, policymakers could use our network approach at both the local and system levels. On the one hand, our topological framework could be used to measure the strength of direct and indirect links at the local level to construct systemic risk rankings of banks, insurers and financial companies. On the other hand, our approach could be useful in building systemic risk indices at the global level. More generally, our framework offers policymakers a useful toolbox for exploring the real-time topology of the complex structure of dependencies in financial systems and for measuring the consequences of regulatory decisions.

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Appendix

Proposition 1. Let $c_{i,j}$ be the correlation of asset returns r_i and r_j and let $d(.)$ be a distance function that maps $c_{i,j}$ defined on $[-1;1]$ onto $[0;+\infty[$ as

$$d(c_{i,j}) = \sqrt{2(1-c_{i,j})}; \tag{1}$$

then, $d(.)$ defines a Euclidean distance, and we denote by $d(i,j)$ the Euclidean distance between asset returns i and j.

Proof. The Pearson correlation between two asset returns r_i and r_j is defined as

$$\begin{aligned} c_{i,j} &= Corr(r_i, r_j), \\ &= \frac{Cov(r_i, r_j)}{\sigma_i \sigma_j}, \\ &= \frac{1/2 \sum (r_i - \mu_i)(r_j - \mu_j)}{\sigma_i \sigma_j}, \end{aligned} \tag{2}$$

where μ_i and μ_j are the mean returns of the two assets i and j, respectively, and σ_i and σ_j are their respective volatilities. If r_i and r_j are standardized (i.e., $\mu_i = \mu_j = 0$ and $\sigma_i = \sigma_j = 1$), then

$$c_{i,j} = 1/2 \sum r_i r_j. \tag{3}$$

Meanwhile, the Euclidean distance between two vectors of asset returns is defined by

$$d(i,j) = \sqrt{\sum (r_i - r_j)^2}, \tag{4}$$

which we can rewrite as

$$d(i,j) = \sqrt{\sum r_i^2 + \sum r_j^2 + 2 \sum r_i r_j}. \tag{5}$$

As asset returns are standardized, we have $\sum r_i^2 = \sum r_j^2 = 1$ and

$$d(i,j) = \sqrt{1 + 1 + 2\sum r_i r_j},$$
$$= \sqrt{2(1 + \sum r_i r_j)}. \tag{6}$$

Thus, for standardized data, we can write the correlation between asset returns r_i and r_j (Eq. 3) in terms of the squared distance between them:

$$d(i,j) = \sqrt{2(1 - c_{i,j})}; \tag{7}$$

then, by construction, we conclude that $d(i,j)$ is the Euclidean distance between the two vectors of asset returns r_i and r_j. $\square$