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Research article

Centrality measures of financial system interconnectedness: A multiple crises study

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ABSTRACT

We explore how asset returns could be a good proxy to detect interlinkages in the financial system. This paper employs a US dataset for the 2002–2021 period. Pairwise returns correlation indicate the interconnectedness at the preliminary stage. The Principal Component Analysis captures a significant portion of variance and detects the co-movement and highly connected state of the financial market during crises. Granger centrality tested with pairwise directional variance decomposition indicates the importance of banks and insurance companies in the US financial system. This paper recommends policymakers use multiple network models to validate and calibrate the SIFIs list.

1. Introduction

The endogenous effects of intercorrelated exposure as stated in the balance sheet are catastrophic and could trigger bank failure and create systemic risk. The nature of interconnectedness is difficult to avoid since interbank borrowing and lending are common in banks' daily operational activities. These serve to manage extra cash and source liquidity shortage, which keeps the banks running and earns interest as their main income. This paper extends investigation to the effect of correlated exposures across industries to include insurances, government support entities, and separate classes of investment and commercial banks. To account for multiple sectors in one broad calculation is highly relevant, as we know that contagion effect encompasses multiple industries during financial crises.

Allen and Gale [1] indicated how market structure completeness could affect financial contagion. Although their data focused on banking, it partly showed that risk allocation to other industries could be a way to mitigate systemic risk. The global financial crises in 2007–2008 provided an excellent example, including the failure of Lehman Brothers triggered by subprime mortgage investment losses, insurances companies AIG and Prudential due to risk transferred through contracts and credit default swap mechanism, and government support entities in the housing sector such as Fannie Mae and Freddie Mac. Apart number of papers discussed systemic institutions, much research has elaborated institution effect using banks' data or operational assumptions to propose models. Pre-global financial crises examples are Allen and Gale [1]; Freixas, Parigi [2]; Eisenberg and NOE [3]; Lehar [4]; Nier, Yang [5]; Elsinger, Lehar [6]; and Elsinger, Lehar [7]. Post-global financial crises examples are Acharya [8], Gai and Kapadia [9], Krause and Giansante [10], Billio, Getmansky [11], Brämer and Gischer [12], Drehmann and Tarashev [13], Pais and Stork [14], Akhter and Daly

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[15], Daly, Batten [16], Salim and Daly [17], and Rizan, Salim [18]. Although banking is the dominant force in many countries' economies, incorporating other industries into one analysis package could provide a more comprehensive picture of risk pattern and contagion effect. Our study contributes to fill the gap by estimate interconnectedness during past major shocks to global financial markets; the subprime mortgage crisis (2008–2009), European debt crisis (2010–2011), and Russian rubble crisis (2014–2015). The study also among the first to elaborate the interconnectedness in the financial system during the Covid-19 pandemic crisis. Further, instead of focusing on banking sector, this manuscript analyses the systemically important financial institutions (SIFIs) based on market data covering investment banks, commercial banks, insurances companies and government support entities.

This paper raises the questions of: 1) Can market data (e.g., share price and asset returns) indicate risk in the financial system and interconnection? 2) What financial companies or sectors are dominant and systemic in the economy? and 3) How are the results compared to the pairwise directional variance decomposition outcome? To answer these questions, we follow Billio, Getmansky [11] method of using Principal Component Analysis (PCA) to scale the risk commonality and risk direction. This paper also uses Granger causality to scrutinise SIFIs across the entire economic system. In the latter part of our analysis, we also compute spillover among entities using Diebold and Yılmaz [19] to calibrate the method. Outcomes from this research broaden our views on systemic risk and interconnectedness, risk spread and escalation both from and to sectors. The results benefit regulators in making policy judgements and provide insight to calibrate and validate measurements of comprehensive risk in the financial system.

The findings of this paper are as follows.

1. Pairwise returns correlation is significant at the 5% confidence level and indicates the interconnectedness and co-movement.
2. The first three principal components of PCA capture the notable portion of the returns variance. The outcome shows a highly interconnected state in the US financial market during financial crises, in which the banking sector is the key player.
3. Granger centrality methods indicate the dominance of banks and insurance companies in the US financial network, with this result being consistent both during and after crises.
4. SIBs are noted using pairwise direction variance decomposition and broadly in line with Granger centrality results. Use of multiple methods to validate SIFIs could aid policymakers.

This paper is structured as follows. Section 2 reviews the literature and highlights the importance of the network model approach in systemic risk study. Section 3 details the methodology used. Section 4 presents the analytical results and interpretation. Section 5 draws conclusions and makes policy recommendations.

2. Literature review

'Systemic risk' is defined as a risk of disruption to financial services caused by an impairment of all or parts of the financial system, with potential negative consequences for the real economy [20]. ECB [21] defines systemic risk as the risk of financial instability that impairs the functioning of a financial system to the point that economic growth and welfare suffer significantly. From the researcher perspective, De Bandt and Hartmann [22] define systemic risk as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system. Other definitions include intercorrelated exposures [23] and a set of circumstances that threatens the stability of public confidence in the financial system [11]. The elements of such system are interdependent on one another, between two elements or among elements. An event in the past representing one element can affect a future event of another element [24]. In short, there is no broad consensus on a single definition of systemic risk, but we can infer from all definitions that they would include the collapse of SIFIs or 'too big to fail' financial entities, the resulting system contagion, system-wide effects, and economic downturn as systematic risk.

Systemic risk studies use different model estimations, data, and variables, as classified by Bisias, Flood [25], who segregate studies in this area by scope, variables employed and research method. Example papers using a cross-section analysis are Adrian and Brunnermeier [26] (who used CoVaR to estimate the value at risk (VaR) of banks and its risk contribution to the whole system; CoVaR is the difference of the financial system VaR condition when firm *i* is in the financial distress versus the financial system VaR when firm *i* is in a median state); Acharya, Pedersen [23] (who used MES and SES to measure financial institutions' expected losses when the market falls below a predefined threshold over a given time horizon); and Brownlees and Engle [27] (who introduced SRISK to capture the expected capital shortage of a firm given its degree of leverage and MES as the expected loss an equity investor in a financial firm would experience if the overall market declined substantially). Estimation of capital shortfall uses bivariate daily equity returns of firms and market index, where volatilities follow asymmetric GARCH and DCC processes. Cross-section analysis in systemic risk is popular among scholars, as it is relatively simple and uses publicly available capital market data.

Our study employs the network model approach to measure the interconnectedness among financial entities. Prior studies have mapped the interlinkages between banks and their failure impact on other sectors such as insurance companies. Prominent papers that used the network approach include Allen and Gale [1]; Eisenberg and NOE [3]; Gai and Kapadia [9]; Gai, Haldane [28]; Nier, Yang [5]; Krause and Giansante [10]; and Billio, Getmansky [11]. In the network theory model, nodes represent entities or institutions. The nodes interact through edges [3,9], which arise as consequences of overlapped assets or liabilities, such as risk transfer activities from banks to insurance companies (e.g., subprime mortgages before and during the 2007–2008 global financial crises). Gai and Kapadia [9] model bank solvency as $(1-\varnothing)A_i^{IB} + qA_i^M - L_i^{IB} - D_i > 0$ or in the other form $\varnothing < \frac{K_i-(1-q)A_i^M}{A_i^{IB}}$ *for* $A_i^{IB} \neq 0$, where $K_i = A_i^{IB} + A_i^M - L_i^{IB} - D_i$ is the capital buffer. For the crisis to spread to other banks in the system, $\frac{K_i-(1-q)A_i^M}{A_i^{IB}} < \frac{1}{j_i}$.

Allen and Gale [1], in their prominent study on systemic risk, demonstrated that market structure is important for understanding systemic risk effect. Their findings show that when the market structure is complete, where all participants have edges to others in the network, the market is more resilient to financial shock than an incomplete market. They explain that some portions of shocks are distributed to many participants in system. A wider system is more robust compared to only one institution absorbing all the counterpart failure.

Eisenberg and NOE [3] proposed the general model of clearing system. The clearing vector represents the payments from nodes to others in the financial system. It simulated the conditions of proportional repayments of liabilities in default, limited liability of equity and absolute priority of debt over equity. Cont, Moussa [29] investigated Brazilian banks, employing the balance sheet and network structure in 2007–2008 and failed banks' contribution to systemic risk. They produced the Contagion Index as a metric for the systemic importance of institutions. This measures the expected loss to the network triggered by the default of an institution in a macroeconomic stress scenario. Krause and Giansante [10] developed a model of interbank loans given and received by banks of different sizes. In their findings, the size of a failing bank has limited effect on the number of banks affected by contagion. They concluded that banks' network structure has a much more significant effect on systemic risk. Elsinger, Lehar [6] extended the model used by Eisenberg and NOE [3] to include uncertainty to quantify the correlated exposure and domino effect, and Elsinger, Lehar [7] analyzed the network analysis correlated exposure and mutual credit relation that may cause domino effect. Using multivariate causal relationship, Bai, Wong [24] extended the model developed by Hiemstra and Jones [30] in determining the causality relationship between stock prices and trading stationary using stationary residuals from linear causality relationship. Bai, Wong [24] used vector samples from strictly stationary, weekly dependent, and satisfy the mixing conditions of Denker and Keller [31]. Other studies examine the systemic risk using financial network like Härdle, Wang [32] with tail event and network dynamics to rank the systemic risk transmitter and receiver using the US financial market over 2007–2012. Härdle, Wang [32] are able to analyse the network and the behaviour of each financial industrial group using semiparametric technique. Hautsch, Schaumburg [33] proposed the realized systemic risk beta to estimate the US financial companies' contribution to system wide from 2000 to 2008 using firm's Value at risk (VaR) and found that its approach can be used to monitor the contribution of each company to systemic risk in the US financial system. Wang, Yi [34] proposed the multilayer spillover network for 24 Chinese publicly listed companies during 2008–2018 to measure interconnectedness using Granger causality test in mean, volatility, and risk. Wang, Yi [34] found that using multilayer networks, they could detect the unique characteristics of each layer which is difficult to measure using single layer approach. Wang, Xie [35] used CAViaR to present VaR and the Granger causality test evidence over financial institutions listed at the S&P 500 index during the period 2006–2015. Wang, Xie [35] found that the network effects are influenced by the time-lag. Ando [36] explored the stock return comovement of 52 stock markets from 2001 to 2018 using US as the benchmark and found that the international financial connection predicted the returns of the destination economy.

Further, Raddant and Kenett [37] explored the inter and intra interconnectedness and comovement of stock market in 15 countries using GARCH DCC framework. The results are the energy, materials, and financial sectors playing a leading role to connect the markets and the fine structure of stock returns time variation. The sectoral effects do exist but limited to some parts of the market only. They also quantify the interconnectedness using network theory to present the relationship among sectors and capital markets.

As discussed previously, most previous studies develop models based on banking operation activities assumption before the Covid-19 crises period. Instead of focusing on banking sector, this manuscript analyses the systemically important financial institutions (SIFIs) based on market data covering investment banks, commercial banks, insurances companies and government support entities. It is also among the few studies so far to investigate the interconnectedness in the financial system during the Covid-19 pandemic crisis.

Our study explores how financial entities' variance could explain the risk build up, identify SIFIs and explain how risk propagates within a network. Instead of focusing on one specific banking class (like most of network model studies of systemic risk), our analyses encompass other financial institutions like insurance companies, commercial banks, investment banks and government support entities. This study aims to highlight the interconnection by employing PCA and Granger causality, following Billio, Getmansky [11]. We build on the extant research through model outcome and prove that 'central bank' status is not solely a matter of size. The results are useful for policymakers to monitor and mitigate systemic risk and connection path failure in both the banking sector and whole financial system.

3. Data and methodology

3.1. Data source

The datasets represent all financial sectors listed on the New York Stock Exchange in the period 2002–2021. The datasets encompass commercial banks, investment banks, insurance companies and government support entities. As we examine SIFIs, we select 20 major financial institutions as representative of each sector—six investment banks (IB), seven commercial banks (CB), five insurance companies (IC) and two government support entities (GSE). Our sample selection to encompasses multi entities of businesses in the US financial system wide is intended to capture the inter correlated exposures among them. The multi periods of crises such as 2008 global financial crises and Covid-19 crises also highlight the importance of study simultaneously assessed across all institutions within the system.

We collate the data of share price (daily), trading volume (daily), outstanding shares (daily), market capitalisation (daily), total assets and equity (quarterly), and separate accounts for insurance companies (quarterly). There are also states variables such as the Fed fund rate, VIX index, and some like T-bill delta, and excess returns. Data was sourced from the Eikon Thomson Reuters databases compiled by Belluzo [38] for 2002–2019 and we extend it further up to December 2021 to cover the current Covid-19 pandemic crises.

MATLAB R2021a was used for analyses.

We use two methods. First, we use PCA to measure the interconnectedness of asset returns of US financial institutions. PCA has the advantages of reducing data dimension, increasing interpretability, and minimising information loss [39]. PCA can also detect the risk of large financial institutions' failure [11,40]. Second, we employ Granger causality to evaluate the risk spread direction among banks. This consists of several network indicators: degree of causality, number of connections, closeness, and eigenvector centrality. Granger causality allows scholars to map those institutions that could trigger systemic risk within a financial network [11,41–43]. For PCA and Granger causality, we follow Billio, Getmansky [11] methodology.

3.2. Principal Component Analysis

High-frequency data and PCA as an adaptive descriptive statistic are used in many research fields. PCA has been used to analyse systemic risk in Billio, Getmansky [11], Fang, Xiao [44]; and Baek, Cursio [40]. We follow Billio, Getmansky [11] in measuring the degree of interconnectedness of asset returns of financial institutions into orthogonal factors of decreasing explanatory power:

R^i = stock return of institutions i, $i = 1, \ldots, N$, system aggregate return $R^s = \sum_i R^i$,

$E[R^i] = \mu_i$ and $Var[R^i] = \sigma_i^2$ to have:

$$\sigma_s^2 = \sum_{i=1}^{N} \cdot \sum_{j=1}^{N} \sigma_i \sigma_j \, E\left[z_i \, z_j\right] \tag{1}$$

$$Z_k \equiv \frac{\left(R^k - \mu_k\right)}{\sigma_k} \quad k = i, j \tag{2}$$

where z_k is the standardised return of institutions k and σ_s^2 is the variance of the system. If we put λ_k the k-th eigenvalue with N zero mean uncorrelated variables:

$$\mathrm{E}\left[\zeta_k \zeta_l\right] = \begin{cases} \lambda_k, if\ k = 1 \\ 0, if\ k = 0 \end{cases} \tag{3}$$

$$Z_i = \sum_{k=1}^{N} L_{ik} \zeta_k \tag{4}$$

where L_{ik} is a factor loading for ζ_k for institutions i. Then we have:

$$\mathrm{E}\left[Z_i Z_j\right] = \sum_{k=1}^{N} \cdot \sum_{l=1}^{N} L_{ik} L_{jl} \, \mathrm{E}\left[\zeta_k \zeta_l\right] = \sum_{k=1}^{N} L_{ik} L_{jk} \lambda_k \tag{5}$$

$$\sigma_s^2 = \sum_{i=1}^{N} \cdot \sum_{j=1}^{N} \cdot \sum_{k=1}^{N} \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k \tag{6}$$

We focus on subset $n < N$, as this set captures most of the volatility during crises and indicates the increase of interconnectedness among banks. If total risk of the system is defined as $\Omega \equiv \sum_{k=1}^{N} \lambda_k$ and $\omega_n \equiv \sum_{k=1}^{N} \lambda_k$, the risk associated with the first principal components is $\frac{\omega_n}{\Omega} \equiv h_n \geq H$. The contribution, $PCA_{i,n}$, of institution i to system risk is:

$$PCAS_{i,n} = \frac{1}{2} \frac{\sigma_i^2}{\sigma_s^2} \frac{\vartheta \sigma_s^2}{\vartheta \sigma_i^2} \bigg| \, h_n > H \tag{7}$$

$$PCAS_{i,n} = \frac{1}{2} \frac{\sigma_i^2}{\sigma_s^2} \frac{\vartheta \sigma_s^2}{\vartheta \sigma_i^2} \bigg| \, h_n \geq H = \sum_{k=1}^{N} \frac{\sigma_i^2}{\sigma_s^2} L_{ik}^2 . \lambda_k \bigg| h_n \geq H \tag{8}$$

3.3. Granger causality

Using Granger causality (in conjunction with the network approach) builds on its ability to predict the forecast of value based on other time series past information. In the capital market where frictions exist, Granger causality appears in the assets return based on other institutions' returns, indicating the spillover risk [11,41–43]. We use Granger causality to evaluate the direction of risk spreading in a financial system during crises. Please refer to Billio, Getmansky [11] for the complete formula description:

$$(j \rightarrow i) = \begin{cases} 1, \text{if j Granger causes i} \\ 0, \text{otherwise} \end{cases} \tag{9}$$

The interconnectedness measures consist of.

a. *Degree of Granger causality* (DGC)—measures the association of N(N–1) pairs of N entities:

$$DGC \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} . \sum_{j \neq 1} .(j \rightarrow i) \tag{10}$$

b. *Number of connections*—captures the importance of entities during the systemic event:

$$\#Out : (j \rightarrow S) \Big| DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} .(j \rightarrow i) \Big| DGC \geq K' \tag{11}$$

$$\#In : (S \rightarrow j) \Big| DGC \geq K = \frac{1}{(N-1)} \sum_{i \neq j}^{N} .(i \rightarrow j) \Big| DGC \geq K' \tag{12}$$

$$\#In + Out : (j \leftrightarrow S) \Big| DGC \geq K = \frac{1}{2(N-1)} \sum_{i \neq j}^{N} .(i \rightarrow j) + (j \rightarrow i) \Big| DGC \geq K' \tag{13}$$

where S = system, *#Out* = number of financial institutions Granger-caused by institution *j*, *#In* = number of financial institutions Granger-caused by institution *j*, and *#In* + *Out* = the sum of these.

c. Sector-conditional connections—used to analyse types of financial institutions that affect other classes:

$$\#Out - to - Other : \frac{1}{\frac{(M-1)N}{M}} \sum_{\beta \neq \alpha} . \sum_{i \neq j} .((j|\alpha) \rightarrow (i|\beta)) \Big| DGC \geq K' \tag{14}$$

$$\#In - from - Other : \frac{1}{\frac{(M-1)N}{M}} \sum_{\beta \neq \alpha} . \sum_{i \neq j} .((i|\beta) \rightarrow (j|\alpha)) \Big| DGC \geq K' \tag{15}$$

$$\#In + Out - Other : \frac{\sum \beta \neq \alpha \sum i \neq j((i|\beta) \rightarrow (j|\alpha)) + ((j|\alpha) \rightarrow (i|\beta)) \; |DGC \geq K'}{2(M-1)N/M} \tag{16}$$

where M = financial institutions type (IB, CB, IC, GSE), *#Out-to-Other* = number of other types of institutions Granger-caused by institution *j*, *#In-from-Other* = number of other types of institutions Granger-cause institution *j*, and *#In* + *Out-Other* = the sum of these.

d. *Closeness*—estimates the shortest edges between financial institutions:

$$C_{jS}|_{DGC \geq K} = \frac{1}{N-1} \sum_{i \neq j} .C_{ji} \left(\overrightarrow{j \xrightarrow{C} i} \right) \Big| DGC \geq K' \tag{17}$$

e. Eigenvector centrality—signal of financial institutions significance within the network based on its connection to other entities:

$$V_j|_{DGC \geq K} = \sum_{i=1}^{N} .[A]_{ji} V_i|_{DGC \geq K'} \tag{18}$$

4. Results

4.1. Statistics summary

The datasets are classified into four groups: investment banks (IB), commercial banks (CB), insurance companies (IC) and government support entities (GSE). This sample was compiled and provided by Belluzo [38], with the MS Excel worksheet containing share price (daily), trading volume (daily), market capitalisation (daily), total assets and equity (quarterly), and US macroeconomic indicators (daily). There are 4689 daily observations for each variable for the period 2002–2021. The sample period includes several major shocks to global financial markets, such as the dotcom bubble (2001–2002), subprime mortgage crisis (2008–2009), European debt crisis (2010–2011), Russian rubble crisis (2014–2015), stock market selloff (2015–2016), and Covid-19 crisis. The sample institutions are listed in Table 1.

To estimate PCA and Granger causality, we use Belluzo [38] Matlab code for systemic risk. Based on analysis of statistics returns, as

Table 1
Dataset sample.

No.	Ticker	Institution	Group
1	GS	Goldman Sachs	IB
2	MS	Morgan Stanley	IB
3	BAC	Bank of America	IB
4	C	Citigroup	IB
5	JPM	JP Morgan Chase	IB
6	LEH	Lehman Brothers	IB
7	USB	US Bancorp	CB
8	WFC	Wells Fargo & Co	CB
9	STT	State Street	CB
10	PNC	PNC Financial Services	CB
11	AXP	American Express	CB
12	COF	Capital One Financial	CB
13	BK	Bank of New York Mellon	CB
14	AIG	American International Group	IC
15	ALL	Allstate Corp	IC
16	BRK	Berkshire Hathaway	IC
17	MET	Metlife	IC
18	PRU	Prudential Financial	IC
19	FMCC	Federal Home Loan Mortgage Corp/Freddie Mac	GSE
20	FNMA	Federal National Mortgage Association/Fannie Mae	GSE

shown in Table 2, we can see that over the sample window, shareholder investment returns are positive except for GSE in 2005–2007 and GSE and CB in 2008–2010 (i.e., financial crises). We know that CB and GSE were two businesses heavily affected by the subprime mortgage crisis in 2008. GSE also have the highest volatility of return, as exhibit in the kurtosis >3 in all periods, which is leptokurtic and in line with the highest standard deviation compared to other sample groups. The Covid-19 crises also detected higher volatility across all US financial institutions.

The results of investigating individual entities' returns confirm the group data. As shown in Table 3, the FMCC and FNMA returns

Table 2
Summary statistics of daily returns in group.

2020–2021	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0008	0.0268	−0.1559	0.1823	0.0002	0.30221	10.6202
Commercial Banks	0.0008	0.0268	−0.1559	0.1823	0.0002	0.30221	10.6202
Insurance Companies	0.0006	0.0243	−0.1451	0.1497	0.0013	−0.4274	9.66803
Govt Support Entities	0.0013	0.0350	−0.2387	0.1875	0.0009	−0.2554	8.75135
2017–2019	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0005	0.0127	−0.0491	0.0501	−0.0001	−0.1704	1.8954
Commercial Banks	0.0003	0.0105	−0.0507	0.0455	0.0002	−0.4323	2.6957
Insurance Companies	0.0002	0.0101	−0.0525	0.0445	0.0005	−0.7604	3.7225
Govt Support Entities	0.0005	0.0401	−0.2255	0.4280	−0.0028	2.2306	25.8118
2014–2016	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0005	0.0143	−0.0819	0.0661	0.0009	−0.2163	3.0495
Commercial Banks	0.0003	0.0115	−0.0638	0.0421	0.0008	−0.3833	2.5397
Insurance Companies	0.0003	0.0110	−0.0646	0.0443	0.0008	−0.2746	2.8256
Govt Support Entities	0.0014	0.0473	−0.3715	0.4574	−0.0029	1.3449	22.5235
2011–2013	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0005	0.0213	−0.1333	0.1074	0.0006	−0.1316	4.8545
Commercial Banks	0.0007	0.0145	−0.0956	0.0689	0.0004	−0.2353	5.2592
Insurance Companies	0.0006	0.0156	−0.0864	0.0742	0.0006	−0.0992	4.3880
Govt Support Entities	0.0052	0.0681	−0.3952	0.5237	−0.0029	1.2806	12.1369
2008–2010	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	−0.0005	0.0471	−0.2775	0.3320	−0.0012	0.9729	10.5597
Commercial Banks	0.0007	0.0390	−0.1739	0.2072	−0.0001	0.6611	5.8978
Insurance Companies	0.0003	0.0385	−0.1545	0.1967	0.0001	0.5077	5.9724
Govt Support Entities	−0.0003	0.0997	−0.8619	0.8995	−0.0100	1.3043	20.8201
2005–2007	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0003	0.0126	−0.0565	0.0662	0.0004	−0.0319	4.6492
Commercial Banks	0.0002	0.0105	−0.0650	0.0553	0.0000	−0.1286	6.1507
Insurance Companies	0.0004	0.0084	−0.0408	0.0452	0.0004	0.0963	4.0320
Govt Support Entities	−0.0006	0.0211	−0.2676	0.1873	−0.0005	−1.4853	43.2596
2002–2004	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Investment Banks	0.0004	0.0172	−0.0831	0.0903	−0.0002	0.3658	3.2758
Commercial Banks	0.0005	0.0155	−0.0626	0.0630	0.0004	0.1124	2.7498
Insurance Companies	0.0004	0.0117	−0.0477	0.0756	0.0003	0.6283	5.2414
Govt Support Entities	0.0001	0.0153	−0.1045	0.0768	0.0002	−0.2635	4.5743

Table 3
Summary statistics of daily returns: All samples.

	SP500	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA
2002–2004																					
Mean	0.000	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.001	0.001	0.000	0.000
SD	0.012	0.020	0.013	0.011	0.017	0.016	0.014	0.020	0.017	0.024	0.019	0.022	0.019	0.020	0.033	0.017	0.019	0.016	0.012	0.016	0.016
Min	−0.038	−0.104	−0.069	−0.057	−0.072	−0.083	−0.101	−0.157	−0.065	−0.181	−0.068	−0.110	−0.085	−0.155	−0.398	−0.148	−0.114	−0.086	−0.040	−0.161	−0.069
Max	0.057	0.098	0.061	0.073	0.110	0.080	0.083	0.126	0.072	0.160	0.085	0.080	0.110	0.094	0.128	0.076	0.079	0.068	0.066	0.066	0.095
Median	0.000	−0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000
Skewness	0.350	0.218	0.347	0.677	0.456	0.065	−0.597	−0.092	0.275	0.311	0.384	0.114	0.428	−0.322	−2.534	−1.213	−0.207	−0.116	0.378	−1.134	0.224
Kurtosis	2.247	4.181	2.794	5.862	4.508	2.980	6.772	9.345	1.425	9.415	1.562	1.814	3.855	6.942	30.334	12.240	3.757	2.906	2.802	12.852	3.307
2005–2007																					
Mean	0.000	0.000	0.000	0.001	0.001	0.001	0.000	−0.001	0.001	0.000	0.001	0.000	0.000	0.001	−0.001	0.000	0.001	0.000	0.000	−0.001	0.000
SD	0.008	0.013	0.011	0.008	0.014	0.013	0.010	0.013	0.016	0.012	0.019	0.017	0.013	0.014	0.017	0.012	0.015	0.010	0.011	0.021	0.023
Min	−0.035	−0.080	−0.060	−0.046	−0.068	−0.059	−0.053	−0.081	−0.067	−0.057	−0.077	−0.081	−0.056	−0.053	−0.156	−0.051	−0.075	−0.044	−0.066	−0.287	−0.248
Max	0.029	0.060	0.055	0.042	0.121	0.066	0.052	0.069	0.085	0.063	0.100	0.074	0.064	0.120	0.090	0.066	0.085	0.064	0.062	0.188	0.186
Median	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	−0.001	−0.001
Skewness	−0.316	−0.245	0.074	0.177	0.930	0.240	−0.125	−0.384	0.080	0.360	0.163	−0.228	0.069	1.086	−0.906	0.451	0.393	0.665	0.095	−1.711	−0.939
Kurtosis	2.404	7.133	5.035	4.431	10.163	2.982	4.380	7.729	2.693	4.155	3.144	3.400	3.503	10.470	12.211	4.145	5.093	6.397	6.925	53.000	26.580
2008–2010																					
Mean	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.001	−0.022	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.000
SD	0.019	0.083	0.035	0.021	0.049	0.055	0.058	0.062	0.037	0.043	0.131	0.059	0.039	0.041	0.051	0.045	0.050	0.039	0.049	0.107	0.100
Min	−0.090	−0.608	−0.212	−0.121	−0.268	−0.247	−0.262	−0.390	−0.167	−0.179	−1.000	−0.259	−0.176	−0.272	−0.250	−0.261	−0.419	−0.182	−0.190	−0.827	−0.896
Max	0.116	0.660	0.217	0.161	0.280	0.383	0.353	0.578	0.265	0.251	0.464	0.870	0.206	0.248	0.264	0.371	0.313	0.228	0.328	1.284	0.706
Median	0.001	−0.002	0.000	−0.001	−0.001	0.001	−0.001	−0.001	−0.001	−0.001	−0.010	−0.001	0.001	−0.001	0.000	0.000	−0.001	0.000	−0.001	−0.009	−0.010
Skewness	0.093	0.903	0.092	1.339	0.516	0.886	0.846	1.161	1.170	0.976	−4.141	4.412	0.501	0.695	0.384	1.156	−0.126	0.601	1.492	2.650	0.892
Kurtosis	6.413	17.154	10.656	14.197	8.397	9.220	8.024	16.434	10.249	6.614	30.509	66.319	4.650	8.578	4.952	11.510	14.391	6.167	9.436	35.317	17.680
2011–2013																					
Mean	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.000	0.001		0.001	0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.005	0.005
SD	0.010	0.022	0.014	0.012	0.021	0.020	0.026	0.024	0.019	0.019		0.027	0.014	0.018	0.018	0.016	0.017	0.015	0.017	0.069	0.069
Min	−0.067	−0.100	−0.065	−0.061	−0.099	−0.108	−0.203	−0.164	−0.101	−0.094		−0.145	−0.088	−0.097	−0.121	−0.082	−0.101	−0.090	−0.090	−0.387	−0.403
Max	0.047	0.103	0.076	0.081	0.089	0.092	0.167	0.138	0.095	0.084		0.166	0.071	0.076	0.085	0.067	0.107	0.082	0.081	0.543	0.504
Median	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.000		0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	−0.002
Skewness	−0.474	−0.088	0.283	0.724	−0.158	−0.223	−0.073	−0.196	−0.021	0.002		0.224	−0.226	−0.098	−0.068	−0.120	0.075	−0.180	−0.121	1.305	1.203
Kurtosis	5.542	2.820	4.191	8.154	2.541	4.104	8.257	5.491	3.600	3.721		5.037	3.895	3.257	4.835	3.449	5.307	6.111	4.415	12.195	11.415
2014–2016																					
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001		0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.001
SD	0.008	0.012	0.010	0.009	0.016	0.016	0.017	0.016	0.014	0.013		0.017	0.013	0.014	0.015	0.012	0.016	0.011	0.012	0.047	0.048
Min	−0.039	−0.073	−0.101	−0.041	−0.107	−0.095	−0.074	−0.094	−0.071	−0.069		−0.102	−0.121	−0.085	−0.131	−0.064	−0.088	−0.056	−0.050	−0.375	−0.368
Max	0.039	0.073	0.057	0.032	0.071	0.064	0.071	0.073	0.059	0.083		0.071	0.090	0.046	0.082	0.048	0.093	0.044	0.076	0.457	0.458
Median	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000		0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.000	−0.003	−0.003
Skewness	−0.338	−0.012	−1.065	0.077	−0.600	−0.369	−0.135	−0.272	−0.275	0.086		−0.236	−0.891	−0.536	−0.864	−0.244	−0.384	−0.318	0.268	1.256	1.413
Kurtosis	2.401	4.218	14.870	1.875	5.143	3.225	2.362	3.805	1.868	3.954		3.338	13.145	3.533	10.127	2.136	4.854	2.373	3.502	21.889	22.582
2017–2019																					
Mean	0.001	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.001		0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001

(*continued on next page*)

Table 3 (*continued*)

	SP500	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA
SD	0.008	0.013	0.011	0.010	0.013	0.014	0.014	0.014	0.014	0.012		0.015	0.011	0.013	0.014	0.012	0.015	0.010	0.013	0.040	0.041
Min	−0.041	−0.090	−0.070	−0.060	−0.086	−0.101	−0.059	−0.053	−0.075	−0.048		−0.056	−0.056	−0.095	−0.064	−0.056	−0.085	−0.043	−0.092	−0.235	−0.231
Max	0.050	0.068	0.055	0.051	0.051	0.049	0.072	0.052	0.095	0.047		0.062	0.076	0.057	0.086	0.047	0.090	0.041	0.046	0.428	0.428
Median	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000		0.000	0.001	0.001	0.000	0.001	0.000	0.001	0.000	−0.003	−0.003
Skewness	−0.604	−0.813	−0.607	−0.415	−0.717	−1.010	−0.094	−0.087	−0.033	0.015		−0.049	0.056	−0.801	−0.068	−0.553	−0.213	−0.376	−0.535	2.103	2.250
Kurtosis	5.875	7.826	6.826	6.598	4.064	5.424	2.809	1.656	4.202	1.955		1.657	5.585	6.011	3.828	2.254	4.646	2.230	4.197	25.856	23.883
2020–2021																					
Mean	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.000	0.001	0.001		0.002	0.001	0.001	0.001	0.001	0.001	0.000	0.000	−0.001	−0.002
SD	0.016	0.034	0.021	0.016	0.029	0.032	0.028	0.032	0.026	0.026		0.028	0.031	0.025	0.035	0.028	0.029	0.029	0.031	0.046	0.046
Min	−0.120	−0.208	−0.141	−0.085	−0.166	−0.201	−0.154	−0.193	−0.127	−0.150		−0.156	−0.148	−0.145	−0.239	−0.159	−0.189	−0.144	−0.159	−0.368	−0.321
Max	0.094	0.188	0.107	0.113	0.173	0.210	0.178	0.180	0.176	0.180		0.198	0.219	0.156	0.188	0.129	0.223	0.174	0.145	0.290	0.293
Median	0.002	0.002	0.001	0.001	0.001	0.000	0.001	−0.001	0.000	0.000		0.002	0.001	0.001	0.001	0.001	0.001	0.000	0.001	−0.004	−0.004
Max	0.094	0.188	0.107	0.113	0.173	0.210	0.178	0.180	0.176	0.180		0.198	0.219	0.156	0.188	0.129	0.223	0.174	0.145	0.290	0.293
Median	0.002	0.002	0.001	0.001	0.001	0.000	0.001	−0.001	0.000	0.000		0.002	0.001	0.001	0.001	0.001	0.001	0.000	0.001	−0.004	−0.004
Skewness	−0.668	−0.479	−0.699	−0.053	−0.239	−0.209	0.395	−0.089	0.219	0.425		0.643	1.337	0.032	−0.255	0.032	0.287	0.263	0.020	0.195	0.674
Kurtosis	13.818	7.839	8.631	9.244	8.591	11.239	9.107	8.301	9.112	10.630		12.730	13.862	9.285	8.751	6.633	11.298	7.121	4.624	15.655	13.092

Table 4
Pairwise returns correlation at 5% confidence level.

	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA
AIG	1																			
ALL	0.4411*	1																		
	0.0000																			
BRK	0.3557*	0.5392*	1																	
	0.0000	0.0000																		
MET	0.5119*	0.6869*	0.5027*	1																
	0.0000	0.0000	0.0000																	
PRU	0.4915*	0.6990*	0.5438*	0.8183*	1															
	0.0000	0.0000	0.0000	0.0000																
BAC	0.5483*	0.5965*	0.5233*	0.6911*	0.7115*	1														
	0.0000	0.0000	0.0000	0.0000	0.0000															
C	0.5962*	0.5686*	0.4809*	0.6809*	0.6777*	0.8103*	1													
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000														
GS	0.4495*	0.5964*	0.5255*	0.6434*	0.6641*	0.6973*	0.7002*	1												
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000													
JPM	0.5089*	0.6098*	0.5409*	0.6847*	0.6764*	0.8018*	0.7595*	0.7499*	1											
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000												
LEH	0.7069*	0.3048*	0.0683*	0.3070*	0.3484*	0.4657*	0.5081*	0.5807*	0.3869*	1										
	0.0000	0.0000	0.0043	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000											
MS	0.4704*	0.6109*	0.4922*	0.6491*	0.6834*	0.6737*	0.6744*	0.8160*	0.6826*	0.6092*	1									
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000										
AXP	0.4973*	0.6060*	0.5310*	0.6656*	0.6834*	0.6850*	0.6480*	0.6750*	0.7190*	0.4370*	0.6562*	1								
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000									
BK	0.4763*	0.5901*	0.4831*	0.6681*	0.6599*	0.7053*	0.6806*	0.7016*	0.7438*	0.4117*	0.6919*	0.6738*	1							
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000								
COF	0.4379*	0.5718*	0.4515*	0.6341*	0.6626*	0.6733*	0.6250*	0.6189*	0.6925*	0.3134*	0.5879*	0.7293*	0.6414*	1						
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000							
PNC	0.4569*	0.5748*	0.5025*	0.6867*	0.6793*	0.7708*	0.6911*	0.6434*	0.7969*	0.3275*	0.6014*	0.6822*	0.6940*	0.6625*	1					
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000						
STT	0.4278*	0.5653*	0.4783*	0.6571*	0.6662*	0.6724*	0.6278*	0.6771*	0.7103*	0.3748*	0.6409*	0.6405*	0.7666*	0.6251*	0.7059*	1				
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000					
USB	0.4865*	0.6132*	0.5015*	0.6903*	0.6826*	0.7738*	0.6848*	0.6445*	0.7858*	0.3465*	0.5978*	0.7049*	0.6947*	0.6887*	0.7941*	0.6672*	1			
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000				
WFC	0.4892*	0.6032*	0.5004*	0.6904*	0.7100*	0.8225*	0.7320*	0.6702*	0.7922*	0.3646*	0.6230*	0.7035*	0.6999*	0.6875*	0.8048*	0.6936*	0.8253*	1		
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
FMCC	0.3131*	0.1970*	0.1556*	0.2274*	0.2213*	0.2832*	0.3017*	0.2527*	0.2536*	0.4741*	0.2404*	0.2377*	0.2166*	0.2150*	0.2259*	0.2023*	0.2287*	0.2448*	1	
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
FNMA	0.2952*	0.2112*	0.1711*	0.2402*	0.2337*	0.2906*	0.3017*	0.2637*	0.2617*	0.3730*	0.2356*	0.2493*	0.2174*	0.2202*	0.2279*	0.2070*	0.2314*	0.2528*	0.9025*	1
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	

are more volatile with extreme tail, as represent in the kurtosis value. From this table, we also note that during the global financial crises, as exhibited in the 2008–2010 window, shareholders took the hit and suffered losses, with the minimum negative value being much lower and the maximum also tending to be higher compared to other periods. Individual returns for LEH are calculated up to their last trading day in September 2008. The negative skewness returns of normal distribution and its complete loss (appearing as −1 minimum value) speak for the condition of the company as it neared bankruptcy.

Further, for the preliminary perspective of correlation existence in the US capital market, we run pairwise returns correlation test, with the results displayed in Table 4. The results for all entities are significant at the 5% confidence level. This confirms our research assumption of interconnectedness and co-movement among the sample. Indication of co-movement of stock return results warrants deeper investigation. For insight, we run simple linear regression for all samples using the benchmark index SP 500 as the dependent variable. Although this did not explicitly show interconnectedness among the sample, the results in line and provided a different perspective of direction (see Robustness test 1).

4.2. Empirical analysis

4.2.1. PCA

As discussed in Section 3.2, if, using a small number of institutions, PCA can explain the volatility within the market, then the system is highly interconnected, stated in the condition $h_n > H$. To assess the time variation of h_n, we could detect accumulation of interconnectedness or correlation and integration that contributes to systemic risk [25]. The cumulative risk fraction represented by eigenvalues are exhibited in Table 5. We note that during the Covid-19 crises cumulative risk is the highest at score 96.37% with eigenvalue 5.48. The state of high risk also detected during global financial crises in 2008 at score 93.49% with eigenvalue 5.14. Another interesting point is the higher PC 1–3 during the subprime mortgage crisis in 2008–2009, European debt crisis in 2010–2011, Russian rubble crisis in 2014–2015 and stock market selloff in 2015–2016 compared to pre-crisis. The first three are well represented, as PC 1–3 captures a significant portion of the variance. The results are consistent when we examine PC 1–10. Our result of principal component capturing and explaining the majority of variance within the sample periods is consistent with Billio, Getmansky [11].

Referring to Fig. 1 for eigenvalue λ_k, we can spot the same direction as displayed in Table 5. The higher PC 1–3 portion shows that intercorrelated exposures within the sample become higher and more persistent. The highest linkage was during Covid-19 crises, as dated in our sample windows. Additionally, the same patterns direction along the curve PC 1–PC 3 reflect the co-movement return in the sample. When the sample is deconstructed into groups, it is clear that investment and commercial banks dominate the US financial capital market during all periods. The figures are the same pre- and post-2008 (see Table 6). Identification of the dominance of banks using PCA methodology to capture covariance movement aligns with Baek, Cursio [40]. Each entity is significant in the US financial market, as shown in Fig. 2 using two dimensions of component loading. Stata calculation shows changes across periods; prior to the crises (Fig. 2A), the companies have some distance between each other (i.e., not much overlapping exposure between groups of industries). Over the 2008–2010 period (Fig. 2B), during the global financial crises, FMCC, FNMA, LEH and AIG contribute more than others to financial system risk. As we know, these companies were badly affected by the crises. After the crises (Fig. 2C), there is a tendency of interlinkages between US financial firms. The investment and commercial banks stay in groups, while the insurance companies and government support entities group together. Based on the same figures for the most recent period of 2020–2021 (Fig. 2D), regulators also should pay attention to large contributors to systemic risk, such as JPM, MS, BAC, C, GS, BK and WFC. The appearance of these companies in our results is in line with the 2021 G-SIBs list issued by FSB [45].

4.2.2. Granger causality

Granger causality has been used to identify correlated exposure and interconnectedness of financial institutions in prior studies [11,41,42]. The outputs of several centrality measures, presented in Table 7 and Fig. 3, provide important information.

a. *Degree centrality*—the number of edges point to a node, that is, an institution via which many banks conduct transactions. Based on analysis of the full sample window, FMCC is the key institution in the US financial system in terms of network adjacency, followed by BRK, COF, PRU, and JPM. These institutions likely also facilitate other banks' financial transaction needs, such as mortgage, risk

Table 5
Cumulative risk and eigenvalue during the period 2002–2021.

Cumulative Risk Fraction (First 10) and Eigenvalue (First 3)					
Investment Banks, Commercial Banks, Insurance Companies, Govt. Support Entities					
Sample Period	PC 1	PC 1-3	PC 1-5	PC 1-10	Eigenvalue λ_k
2020–2021	75.05%	86.60%	90.55%	96.37%	5.485
2017–2019	60.02%	74.53%	81.23%	92.04%	4.720
2014–2016	65.88%	79.49%	85.22%	93.97%	5.034
2011–2013	65.77%	79.37%	84.51%	93.05%	5.027
2008–2010	61.10%	77.09%	84.31%	93.49%	5.139
2005–2007	55.34%	66.07%	73.57%	86.81%	4.404
2002–2004	56.94%	68.15%	75.97%	87.74%	4.544

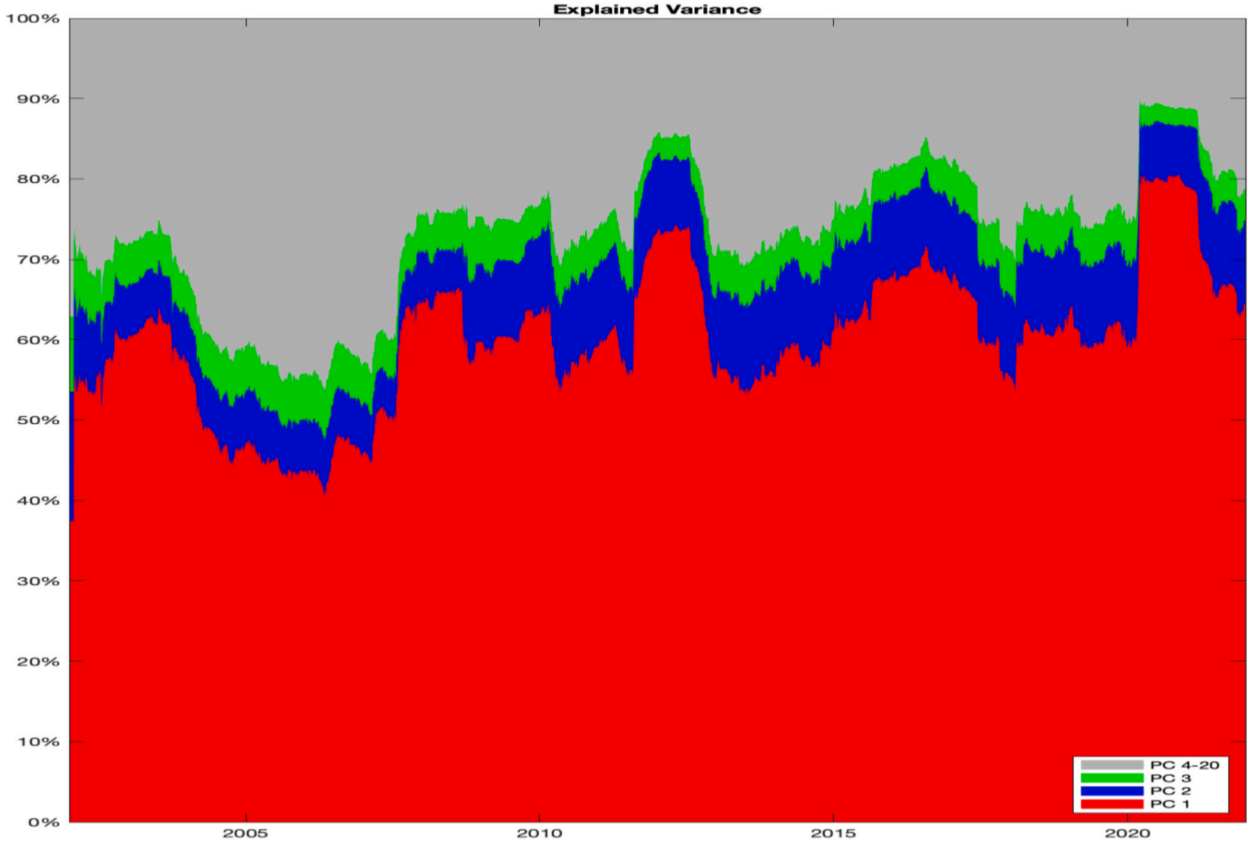


Fig. 1. Principal component explained variance.

transfer insurance, investment, billing payment, etc. During the Covid-19 pandemic crises, the list was led by C, MET, JPM, PRU and BRK.

b. *Closeness centrality*—the average shortest edges built on all observation periods to reach nodes interconnectedness is through AIG, C, FMCC, BK and AXP. This is the most vital information in terms of contribution to systematic risk. However, this list is quite volatile, likely due to dynamic transactions that keep the financial market rolling. During times of crises, C, MET, ALL, JPM and PRU have extensive networks in the system.
c. *Eigenvector centrality*—translated as not only how many edges but also how many really count or matter. The key players in the US financial system are once again AIG, C, FMCC, COF, and STT. At the time of the Covid-19 crises, the key players were C, ALL, MET, PRU and JPM.

Based on centrality measures for the full sample window, US policymakers should monitor AIG and STT (insurance companies); C, JPM, BAC, COF, BK (banks) and FMCC (government support entity). The importance of these firms' connections—that is, posed systematic risk—is highlighted in Fig. 4A for the full period and in Fig. 4B for during global financial crises in 2018. As the PCA subset principles yields explain and show the indicative of increasing interconnectedness through eigenvalues (as shown in Table 5 and Fig. 1), the Granger causality complement the PCA assessment by mapping the 'central banks' in the financial system wide network. Our Granger centrality results in Table 7 are also considerably higher during the Covid-19 pandemic crises as opposed to the full period estimation outcome. The findings are in line with the PCA results for subset PC 1–3 where for the same period is at 86.60% or higher compared to other periods.

Further, to capture the time varying effect on financial institutions interactions we employ vector autoregression (VAR) model. To check the dynamics of causality changes we run test over the period of Covid-19 crises from 2020 to 202. Based on the robustness test the optimal lagged VAR for TGVC is either lag 1 or 2 (see Robustness test 2). The TGVC results are presented in Table 8 below .[1]

During the period of Covid-19 crises, the post estimation VAR of the Granger wald test exhibit that JPM, AXP, BRK, and FMCC-FNMA are at the top of each respective group that have connections to other financial institutions (see Table 9).

[1] Due to pages restriction concern, we present sample results for insurance and investment bank group. The full table calculation is available for those who need it.

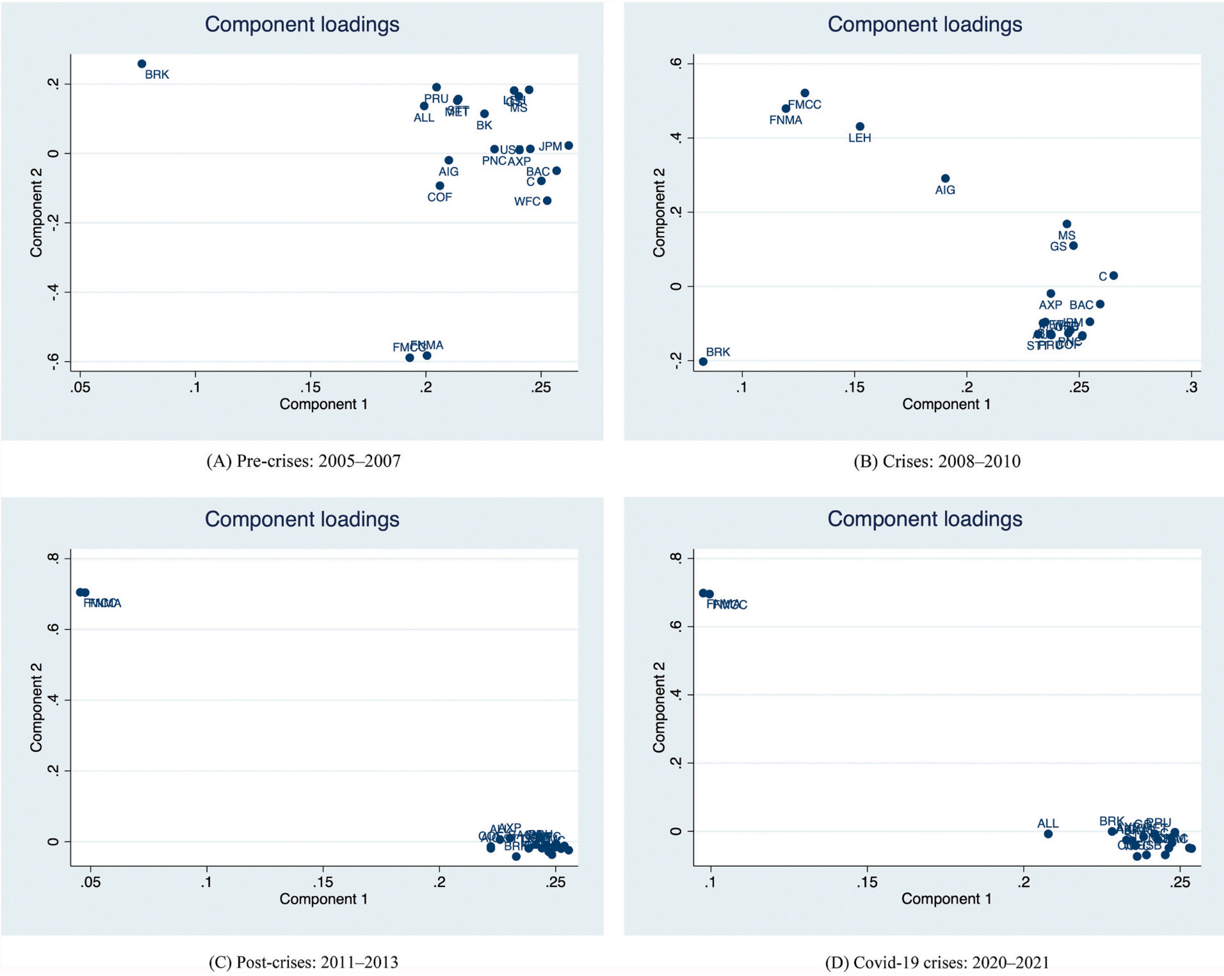
Table 6
PCA statistics for all samples.

	2020–2021					2008–2010				
	PC 1	PC 1-3	PC 1-5	PC 1-10	PC 1-20	PC 1	PC 1-3	PC 1-5	PC 1-10	PC 1-20
Investment Banks										
Mean	0.248	0.052	0.030	−0.020	−0.022	0.237	0.076	0.062	−0.005	−0.018
Min	0.242	−0.177	−0.258	−0.525	−0.716	0.152	−0.433	−0.433	−0.462	−0.641
Max	0.254	0.254	0.254	0.352	0.568	0.265	0.431	0.431	0.431	0.431
Commercial Banks										
Mean	0.239	0.036	0.018	0.033	0.027	0.243	0.061	0.042	0.020	0.022
Min	0.235	−0.238	−0.513	−0.513	−0.513	0.232	−0.170	−0.190	−0.614	−0.614
Max	0.246	0.246	0.371	0.722	0.804	0.251	0.251	0.436	0.504	0.504
Insurances										
Mean	0.233	0.144	0.092	0.051	0.023	0.196	0.033	0.019	0.057	0.039
Min	0.208	−0.092	−0.540	−0.593	−0.593	0.083	−0.356	−0.484	−0.513	−0.513
Max	0.248	0.767	0.767	0.767	0.767	0.238	0.291	0.906	0.906	0.906
Govt. Support Ent.										
Mean	0.099	0.252	0.158	0.083	0.045	0.124	0.356	0.214	0.134	0.066
Min	0.098	−0.050	−0.050	−0.050	−0.643	0.119	0.119	−0.041	−0.055	−0.498
Max	0.100	0.699	0.699	0.699	0.699	0.128	0.521	0.521	0.521	0.521
	2014–2016					2005–2007				
Investment Banks										
Mean	0.257	0.040	0.001	−0.015	−0.007	0.249	0.085	0.024	−0.003	−0.009
Min	0.253	−0.233	−0.233	−0.457	−0.591	0.238	−0.147	−0.271	−0.271	−0.626
Max	0.262	0.262	0.262	0.262	0.568	0.262	0.262	0.320	0.320	0.566
Commercial Banks										
Mean	0.237	0.058	0.036	0.031	0.014	0.231	0.064	0.013	0.010	0.012
Min	0.182	−0.112	−0.294	−0.491	−0.491	0.206	−0.136	−0.301	−0.535	−0.788
Max	0.257	0.257	0.908	0.908	0.908	0.253	0.253	0.253	0.842	0.842
Insurances										
Mean	0.220	0.162	0.124	0.056	0.046	0.181	0.186	0.166	0.098	0.052
Min	0.178	−0.149	−0.149	−0.720	−0.720	0.077	−0.045	−0.254	−0.711	−0.711
Max	0.245	0.809	0.809	0.809	0.809	0.214	0.904	0.904	0.904	0.904
Govt. Support Ent.										
Mean	0.081	0.268	0.164	0.085	0.042	0.197	−0.090	0.017	0.026	0.011
Min	0.080	0.022	−0.002	−0.016	−0.706	0.193	−0.589	−0.589	−0.589	−0.647
Max	0.081	0.701	0.701	0.701	0.706	0.201	0.201	0.302	0.302	0.639
	2011–2013					2002–2004				
Investment Banks										
Mean	0.248	−0.032	0.011	0.008	0.006	0.249	0.029	0.019	−0.039	−0.016
Min	0.241	−0.421	−0.421	−0.421	−0.652	0.241	−0.151	−0.297	−0.424	−0.659
Max	0.256	0.256	0.275	0.275	0.543	0.257	0.257	0.257	0.257	0.719
Commercial Banks										
Mean	0.241	0.133	0.065	0.028	0.014	0.230	0.019	0.036	0.060	0.023
Min	0.222	−0.037	−0.417	−0.609	−0.694	0.187	−0.239	−0.466	−0.466	−0.619
Max	0.254	0.374	0.501	0.501	0.741	0.252	0.252	0.358	0.724	0.724
Insurances										
Mean	0.233	0.114	0.064	0.044	0.030	0.188	0.156	0.057	0.045	0.031
Min	0.222	−0.042	−0.482	−0.482	−0.482	0.094	−0.326	−0.401	−0.409	−0.569
Max	0.250	0.250	0.752	0.752	0.752	0.236	0.650	0.650	0.759	0.759
Govt. Support Ent.										
Mean	0.047	0.250	0.149	0.073	0.038	0.178	0.311	0.227	0.108	0.057
Min	0.046	−0.007	−0.016	−0.024	−0.706	0.174	0.114	−0.053	−0.069	−0.529
Max	0.048	0.705	0.705	0.705	0.705	0.182	0.634	0.634	0.634	0.634

4.2.3. *Variance decomposition*

To map the risk direction of systemic failure in the US financial market, we used Diebold and Yılmaz [19] model. Application of their model provides a different perspective of spillover risk between entities in the system. The model is based on pairwise direction connectedness from j to i $C^H_{i\leftarrow j} = d^H_{ij}$, where $C^H_{i\leftarrow j} \neq C^H_{j\leftarrow i}1$. Net pairwise $\frac{N^2-N}{2}$ is analogous to bilateral interbank balances. As shown in Table 10, total directional connectedness from others to i is defined as $C^H_{i\leftarrow \circ} = \sum_{j=1}^{N} d^H_{ij}\ j \neq i$, and the opposite of total directional connectedness to others from j as $C^H_{\circ\leftarrow j} = \sum_{i=1}^{N} d^H_{ij}\ i \neq j$. The grand total off-diagonal entries, equivalent of the sum 'from' and 'to' measures of total connectedness, is $C^H = \frac{1}{N}\sum_{i,j=1}^{N} d^H_{ij}\ i \neq j$.

The results, shown in Table 11, show that net position is mostly zero, which reflects the accuracy of calculation with some excess of error. During the 2008 global financial crises, the banking groups are dominant or absorb many interlinkages (both liabilities and assets) from other financial market participants. This outcome stresses the importance of the banking sector to the US financial market over the sample period. The results also indicate a higher spillover in the beginning period of Covid-19 crises (17.42) compared to other times of the crises. The highest individual entities' variance spillover is for JPM, C, BAC, and PRU. The appearance of C and JPM



(A) Pre-crises: 2005–2007

(B) Crises: 2008–2010

(C) Post-crises: 2011–2013

(D) Covid-19 crises: 2020–2021

Fig. 2. Two dimension component loading.

Table 7
Centrality value of all samples.

Firms	Closeness Centrality		Degree Centrality		Eigenvector Centrality	
	Full	Crises	Full	Crises	Full	Crises
AIG	0.792	0.845	1.105	0.989	0.083	0.092
ALL	0.594	0.792	0.526	0.789	0.046	0.125
BRK	0.613	0.776	1.368	0.889	0.049	0.071
MET	0.679	0.792	0.684	1.125	0.061	0.083
PRU	0.576	0.760	1.263	1.142	0.043	0.097
BAC	0.633	0.633	0.842	0.984	0.052	0.079
C	0.731	0.905	1.053	1.316	0.071	0.175
GS	0.528	0.620	1.105	1.289	0.028	0.210
JPM	0.613	0.764	1.158	1.347	0.048	0.163
LEH	0.396	0.000	0.105	0.000	0.005	0.000
MS	0.613	0.633	1.105	1.179	0.046	0.063
AXP	0.704	0.724	0.842	0.863	0.059	0.072
BK	0.704	0.642	0.632	0.667	0.057	0.058
COF	0.703	0.758	1.368	0.982	0.064	0.012
PNC	0.633	0.648	1.053	0.937	0.054	0.034
STT	0.679	0.681	0.737	0.968	0.063	0.029
USB	0.594	0.576	1.000	0.996	0.039	0.044
WFC	0.500	0.633	0.895	0.898	0.023	0.089
FMCC	0.704	0.722	1.421	1.457	0.068	0.249
FNMA	0.576	0.702	0.895	0.884	0.043	0.183

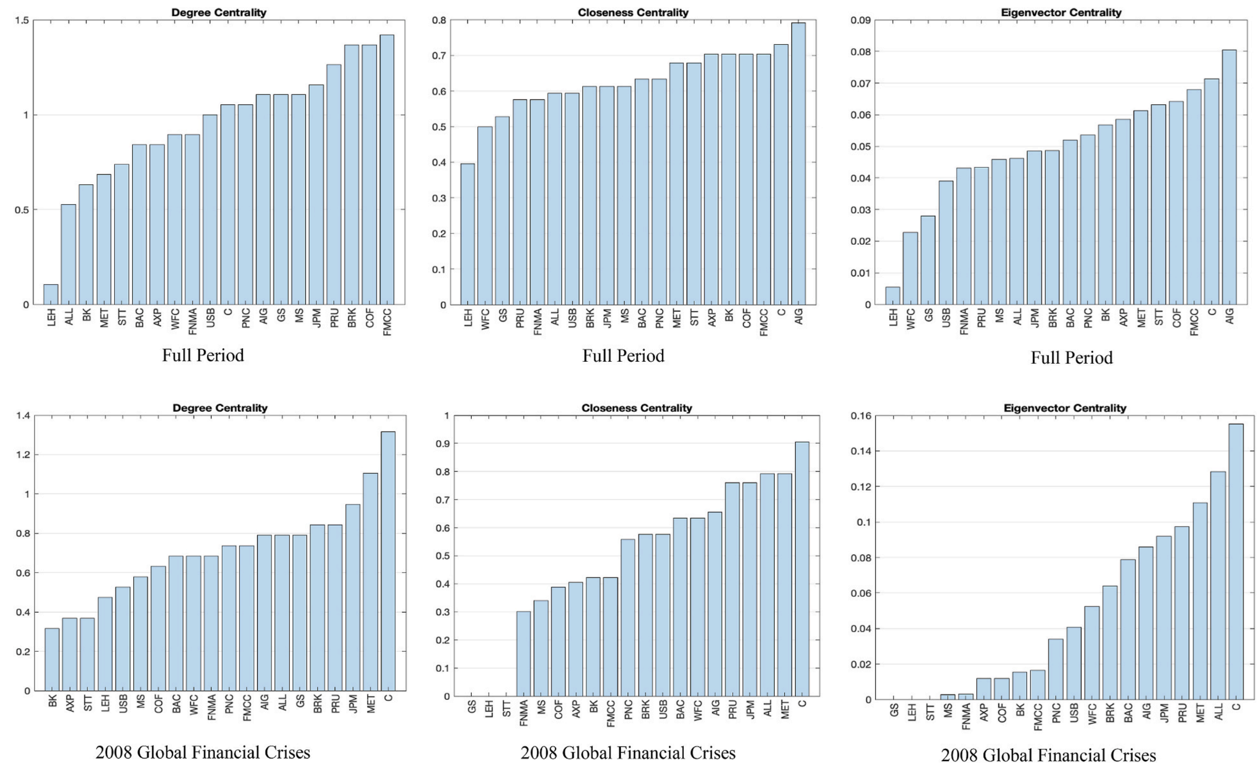
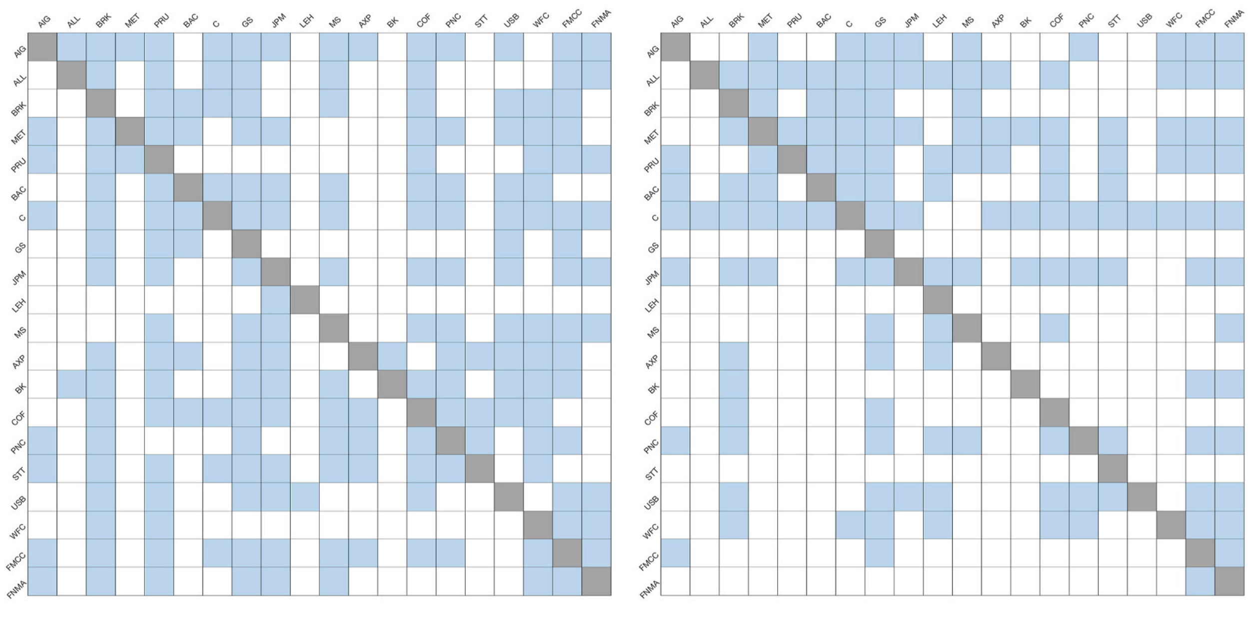


Fig. 3. Centrality measures: Full period and crises.



(A) Full Period (B) 2008 Global Financial Crises

Fig. 4. Network matrix adjacency.

in this list is consistent with the Granger analysis results presented in Section 4.2.2. Note that although some insurance companies like ALL, MET and PRU are repeatedly listed as systemically important institutions based on Granger methodology, their pairwise directional connectedness is still below that of the sampled banking entities. An explanation for this could be that these insurance

Table 8
Time varying granger causality lagged (1/2).

	Coefficient	Std.err	z	P > z
AIG				
ALL				
L1.	−0.064	0.113	−0.570	0.570
L2.	−0.162	0.112	−1.450	0.148
BRK				
L1.	−0.238	0.188	−1.270	0.204
L2.	−0.079	0.186	−0.420	0.674
MET				
L1.	0.277	0.173	1.610	0.108
L2.	0.105	0.179	0.590	0.558
PRU				
L1.	−0.299	0.170	−1.760	0.078
L2.	−0.112	0.171	−0.660	0.511
BAC				
L1.	0.056	0.208	0.270	0.789
L2.	−0.140	0.204	−0.680	0.494
C				
L1.	0.095	0.130	0.730	0.466
L2.	−0.135	0.132	−1.020	0.306
GS				
L1.	−0.197	0.164	−1.200	0.231
L2.	0.212	0.162	1.300	0.192
JPM				
L1.	−0.467	0.211	−2.210	0.027[a]
L2.	0.446	0.204	2.190	0.029[a]
MS				
L1.	0.124	0.150	0.830	0.408
L2.	0.160	0.148	1.080	0.279
AXP				
L1.	0.080	0.111	0.720	0.471
L2.	−0.135	0.112	−1.210	0.227
BK				
L1.	0.153	0.141	1.090	0.276
L2.	0.028	0.143	0.200	0.845
COF				
L1.	0.264	0.107	2.450	0.014[a]
L2.	0.202	0.108	1.860	0.063
PNC				
L1.	0.032	0.158	0.200	0.840
L2.	−0.232	0.157	−1.490	0.137
STT				
L1.	−0.208	0.125	−1.670	0.095
L2.	0.068	0.123	0.550	0.580
USB				
L1.	−0.283	0.158	−1.790	0.073
L2.	−0.229	0.160	−1.430	0.152
WFC				
L1.	0.124	0.108	1.150	0.250
L2.	0.051	0.109	0.470	0.639
FMCC				
L1.	−0.076	0.117	−0.650	0.514
L2.	−0.026	0.116	−0.220	0.823
FNMA				
L1.	0.056	0.118	0.480	0.632
L2.	0.060	0.117	0.510	0.609
C				
AIG				
L1.	0.237	0.091	2.610	0.009[a]
L2.	−0.096	0.092	−1.040	0.297
ALL				
L1.	−0.096	0.106	−0.910	0.361
L2.	−0.161	0.104	−1.540	0.123
BRK				
L1.	−0.185	0.175	−1.050	0.292
L2.	0.136	0.174	0.780	0.434
MET				
L1.	0.373	0.161	2.310	0.021[a]
L2.	0.130	0.167	0.770	0.439

(continued on next page)

Table 8 (*continued*)

	Coefficient	Std.err	z	P > z
PRU				
L1.	−0.318	0.159	−2.010	0.045
L2.	−0.054	0.160	−0.340	0.733
BAC				
L1.	0.022	0.194	0.110	0.910
L2.	0.045	0.191	0.240	0.812
GS				
L1.	−0.170	0.154	−1.110	0.268
L2.	0.139	0.152	0.920	0.358
JPM				
L1.	−0.342	0.197	−1.740	0.083
L2.	0.176	0.190	0.930	0.354
MS				
L1.	0.080	0.141	0.570	0.567
L2.	0.130	0.138	0.940	0.346
AXP				
L1.	−0.068	0.104	−0.660	0.511
L2.	0.005	0.104	0.040	0.965
BK				
L1.	0.241	0.132	1.830	0.067
L2.	−0.021	0.133	−0.160	0.875
COF				
L1.	0.328	0.100	3.270	0.001[a]
L2.	0.099	0.101	0.980	0.326
PNC				
L1.	0.067	0.147	0.450	0.651
L2.	−0.170	0.146	−1.160	0.245
STT				
L1.	−0.157	0.116	−1.350	0.178
L2.	0.035	0.115	0.310	0.758
USB				
L1.	−0.394	0.148	−2.670	0.008[a]
L2.	−0.067	0.149	−0.450	0.656
WFC				
L1.	0.086	0.101	0.850	0.393
L2.	0.037	0.102	0.360	0.716
FMCC				
L1.	−0.201	0.109	−1.850	0.064
L2.	−0.157	0.108	−1.450	0.147
FNMA				
L1.	0.175	0.110	1.590	0.112
L2.	0.205	0.109	1.880	0.060

[a] Significant at 5%.

Table 9
Summary granger causality wald test (2020–2021).

Companies	Significant at 5%
AIG	JPM, COF
ALL	AIG, JPM, COF
BRK	AIG, MET, JPM, COF, USB
MET	COF, USB
PRU	COF, STT, WFC
BAC	AIG, MET, PRU, COF, USB
C	AIG, COF, USB
GS	MET, PRU, COF
JPM	AIG, ALL, MET, PRU, COF, USB
MS	AIG, MET, PRU
AXP	AIG, MET, PRU, JPM, COF, USB
BK	PRU, COF
COF	AIG, PRU, C, USB
PNC	AIG, PRU, JPM, COF, USB
STT	AIG, MET, PRU, COF
USB	PRU, C, COF, FNMA
WFC	COF
FMCC	GS, MS, AXP, FNMA
FNMA	GS, MS, AXP, PNC

Table 10
Pairwise direction connectedness.

	X_1	X_2	⋯	X_N	From others
$\boldsymbol{X_1}$	d^H_{11}	d^H_{12}	⋯	d^H_{1N}	$\sum_{j=1}^{N} d^H_{1j,}\ j \neq 1$
$\boldsymbol{X_2}$	d^H_{21}	d^H_{22}	⋯	d^H_{2N}	$\sum_{j=1}^{N} d^H_{2j,}\ j \neq 2$
⋮	⋮	⋮	⋱	⋮	⋮
$\boldsymbol{X_N}$	d^H_{N1}	d^H_{N2}	⋯	d^H_{NN}	$\sum_{j=1}^{N} d^H_{Nj,}\ j \neq N$
To others	$\sum_{i=1}^{N} d^H_{i1}$ $i \neq 1$	$\sum_{i=2}^{N} d^H_{i1}$ $i \neq 2$	⋯	$\sum_{i=1}^{N} d^H_{iN}$ $i \neq N$	$\frac{1}{N} \sum_{i,j=1}^{N} d^H_{ij}\ i \neq j$

entities may have a wide network, but the banks still have a larger portfolio in terms of assets in custodian and equity. The outcome indicates that regulators must validate and calibrate any measure of systemically important institutions' risk exposure and systematic risk, and that such measurements must consider multiple, complementary factors.

An alternative way to model interconnectedness in the financial system and the interlinkage of transactions is to use detailed balance sheet data using Gai and Kapadia [9] model. Using this model, we can more clearly map the source and risk direction of interlinkage exposures among institutions, including the weight of hit and how much hit one or some entities could sustain based on their equity. However, despite its advantages, this model requires extensive interlinkage assets and liabilities statistics information to which only the bank supervisors and policymakers are privy. The future study also possible to explore undertakes analyses using the market models like of CoVaR [26], Marginal Expected Shortfall (MES) [46] and SRISK [27]. Employing various network models to shortlisted SIFIs would be beneficial for policy maker to validate the results and provide insight from different perspectives.

5. Conclusion and policy implications

This paper investigates the application of market data as a proxy to map the interlinkages of the US financial system. We employ datasets of US statistics covering the period 2002–2019 to capture several crises using PCA and Granger causality. The findings show that the pairwise returns correlation is significant at the 5% level and indicates initial interconnectedness and co-movement in the financial market. Following Billio, Getmansky [11], the first three principal components capture a significant portion of the returns variance. The results indicate an increase of interlinkages in the financial system during crises. As the sample deconstructed into groups it highlights the dominance of the banking sector in the US financial market. The two dimensions of component loading pattern are shown before the 2008 global financial crises. There are distances between entities, and such distances considerably change after the crises suspected to overlapping exposures. The appearance of companies in the results is in line with the G-SIBs list issued by FSB.

Applying Granger causality, banking and insurances entities are identified as systemically important institutions. Using the degree, closeness, and eigenvector centrality, the results show the systemic institutions in financial network. As the PCA subset principles yields explain and show the indicative of increasing interconnectedness through eigenvalues, the Granger causality complements the PCA assessment by mapping the 'central banks' in the financial system wide network. We also use Diebold and Yılmaz [19] pairwise direction variance decomposition to quantify the spillover between entities. Our findings suggest that it is insightful for the regulators to estimate the SIFIs using market data as PCA and Granger causality. It could calibrate and validate the outcome of the SIFIs built on prudential data and Basel methodology.

For the next studies related to interconnectedness, the extensive balance sheet data (as compiled by regulators) to identify SIFIs is appealing. The granular dataset has advantages to provide clearer interaction between institutions to deepen our understanding of systemic risk study. The possible undertakes carry analysis could employs the widely cited market models such as CoVaR, MES and SRISK.

Author contribution statement

Dadang Ramdhan, Ph. D: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

M. Zulkifli Salim, PhD: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Kevin Daly, Professor: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data will be made available on request.

Additional information

Supplementary content related to this article has been published online at [URL].

Table 11
Risk spillover.

TO	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA	TOTAL
2002	0.97	0.67	0.16	0.66	0.67	1.09	1.10	0.96	0.94	1.04	1.09	1.04	0.93	0.45	1.01	1.17	0.88	0.90	0.62	0.65	16.99
2003	0.92	0.54	0.18	0.86	0.91	0.67	1.15	1.06	1.20	0.98	1.09	1.06	1.01	0.67	0.90	0.70	0.96	0.96	0.45	0.64	16.91
2004	0.65	0.65	0.22	0.71	0.80	0.87	1.06	1.01	1.04	0.88	0.91	0.80	0.83	0.76	0.94	0.65	0.74	0.92	0.68	0.56	15.66
2005	0.42	0.58	0.05	0.50	0.53	1.08	0.92	0.79	1.12	0.85	0.64	0.76	0.98	0.45	0.92	0.75	1.02	1.09	0.69	0.59	14.72
2006	0.79	0.52	0.08	0.78	0.58	0.93	0.89	0.90	1.19	0.99	0.96	0.96	0.56	0.47	0.56	0.94	0.84	0.92	0.62	0.90	15.38
2007	0.90	0.66	0.16	0.89	0.85	1.13	1.02	0.97	1.11	1.06	0.92	0.99	1.00	0.83	0.95	0.73	1.06	1.04	0.53	0.61	17.40
2008	0.73	0.78	0.43	0.72	0.85	1.16	1.00	1.00	1.06		0.90	0.97	0.95	1.11	0.97	0.90	1.11	1.10	0.45	0.42	16.60
2009	0.35	0.80	0.57	1.06	1.01	1.07	0.82	0.96	1.09		0.91	0.93	0.96	0.81	0.99	0.91	0.97	1.09	0.49	0.59	16.38
2010	0.45	0.86	0.70	0.94	1.01	1.05	0.80	0.56	1.12		0.89	0.87	0.94	0.89	0.95	0.93	1.08	1.09	0.45	0.42	16.01
2011	0.79	0.85	0.83	1.01	1.02	0.92	1.00	0.90	1.05		0.94	0.89	0.92	0.82	0.99	0.93	0.96	0.96	0.41	0.45	16.66
2012	0.57	0.53	0.65	0.97	0.87	0.99	1.08	1.01	0.85		0.97	0.84	1.03	0.77	0.94	0.79	0.97	1.04	0.46	0.41	15.74
2013	0.76	0.74	0.88	0.91	0.90	0.84	1.01	0.94	0.93		0.99	0.78	1.01	0.68	0.95	0.89	0.71	0.91	0.49	0.49	15.80
2014	0.85	0.61	0.77	1.05	0.98	0.89	0.91	0.94	1.01		0.91	0.93	0.80	0.83	0.99	0.97	1.00	0.91	0.46	0.47	16.29
2015	0.86	0.51	0.82	1.04	1.00	1.02	1.11	1.03	1.11		1.03	0.36	1.03	0.67	1.03	0.94	1.06	1.12	0.43	0.43	16.60
2016	0.87	0.33	0.76	0.87	1.03	1.08	1.12	1.10	1.14		1.10	0.38	0.98	0.91	1.11	0.86	1.08	0.93	0.47	0.44	16.57
2017	0.20	0.34	0.83	0.87	1.02	1.15	1.03	0.93	1.16		1.06	0.68	0.81	0.72	1.15	0.68	1.11	0.85	0.41	0.45	15.47
2018	0.51	0.57	0.89	0.84	1.03	1.08	1.01	0.94	1.13		1.09	0.82	0.84	0.96	0.90	0.76	0.90	0.83	0.43	0.47	16.01
2019	0.52	0.44	0.82	1.03	1.00	1.13	1.13	0.99	1.09		1.12	0.74	0.59	0.88	1.04	0.75	1.07	0.83	0.46	0.45	16.08
2020	0.86	0.79	0.92	1.03	1.06	1.06	1.02	0.96	1.07		1.00	0.97	0.90	0.90	0.99	0.96	1.03	0.94	0.49	0.47	17.42
2021	0.98	0.50	0.73	1.06	1.08	1.08	0.93	0.94	1.03		0.88	0.65	0.91	0.85	1.03	0.88	0.97	0.79	0.48	0.47	16.23
																					324.91
FROM	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA	TOTAL
2002	0.88	0.83	0.56	0.83	0.82	0.89	0.89	0.88	0.88	0.89	0.89	0.89	0.88	0.77	0.89	0.90	0.87	0.88	0.82	0.82	16.99
2003	0.87	0.80	0.54	0.87	0.87	0.84	0.89	0.89	0.89	0.88	0.89	0.89	0.88	0.84	0.88	0.84	0.87	0.88	0.77	0.82	16.91
2004	0.75	0.76	0.54	0.78	0.80	0.81	0.84	0.83	0.84	0.82	0.82	0.80	0.80	0.80	0.82	0.76	0.79	0.82	0.76	0.72	15.66
2005	0.65	0.72	0.15	0.68	0.71	0.84	0.82	0.79	0.84	0.79	0.75	0.77	0.82	0.67	0.81	0.78	0.83	0.84	0.76	0.72	14.72
2006	0.79	0.72	0.31	0.79	0.75	0.82	0.82	0.82	0.86	0.84	0.83	0.82	0.73	0.70	0.74	0.82	0.81	0.82	0.76	0.81	15.38
2007	0.88	0.86	0.64	0.89	0.88	0.91	0.90	0.89	0.91	0.90	0.89	0.89	0.90	0.87	0.89	0.86	0.90	0.90	0.81	0.83	17.40
2008	0.84	0.86	0.78	0.86	0.87	0.90	0.89	0.90	0.90		0.88	0.89	0.89	0.90	0.89	0.89	0.90	0.90	0.65	0.63	16.22
2009	0.68	0.87	0.83	0.89	0.89	0.89	0.86	0.89	0.90		0.88	0.88	0.89	0.87	0.89	0.88	0.89	0.90	0.71	0.74	16.24
2010	0.77	0.87	0.85	0.88	0.89	0.89	0.86	0.82	0.89		0.87	0.87	0.88	0.87	0.88	0.87	0.89	0.89	0.56	0.54	15.85
2011	0.90	0.90	0.90	0.91	0.92	0.91	0.92	0.91	0.92		0.91	0.90	0.91	0.90	0.92	0.91	0.91	0.91	0.54	0.57	16.58
2012	0.80	0.79	0.82	0.87	0.86	0.88	0.88	0.88	0.86		0.87	0.85	0.88	0.84	0.87	0.85	0.87	0.88	0.59	0.56	15.70
2013	0.84	0.84	0.86	0.87	0.86	0.86	0.88	0.87	0.87		0.87	0.84	0.88	0.83	0.87	0.86	0.83	0.86	0.54	0.54	15.66
2014	0.87	0.83	0.86	0.89	0.89	0.88	0.88	0.89	0.89		0.88	0.88	0.87	0.87	0.89	0.89	0.89	0.88	0.64	0.65	16.23
2015	0.88	0.82	0.88	0.91	0.90	0.91	0.91	0.91	0.91		0.91	0.77	0.91	0.86	0.91	0.90	0.91	0.91	0.69	0.69	16.49
2016	0.89	0.76	0.87	0.89	0.90	0.91	0.91	0.91	0.91		0.91	0.78	0.90	0.89	0.91	0.89	0.91	0.89	0.70	0.69	16.44
2017	0.58	0.67	0.85	0.86	0.88	0.89	0.88	0.87	0.89		0.88	0.83	0.85	0.83	0.89	0.83	0.88	0.86	0.57	0.59	15.37
2018	0.82	0.83	0.89	0.88	0.90	0.90	0.90	0.89	0.91		0.90	0.88	0.88	0.89	0.89	0.87	0.89	0.88	0.47	0.49	15.95
2019	0.80	0.74	0.86	0.88	0.88	0.90	0.90	0.89	0.89		0.89	0.84	0.82	0.87	0.89	0.85	0.89	0.86	0.62	0.62	15.89
2020	0.92	0.90	0.92	0.93	0.93	0.93	0.93	0.92	0.93		0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.82	0.82	17.31

(*continued on next page*)

Table 11 (*continued*)

TO	AIG	ALL	BRK	MET	PRU	BAC	C	GS	JPM	LEH	MS	AXP	BK	COF	PNC	STT	USB	WFC	FMCC	FNMA	TOTAL
2021	0.89	0.81	0.86	0.90	0.90	0.90	0.89	0.89	0.90		0.89	0.86	0.89	0.88	0.90	0.89	0.90	0.88	0.51	0.52	16.07
																					323.06
NET	**AIG**	**ALL**	**BRK**	**MET**	**PRU**	**BAC**	**C**	**GS**	**JPM**	**LEH**	**MS**	**AXP**	**BK**	**COF**	**PNC**	**STT**	**USB**	**WFC**	**FMCC**	**FNMA**	
2002	0.09	−0.17	−0.40	−0.18	−0.15	0.19	0.21	0.08	0.06	0.15	0.19	0.15	0.05	−0.33	0.13	0.27	0.01	0.02	−0.20	−0.17	0.00
2003	0.04	−0.26	−0.36	0.00	0.04	−0.17	0.26	0.17	0.30	0.10	0.20	0.17	0.12	−0.17	0.03	−0.14	0.09	0.08	−0.32	−0.19	0.00
2004	−0.10	−0.11	−0.32	−0.07	0.00	0.06	0.23	0.17	0.20	0.06	0.09	0.00	0.03	−0.03	0.12	−0.11	−0.05	0.10	−0.08	−0.17	0.00
2005	−0.24	−0.14	−0.10	−0.18	−0.18	0.25	0.11	0.00	0.28	0.06	−0.11	−0.01	0.15	−0.22	0.10	−0.03	0.19	0.26	−0.07	−0.13	0.00
2006	−0.01	−0.20	−0.23	−0.01	−0.17	0.10	0.07	0.08	0.33	0.15	0.13	0.13	−0.17	−0.23	−0.18	0.12	0.03	0.10	−0.13	0.09	0.00
2007	0.02	−0.20	−0.48	0.00	−0.02	0.22	0.12	0.07	0.20	0.16	0.03	0.10	0.10	−0.04	0.05	−0.13	0.16	0.14	−0.28	−0.22	0.00
2008	−0.11	−0.09	−0.35	−0.13	−0.02	0.25	0.10	0.11	0.16		0.02	0.08	0.06	0.21	0.08	0.02	0.21	0.19	−0.20	−0.21	0.38
2009	−0.33	−0.07	−0.25	0.17	0.11	0.17	−0.03	0.07	0.19		0.03	0.04	0.07	−0.06	0.10	0.03	0.08	0.19	−0.22	−0.16	0.14
2010	−0.33	−0.01	−0.15	0.06	0.13	0.16	−0.07	−0.26	0.23		0.02	0.00	0.06	0.02	0.07	0.06	0.19	0.20	−0.11	−0.12	0.16
2011	−0.11	−0.05	−0.08	0.10	0.10	0.01	0.08	−0.01	0.13		0.03	−0.01	0.01	−0.08	0.08	0.02	0.04	0.05	−0.13	−0.12	0.08
2012	−0.23	−0.26	−0.17	0.10	0.01	0.11	0.19	0.13	0.00		0.09	−0.02	0.16	−0.08	0.07	−0.06	0.10	0.16	−0.13	−0.15	0.04
2013	−0.08	−0.10	0.02	0.05	0.04	−0.02	0.13	0.07	0.06		0.11	−0.05	0.14	−0.15	0.08	0.03	−0.12	0.05	−0.05	−0.06	0.14
2014	−0.02	−0.22	−0.09	0.16	0.09	0.01	0.03	0.05	0.11		0.03	0.05	−0.07	−0.05	0.10	0.09	0.11	0.03	−0.19	−0.18	0.05
2015	−0.02	−0.31	−0.06	0.13	0.09	0.12	0.20	0.13	0.20		0.12	−0.41	0.13	−0.20	0.12	0.04	0.15	0.21	−0.26	−0.26	0.11
2016	−0.02	−0.43	−0.11	−0.02	0.13	0.17	0.21	0.19	0.23		0.19	−0.40	0.08	0.01	0.20	−0.03	0.18	0.04	−0.23	−0.26	0.13
2017	−0.37	−0.33	−0.02	0.02	0.15	0.26	0.15	0.06	0.27		0.17	−0.15	−0.04	−0.11	0.27	−0.15	0.23	−0.01	−0.16	−0.14	0.10
2018	−0.31	−0.26	0.00	−0.04	0.13	0.18	0.11	0.05	0.22		0.18	−0.05	−0.04	0.07	0.01	−0.11	0.02	−0.05	−0.04	−0.02	0.06
2019	−0.28	−0.30	−0.04	0.15	0.12	0.24	0.24	0.11	0.20		0.22	−0.11	−0.23	0.02	0.16	−0.11	0.18	−0.03	−0.16	−0.17	0.19
2020	−0.06	−0.12	0.00	0.10	0.13	0.13	0.10	0.04	0.14		0.08	0.04	−0.01	−0.02	0.07	0.04	0.11	0.01	−0.33	−0.35	0.11
2021	0.08	−0.32	−0.14	0.16	0.18	0.18	0.04	0.05	0.13		−0.01	−0.21	0.02	−0.03	0.13	0.00	0.07	−0.09	−0.04	−0.05	0.16
																					1.85

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A. Robustness Test

1. Linear Regression

To detect the initial correlation among the sample, represented as variable to the benchmark index, we run simple linear regression. The regression results provide the association for each entity variable, as represented by the coefficient to the benchmark. The results also show co-movement, whether positive or negative. Stata calculation shows that the full sample period, all entities except for FMCC, FNMA and COF are statistically significant, with positive correlation at 5% confidence level to the benchmark index SP 500.

Source	SS	df	MS	
				Number of obs = 1749
				F (20, 1728) = 367.48
Model	0.151541	20	0.007577	Prob > F = 0
Residual	0.035629	1728	2.06E-05	R-squared = 0.8096
				Adj R-squared = 0.8074
Total	0.18717	1748	0.000107	Root MSE = 0.00454

SP500	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	
AIG	.032	.007	4.61	0	.018	.045	***
ALL	.041	.012	3.40	.001	.017	.064	***
BRK	.023	.011	1.98	.048	0	.045	**
MET	.062	.01	6.23	0	.043	.082	***
PRU	.037	.01	3.76	0	.018	.056	***
BAC	−.055	.012	−4.51	0	−.078	−.031	***
C	.059	.011	5.21	0	.037	.081	***
GS	.09	.011	7.90	0	.068	.112	***
JPM	.046	.01	4.85	0	.028	.065	***
LEH	−.015	.004	−3.79	0	−.023	−.007	***
MS	.044	.01	4.44	0	.025	.064	***
AXP	.116	.01	11.40	0	.096	.136	***
BK	.045	.009	4.74	0	.026	.063	***
COF	.007	.005	1.25	.211	−.004	.017	
PNC	.05	.011	4.53	0	.028	.071	***
STT	.053	.009	5.67	0	.034	.071	***
USB	.049	.013	3.79	0	.023	.074	***
WFC	−.043	.012	−3.62	0	−.066	−.02	***
FMCC	−.011	.006	−1.77	.077	−.023	.001	*
FNMA	.005	.006	0.93	.354	−.006	.016	
Constant	0	0	−0.73	.469	0	0	

Mean dependent var	0.000	SD dependent var	0.010
R-squared	0.810	Number of obs	1749
F-test	367.485	Prob > F	0.000
Akaike crit. (AIC)	−13886.193	Bayesian crit. (BIC)	−13771.390

***p < .01, **p < .05, *p < .1.

Durbin–Watson d-statistic (21, 1749) = 2.054002.

2. Lag Order of Granger Centrality

Lag-order selection criteria (Covid-19)	Number of obs = 497
Sample: January 02, 2020 thru December 31, 2021	

(continued on next page)

(*continued*)

Lag-order selection criteria (Covid-19)
Sample: January 02, 2020 thru December 31, 2021

Number of obs = 497

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	27561.51				2.8e-72	−110.835	−110.772*	−110.674*
1	27943.8	764.52	361	0.00	2.6e-72	−109.658	−109.658	−107.703
2	28343.7	799.8	361	0.00	2.2e-72*	−108.614*	−108.614	−104.802
3	28673.2	658.95	361	0.00	2.6e-72	−107.288	−107.288	−101.619
4	28966.9	587.41	361	0.00	3.4e-72	−105.817	−105.817	−98.291
5	29263.2	592.53	361	0.00	4.7e-72	−104.357	−104.357	−94.974
6	29587.2	648.05	361	0.00	5.8e-72	−103.008	−103.008	−91.768
7	29858.5	542.61	361	0.00	9.2e-72	−101.447	−101.447	−88.349
8	30,233	749.09*	361	0.00	9.9e-72	−100.302	−100.302	−85.347

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