Financial network estimation for measuring bank interconnectedness

Aron Denes Hartvig and Aron Pap

February 2021

1 Introduction

Financial shocks hit the stock markets from time to time. The stock market crash in 2020 caused by the COVID-19 pandemic was a major and sudden global stock market crash that began on 20 February 2020 and ended on 7 April.

Since the Global Financial Crisis regulators pay special attention to systematically important financial institutions and the structure of the financial network.

Theory concentrates on the spread of contagion in financial networks. Acemoglu et al. (2015) and (Elliott et al., 2014) showed that there is a trade-off between highly connected networks, where contagion can spread easily and sparsely connected networks, where financial institutions cannot diversify risk properly. Although many theoretical research have been done on this topic, little empirical research has investigated the global bank connectedness. Furthermore, while theoretical research focus on the network of cross-holdings due to the lack of data, quantitative methods measure correlation or spillovers. The most widely used empirical method to estimate financial networks are Granger causality (Billio et al., 2012), ΔCoVar (Adrian and Brunnermeier, 2011), SES (Acharya et al., 2017) and DY connectedness (Diebold and Yılmaz, 2014). Nevertheless, most methods are not capable of monitoring the financial system on a daily basis. ΔCoVaR and SES relies on balance sheet data therefore they can be only calculated on a quarterly basis. Then, Granger causality network has unweighted edges that limits the analysis to the existence of relationships, but the evolution of the connections cannot be observed. Finally, Diebold-Yilmaz (DY) connectedness is a simple method relying on the forecast error variance decomposition of a vector autoregressive model built on stock returns or volatility. As this framework is applied to daily data it can track the changes in the network promptly.

Of course there are numerous other ways to estimate the interdependencies of time series. Neighborhood selection, Graphical Lasso, SPACE or Sparse Bayesian are widespread methods in biology or traffic analysis. The advantage of these framework is that they can be easily scaled, high dimensional estimation does not cause problem. Although shrinkage methods have also been implemented to DY framework (Demirer et al., 2018), its performance has not been compared to these methods so far.

Aim of the article: compare GLASSO, SPACE, Neighbourhood Selection, Sparse Bayesian and Diebold-Yilmaz framework to find out which quantitative method describes the financial network the best. We estimate and compare the different networks throughout the year of 2020 to explore the effect of the COVID-19 shock on the financial network. Also, we identify the most central financial institutions in the networks and explore the rank correlation between the methods.

The article proceeds as follows. In Section 2...

2 Literature review

2.1 Financial contagion

Since the Global Financial Crisis the literature of financial networks has been growing rapidly. It is essential to monitor the relationships between the financial institutions to track the spread of financial contagion in the system. Interdependence of financial institutions appears due to cross-holdings of shares, investments to common assets or interbank loans and this interdependence has been increasing with globalization. (Acemoglu et al., 2015) and (Elliott et al., 2014) showed that interconnectedness of the financial system can be beneficial until a certain point as it enables diversification. Financial institutions with diversified portfolio are less vulnerable to idiosyncratic shocks preventing failures. However, in some interconnected systems the connections serve as a mechanism for propagation of shocks and lead to a more fragile financial system and even cascade of failures can occur.

(Elliott et al., 2014) created a simulated cross-holding networks to analyse the trade-off between diversification and integration. They showed that middle range diversification and integration can be the most dangerous with respect to cascades of failures as integration helps the spread of contagion, but the imperfectly diversified financial institutions are not enough resistant against idiosyncratic shocks.

2.2 Quantitative methods

2.2.1 Neighborhood Selection

Neighborhood Selection (Meinshausen et al., 2006) is a computationally efficient method for covariance selection, especially for sparse high-dimensional networks. It models the inverse covariance matrix of multivariate normal variables, in which matrix a zero entry means conditional independence between those variables. Neighborhood selection estimates these conditional independence connections for each node separately in the network using a regularised objective function for shrinkage and selection. The method provides consistent estimation with exponentially fast convergence rates, even when the number of variables (or nodes) is higher than the number of observations[1] Neighborhood selection utilizes the *Lasso* (as introduced in (Tibshirani, 1996)) to offer these quite remarkable estimation properties. The computational efficiency is mainly driven by breaking the graph selection problem into a consecutive series of neighborhood selection problems, which reduces the complexity of the search substantially. Another important aspect for the neighborhood selection methodology

[1] Even when the number of variables (or nodes) is higher than the number of observations raised to an arbitrary power.

is setting the penalty parameter (usually denoted by λ) for the *Lasso* objective. Here it can be set via upper-bounding the probability of falsely joining two distinct connectivity components with the estimate of the edge set. In (Meinshausen et al., 2006) the authors provide numerical results for sparse networks, where neighborhood selection clearly outperforms forward selection MLE[2]. These results are for multivariate Gaussian variables, however the authors also show that long-tailed observational noise only increase the error rates of the model slightly. The neighborhood selection method has important practical applications in biology (Valdés-Sosa et al., 2005), (Valdés-Sosa et al., 2006). For our purposes, neighborhood selection is used as a method to estimate *partial correlation networks*, for the returns or volatilities of the share price of financial institutions. This offers a proxy for bank interconnectedness, which would also work in high-dimensional settings, where other methods might fail.

2.2.2 Graphical lasso

Graphical lasso (Friedman et al., 2008) is a fast method for estimating sparse inverse covariance matrices, using an L-1 type penalty for regularization. This method's objective is to maximize the penalized log-likelihood of the data. The graphical lasso algorithm sweeps through the variables and fits a modified lasso regression to each of the variables and then these separate lasso problems are solved via coordinate descent. The authors in (Friedman et al., 2008) show through some simulations the superior computational efficiency of their method[3], which makes it suitable for really high-dimensional problems. The graphical lasso method is widely used in practice for neuroimaging (Smith et al., 2011) or information diffusion and virus propagation for instance (Gomez-Rodriguez et al., 2012). For our project the graphical lasso seems a really convenient and efficient method for estimating the inverse covariance matrices of the returns or volatilities of the share price of financial institutions, thus offering a measure of how connected these entities might be.

2.2.3 SPACE

SPACE (Peng et al., 2009) is a joint sparse regression model, especially well-equipped for model selection purposes by identifying nonzero partial correlations. It is designed with high-dimensional and low-sample size problems in mind, mainly from the field of biological and gene regulatory networks, however it works well in other settings too. The method utilizes the symmetry of the partial correlations and also the expected sparse structures and thus can provide great computational efficiency. This framework could also accommodate and utilize prior knowledge on the problems at hand (e.g. expected network structure or degree distribution) to increase computational efficiency further. The authors in (Peng et al., 2009) propose the `active-shooting` algorithm to implement the SPACE method, however this algorithm could also be modified easily to work for other penalized optimisation problems as well. One potential limitation of SPACE is that the method does not guarantee positive-definiteness of the estimated partial correlation matrix, however based on the authors simulation studies,

[2] Maximum Likelihood Estimation.

[3] Which still provides exact results as opposed to the Neighborhood Selection for instance, which would qualify as an approximation rather.

this shortcoming does not really manifest in practice. The authors also compare the performance of the *SPACE* method to *Neighborhood Selection* and GLASSO as well through several simulation studies and find that *SPACE* usually outperforms the other methods. The authors also show the consistency of SPACE for model selection and parameter estimation, under the required regulatory and sparsity conditions. The SPACE method has important practical applications in genetics (Wu et al., 2013), (Barzel and Barabási, 2013). For our purposes, SPACE is another network estimation method to provide a proxy for bank interconnectedness and it is not known a priori whether in our setting it would outperform the other network estimation methods or not.

2.2.4 Diebold-Yilmaz

DY framework (Diebold and Yilmaz, 2012) relies on N-variable vector autoregressive (VAR) models. The connectedness indices follow directly from the notion of forecast error variance decomposition. Variance decomposition can be calculated from the moving average representation of VAR, but as VAR innovations are contemporaneously correlated in general orthogonal innovations are required. (Diebold and Yilmaz, 2012) instead of applying identification schemes like Cholesky factorization suggest circumventing this problem by exploiting generalized VAR framework (Koop et al., 1996), (Pesaran and Shin, 1998). Generalized VAR framework allows correlated shocks but accounts for them appropriately using the historically observed distribution of errors. Avoiding orthogonal innovations leads to results invariant to ordering and therefore directional connectedness can be measured as well. In this article we only focus on the pairwise connectedness indices. These indices measure the directional spillovers transmitted by variable i to variable j.

The framework has been widely used to estimate networks of various financial assets like equities (Baruník et al., 2016), bonds (Claeys and Vašíček, 2014), exchange rates (Bubák et al., 2011) or commodities (Ma et al., 2019).

2.2.5 Sparse Bayesian networks

Another method to estimate the financial network is to learn a graphical model from the data. There are several ways to achieve this, however since most of our approaches focus on partial correlation networks[4], we also want to include technologies which estimate directed graphical models. These are also called as Bayesian networks or structural equation models. These networks are usually represented as directed acyclical graphs (DAG-s) which can encode an even larger set of conditional independence relations than partial correlation networks. Also, these directed acyclical graphs can also represent causal relations, which could also be an interesting avenue to explore later. But for our current purposes, we will utilise the **sparsebn** package (described in (Aragam et al., 2017)) for learning the structure of large, sparse graphical models with a focus on Bayesian networks. The objective for this algorithm is also a regularized maximum likelihood estimation problem, however there is the special condition that the network is not allowed to contain cycles, which of course modifies the iterative estimation procedure. Directed acyclic graphs are widely used in practice for

[4] Which are undirected/symmetrical.

causal analysis in epidemiology (Shrier and Platt, 2008) or scheduling distributed computing (Gerasoulis and Yang, 1992).

2.2.6 Hyperparameter-tuning

Since most of our models include some hyperparameter/regularization terms, we need methods to tune these parameters. In case of the DAG and SPACE algorithms, we use the stability approach to regularization selection, introduced in (Liu et al., 2010), whereas in case of Glasso and Neighborhood Selection we use a modified rotation information criterion (RIC) from (Lysen, 2009), which is a permutation approach to model selection and highly scalable. For the VAR Lasso we use in-sample mean squared forecast error to select the optimal regularization term.

2.2.7 BRIDGE (RENAME THIS SECTION)

In our analysis we compare the centrality of the financial institutions during the COVID-19 stock market crisis in March, 2020 and during the rapid stock price increase in June, 2020. We use 150-day windows to estimate two snapshots of the financial network. First, we analyse the financial network in March 16, 2020, when the S&P500 index plunged by 11.98%, the greatest one-day drop experienced in March. Then, we calculate the same measures for June 30, 2020 to see how the network changed by the end of the second quarter.

3 Data

We study daily stock returns of 76 financial institutions from 28 economies downloaded from Yahoo Finance, from December 31, 2019 to December 31, 2020. All financial institutions were also included in the analysis of (Demirer et al., 2018) and several of them are "globally systemically important banks" ("GSIBs", as designated by the Basel Committee on Banking Supervision). As Demirer et al. (2018) also noted, the stock price data come from markets with different business hours that could potentially influence the empirical results. The institutions are listed in Table A.3 in the Appendix.

We use daily stock return data to estimate the aforementioned interconnectedness measures between the examined financial institutions. Stock market valuations are imperfect—like all valuations, but as the amount of available information is increasing financial markets are becoming more efficient and stock prices reflect interconnectedness information as relevant for valuation. We summarised the basic descriptive statistics of stock returns for the quarters observed in Table A.3 in the Appendix.

3.1 Descriptive statistics

In Table 1 we summarise some descriptive statistics of the studied networks...

	NS	**GLASSO**	**SPACE**	**DY**	**DAG**
Number of nodes	76	76	76	76	76
Number of edges	463	2	48	2	48
Number of components	15	68	11	15	68
Size of giant component	1285	174	26	174	26
Max edge weight	24	20	7	20	7
Average degree	11.76	27.07	0.85	27.07	0.85

Table 1: Summary statistics and general characteristics of the studied networks with data at 20XX-XX-XX

4 Empirical results

In applications we base connectedness assessment on the methods described in Section X. We estimate five representation of the financial network with the analytical purpose of comparing them based on centrality measures. We provide snapshots of the financial system on six distinct windows throughout the year of 2020 based on logarithmic daily stock returns to find out how financial turmoil affect the different networks.

4.1 Evolution of networks

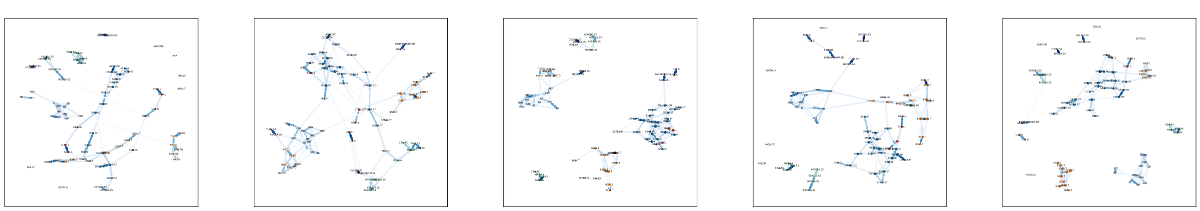
First, we estimate the networks for the end-quarter dates between December 31, 2019 and December 31, 2020 and for March 16, 2020 when the financial distress during the COVID-19 crisis peaked.

4.1.1 Neighborhood Selection Graphs

On Figure X. we present the six networks. Comparison of network figures over time: - number of edges - distribution of out degrees - clusters - investment banks vs commercial banks: commercial banks are expected to be more sensitive to the crisis due to the exposure to

On Figure 1 it is evident to see...

Figure 1: Financial networks estimated with Neighborhood Selection method at different quarters

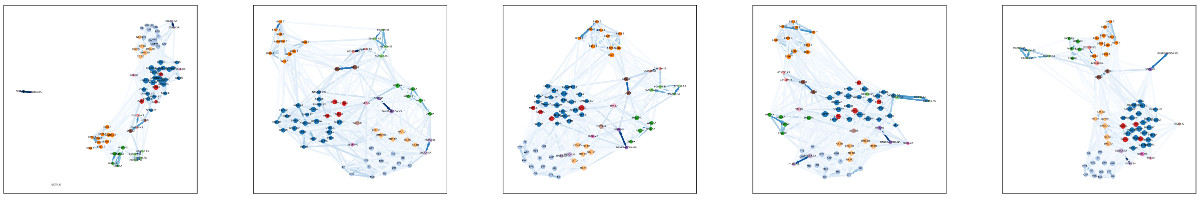


2019-12-31 2020-03-31 2020-06-30 2020-09-30 2020-12-31

4.1.2 Graphical Lasso Graphs

On Figure 2 it is evident to see...

Figure 2: Financial networks estimated with GLASSO method at different quarters

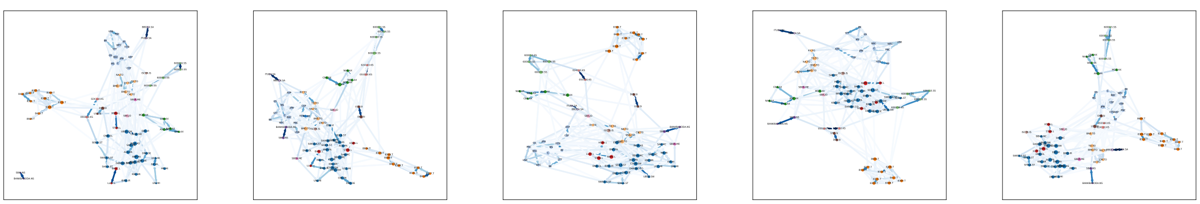


2019-12-31 2020-03-31 2020-06-30 2020-09-30 2020-12-31

4.1.3 SPACE Graphs

On Figure 3 it is evident to see...

Figure 3: Financial networks estimated with SPACE method at different quarters

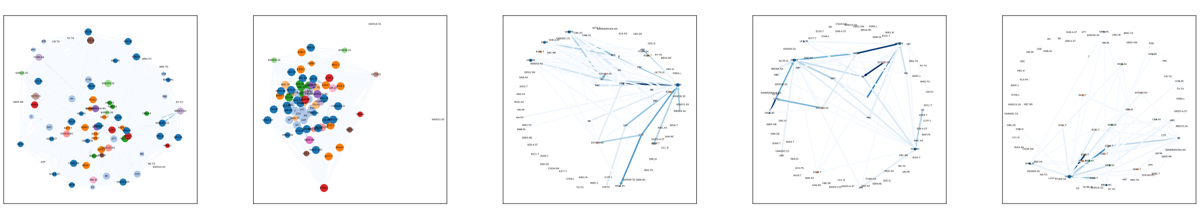


2019-12-31 2020-03-31 2020-06-30 2020-09-30 2020-12-31

4.1.4 Diebold-Yilmaz Graphs

On Figure 4 it is evident to see...

Figure 4: Financial networks estimated with Diebold-Yilmaz method at different quarters

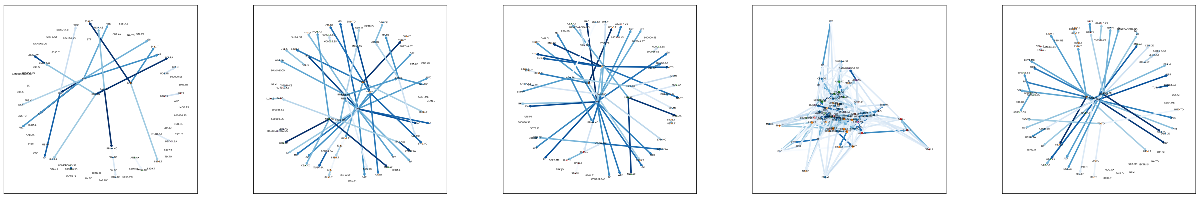


2019-12-31 2020-03-31 2020-06-30 2020-09-30 2020-12-31

4.1.5 Sparse Bayesian Graphs

On Figure 5 it is evident to see...

Figure 5: Financial networks estimated with DAG method at different quarters



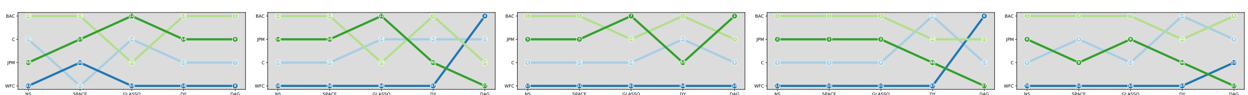
2019-12-31 2020-03-31 2020-06-30 2020-09-30 2020-12-31

4.1.6 Comparison of the networks

Comparison of network figures over time: - Frobenius norm - Centrality measures

On Figure 6 it is evident to see...

Figure 6: Centrality ranking of selected financial institutions in the different estimated networks

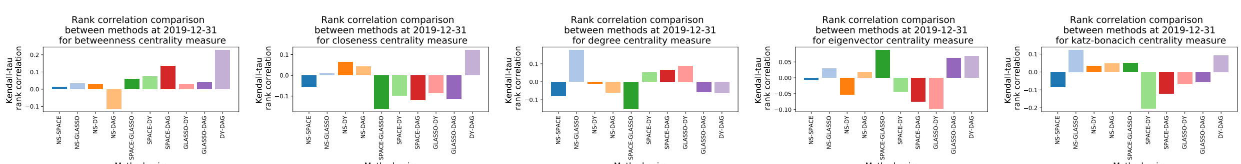


Betweenness Closeness Degree Eigenvector Katz-Bonacich

Network estimated with data at 2019-12-31

On Figure 7 it is evident to see...

Figure 7: Centrality ranking of selected financial institutions in the different estimated networks



Betweenness Closeness Degree Eigenvector Katz-Bonacich

Network estimated with data at 2019-12-31

PLACEHOLDER: US network comparison with cross holdings

4.1.7 Effect of Brexit on UK financial institutions

4.2 Network dynamics

On Figure 8 it is evident to see...

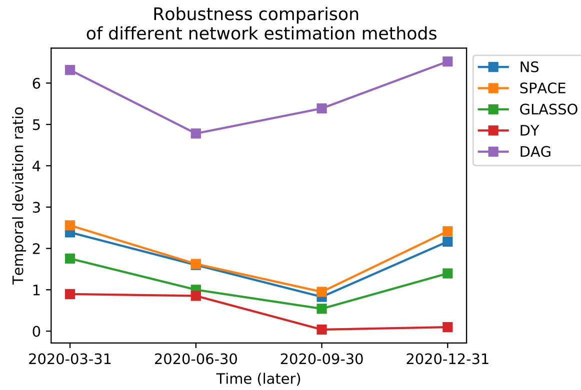


Figure 8: Network estimation robustness dynamics

We summarise robustness results in Table 2...

Explain connection to (Hallac et al., 2017) through our metric, the **Temporal deviation ratio**.

4.3 Sensitivity analysis

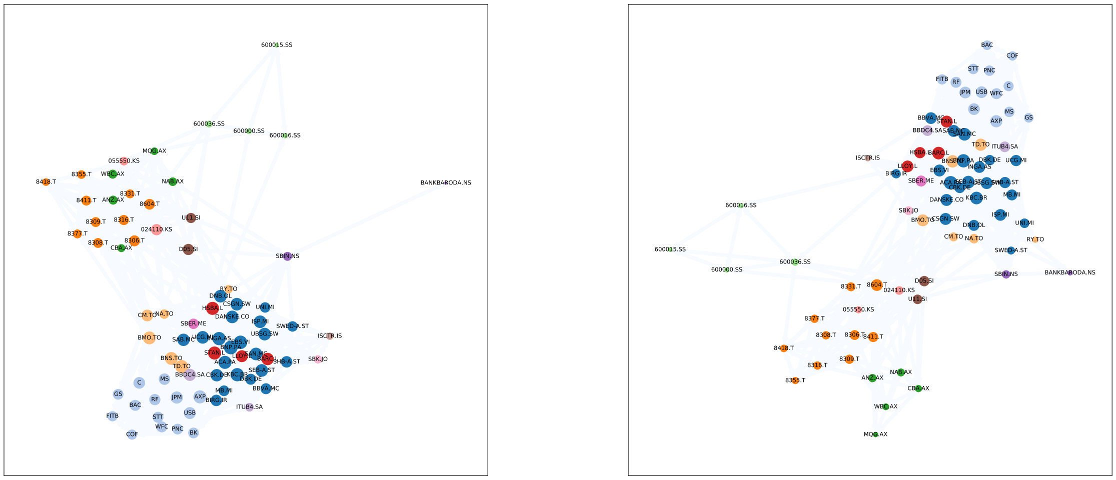
Run the models with 50-day and 100-day window as well. Expected outcome: Frobenius norm for the difference in the estimated networks with different window sizes.

On Figure 9 it is evident to see...
The rest of the methods is shown on Figure 12 in Section A.1 of the Appendix.

The results in Table 3 show...

4.4 Cross holdings of US financial institutions

One potential noisy signal for the latent interconnectedness values is the cross holdings data for financial institutions. To explore this avenue we collected data from NASDAQ about the institutional investors of a small universe of US financial institutions. Then we found the cross holdings values by identifying these financial institutions as institutional investors of each other. Figure 10 shows the results of this analysis and suggests quite substantial cross holdings between the financial institutions. For instance it is evident to see that JP Morgan and Bank of America has high stake both in absolute and relative terms in the other banks and therefore we expect them to be highly interconnected as well, which is supported by our earlier results too.



(a) Window size: 150

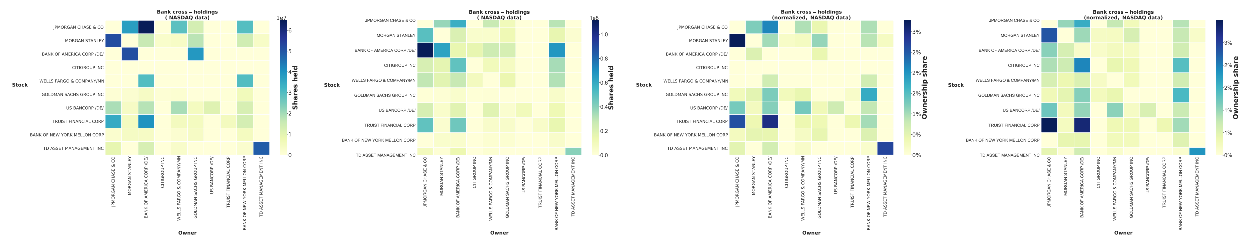
(b) Window size: 100

Figure 9: Financial networks estimated with different window sizes (using GLASSO method)

We also extended our cross holdings analysis to all financial institutions in our sample (there are 76 of them). For that purpose we collected data from FactSet and followed the same procedure as outlined above, except that we used fuzzy matching to get the cross holdings values since the company names are not fully standardized in this dataset and the parent-subsidiary relations are quite tricky to account for. However, as it is evident on Figure 11, we do not obtain very convincing results. The upper left part of the heatmap captures our "small universe" of US financial institutions where we have more reliable data and results. However the rest of the matrix is really sparse with a few random entries and do not show any pattern. Therefore, we concluded that this data source is unfortunately not suitable for this exercise but we will consider this analysis in future extensions of our project.

Further analysis and visualisation for the selected US financial institutions can be found in Section A.2 of the Appendix.

Figure 10: Cross holdings networks of selected US financial institutions



Absolute cross-holdings values at 2020-06-30

Absolute cross-holdings values at 2020-09-30

Relative cross-holdings values at 2020-06-30

Relative cross-holdings values at 2020-09-30

Data from NASDAQ

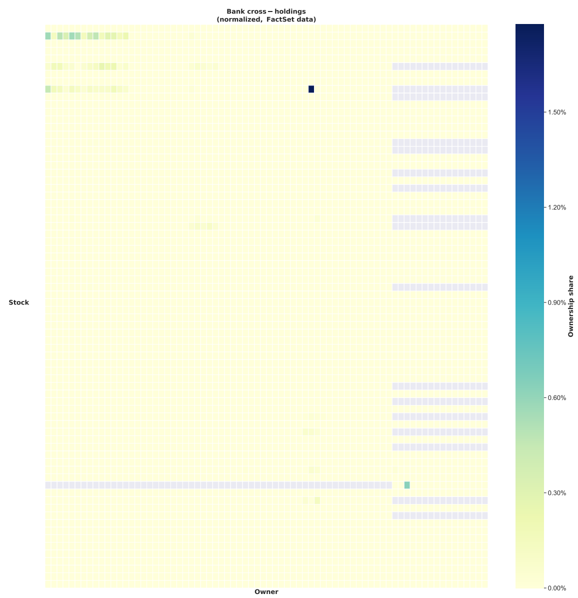
Table 2: Robustness/Persistence of the network estimation methods (measured as the Frobenius-norm of the difference of the adjacency matrices estimated during and after the crisis

Method	Return	Return (factor residual)	Volatility	Volatility (factor residual)
DAG	0	0	0	0
DY	0	0	0	0
GLASSO	0	0	0	0
NS	0	0	0	0
SPACE	0	0	0	0

Table 3: Sensitivity to the window size of the network estimation methods (measured as the Frobenius-norm of the difference of the adjacency matrices estimated with the different window size parameters divided by the average Frobenius-norm of those matrices

Method	DAG	DY	GLASSO	NS	SPACE
Weighted	0.62	0.99	0.3	0.4	0.37
Unweighted	0.65	1.14	0.63	0.69	0.77

Figure 11: Cross holdings networks of all considered financial institutions



Data from FactSet

5 Conclusions and ideas for further research

References

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608.

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017). Measuring systemic risk. *The review of financial studies*, 30(1):2–47.

Adrian, T. and Brunnermeier, M. K. (2011). Covar. Technical report, National Bureau of Economic Research.

Aragam, B., Gu, J., and Zhou, Q. (2017). Learning large-scale bayesian networks with the sparsebn package. *arXiv preprint arXiv:1703.04025*.

Baruník, J., Kočenda, E., and Vácha, L. (2016). Asymmetric connectedness on the us stock market: Bad and good volatility spillovers. *Journal of Financial Markets*, 27:55–78.

Barzel, B. and Barabási, A.-L. (2013). Network link prediction by global silencing of indirect correlations. *Nature biotechnology*, 31(8):720–725.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, 104(3):535–559.

Bubák, V., Kočenda, E., and Žikeš, F. (2011). Volatility transmission in emerging european foreign exchange markets. *Journal of Banking & Finance*, 35(11):2829–2841.

Claeys, P. and Vašíček, B. (2014). Measuring bilateral spillover and testing contagion on sovereign bond markets in europe. *Journal of Banking & Finance*, 46:151–165.

Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1):1–15.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Elliott, M., Golub, B., and Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, 104(10):3115–53.

Friedman, J., Hastie, T., and Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, 9(3):432–441.

Gerasoulis, A. and Yang, T. (1992). A comparison of clustering heuristics for scheduling directed acyclic graphs on multiprocessors. *journal of parallel and distributed computing*, 16(4):276–291.

Gomez-Rodriguez, M., Leskovec, J., and Krause, A. (2012). Inferring networks of diffusion and influence. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, 5(4):1–37.

Hallac, D., Park, Y., Boyd, S., and Leskovec, J. (2017). Network inference via the time-varying graphical lasso. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 205–213.

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, 74(1):119–147.

Liu, H., Roeder, K., and Wasserman, L. (2010). Stability approach to regularization selection (stars) for high dimensional graphical models. In *Advances in neural information processing systems*, pages 1432–1440.

Lysen, S. (2009). Permuted inclusion criterion: a variable selection technique. *Publicly accessible Penn Dissertations*, page 28.

Ma, Y.-R., Zhang, D., Ji, Q., and Pan, J. (2019). Spillovers between oil and stock returns in the us energy sector: Does idiosyncratic information matter? *Energy Economics*, 81:536–544.

Meinshausen, N., Bühlmann, P., et al. (2006). High-dimensional graphs and variable selection with the lasso. *The annals of statistics*, 34(3):1436–1462.

Peng, J., Wang, P., Zhou, N., and Zhu, J. (2009). Partial correlation estimation by joint sparse regression models. *Journal of the American Statistical Association*, 104(486):735–746.

Pesaran, H. H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, 58(1):17–29.

Shrier, I. and Platt, R. W. (2008). Reducing bias through directed acyclic graphs. *BMC medical research methodology*, 8(1):70.

Smith, S. M., Miller, K. L., Salimi-Khorshidi, G., Webster, M., Beckmann, C. F., Nichols, T. E., Ramsey, J. D., and Woolrich, M. W. (2011). Network modelling methods for fmri. *Neuroimage*, 54(2):875–891.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1):267–288.

Valdés-Sosa, P. A., Bornot-Sánchez, J. M., Vega-Hernández, M., Melie-García, L., Lage-Castellanos, A., and Canales-Rodríguez, E. (2006). 18 granger causality on spatial manifolds: applications to neuroimaging. *Handbook of time series analysis: recent theoretical developments and applications*, pages 461–491.

Valdés-Sosa, P. A., Sánchez-Bornot, J. M., Lage-Castellanos, A., Vega-Hernández, M., Bosch-Bayard, J., Melie-García, L., and Canales-Rodríguez, E. (2005). Estimating brain functional connectivity with sparse multivariate autoregression. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1457):969–981.

Wu, L., Candille, S. I., Choi, Y., Xie, D., Jiang, L., Li-Pook-Than, J., Tang, H., and Snyder, M. (2013). Variation and genetic control of protein abundance in humans. *Nature*, 499(7456):79–82.

A Appendix

A.1 Sensitivity analysis results

On Figure 12 it is straightforward to see...

A.2 Small network analysis

On Figure 13 it is evident to see...

On Figure 14 it is evident to see...

On Figure 15 it is evident to see...

On Figure 16 it is evident to see...

Table A.1: U.S. Financial institutions, tickers and quarterly mean of returns between Q4 2019 and Q4 2020.

Financial institution	Ticker	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020
JPMorgan Chase & Co	JPM	0.1729	-0.1168	-0.1846	-0.1264	0.0976
Bank of America	BAC	0.1748	-0.1536	-0.1703	-0.074	0.0515
Citigroup	C	0.1381	-0.2774	-0.2016	-0.2648	0.045
Wells Fargo	WFC	0.1122	-0.3235	-0.4555	-0.3777	-0.0561
Goldman Sachs Group	GS	0.1249	-0.1658	0.0077	-0.003	0.0994
Morgan Stanley	MS	0.1257	-0.1231	0.0618	0.0995	0.2061
Bank of New York Mellon	BK	0.0774	-0.1309	-0.1022	-0.079	0.0131
U.S. Bancorp	USB	0.09	-0.2622	-0.281	-0.1644	0.0729
PNC Financial Services Group	PNC	0.1294	-0.1788	-0.1875	-0.0883	0.1016
Capital One Financial	COF	0.0867	-0.328	-0.2346	-0.1317	0.1136
State Street Corporation	STT	0.2274	0.0686	-0.0253	-0.0203	0.0282
American Express	AXP	0.0312	-0.2193	-0.0928	-0.0806	0.0534
Fifth Third Bancorp	FITB	0.0874	-0.3478	-0.2082	-0.0649	0.0986
Regions Financial	RF	0.14	-0.3025	-0.2268	-0.131	0.1139
Mitsubishi UFJ Financial Group	8306.T	0.1424	-0.0775	-0.1778	-0.0737	0.0436
Mizuho Financial Group	8411.T	0.0815	-0.128	-0.1573	-0.0304	-0.0209
Sumitomo Mitsui Financial Group	8316.T	0.0814	-0.1139	-0.1569	-0.0158	0.0283
Resona Holdings	8308.T	0.0685	-0.0791	-0.1129	0.0378	-0.0182
Nomura Holdings	8604.T	0.3469	0.0875	-0.0484	0.0568	0.098
Sumitomo Mitsui Trust Holdings	8309.T	0.0798	-0.017	-0.202	-0.1129	-0.0033
Chiba Bank	8331.T	0.1151	-0.0448	-0.0553	0.1961	0.078
Hokuhoku Financial Group	8377.T	0.0145	0.0631	-0.1045	0.095	0.016
Shizuoka Bank	8355.T	0.06	0.0333	-0.0802	0.1299	0.0211
Yamaguchi Financial Group	8418.T	-0.0294	-0.0113	-0.0324	0.1072	-0.0881
Toronto-Dominion Bank	TD.TO	0.0381	-0.1184	-0.1197	-0.0135	0.1019
Royal Bank of Canada	RY.TO	0.0076	-0.0726	-0.0705	-0.0097	0.0756
Bank of Nova Scotia	BNS.TO	0.0575	-0.1231	-0.1432	-0.102	0.137
Bank of Montreal	BMO.TO	0.0409	-0.137	-0.2025	-0.0643	0.2309
Canadian Imperial Bank of Commerce	CM.TO	0.0435	-0.1224	-0.1062	0.0291	0.1223
National Bank of Canada	NA.TO	0.1215	-0.0723	-0.0794	0.0014	0.097
Unicredit	UCG.MI	0.1364	-0.2481	-0.2138	-0.144	-0.0389
Intesa Sanpaolo	ISP.MI	0.1823	-0.1941	-0.1547	-0.2029	0.0377
Unipol Gruppo Finanziario	UNI.MI	0.1502	-0.2621	-0.3244	-0.109	0.0722
Mediobanca Banca di Credito Finanziario	MB.MI	0.1696	-0.3705	-0.3373	0.0192	0.2099
National Australia Bank	NAB.AX	-0.0309	-0.2998	-0.3257	-0.293	0.0534
Commonwealth Bank of Australia	CBA.AX	0.0284	-0.1454	-0.2034	-0.2496	0.0855
Australia and New Zealand Banking Group	ANZ.AX	-0.0635	-0.2659	-0.1769	-0.194	0.1122
Westpac Banking	WBC.AX	-0.0676	-0.3337	-0.214	-0.2049	0.0429
Macquarie Group	MQG.AX	0.1205	-0.2194	-0.0676	-0.0647	0.1124
China Merchants Bank	600036.SS	0.0546	-0.0552	-0.0831	0.0059	0.2315
Shanghai Pudong Development Bank	600000.SS	0.0642	-0.06	-0.0025	-0.0402	0.0092
China Minsheng Banking Corp	600016.SS	0.073	0.0181	-0.0296	-0.042	6.00E-04
Hua Xia Bank	600015.SS	0.0348	-0.0834	-0.112	-0.0874	0.0226
HSBC Holdings	HSBA.L	-0.0291	-0.1375	-0.2341	-0.3435	-0.0072
Barclays	BARC.L	0.1064	-0.2174	-0.2013	-0.1736	0.2177
Lloyds Banking Group	LLOY.L	0.0733	-0.2953	-0.3784	-0.3291	0.1069
Standard Chartered	STAN.L	0.0392	-0.2046	-0.2509	-0.2537	0.0577
Banco Santander	SAN.MC	-0.036	-0.2774	-0.3385	-0.5016	0.0997
Banco Bilbao Vizcaya Argentaria	BBVA.MC	0.014	-0.2502	-0.3038	-0.3954	0.1451
Banco de Sabadell	SAB.MC	0.0397	-0.2984	-0.7813	-0.601	0.0865
Svenska Handelsbanken	SHB-A.ST	0.0376	0.0119	0.0214	-0.1673	-0.1221
Skandinaviska Enskilda Banken	SEB-A.ST	-7.00E-04	-0.0962	0.0317	-0.0699	-0.0268
Swedbank	SWED-A.ST	-0.022	-0.0188	-0.0417	-0.1374	-0.023
BNP Paribas	BNP.PA	0.1537	-0.2717	-0.1675	-0.1087	0.1562
Credit Agricole	ACA.PA	0.1378	-0.2994	-0.2652	-0.2123	0.1313
Shinhan Financial Group	055550.KS	-0.0705	-0.2195	-0.2232	-0.1168	-0.0353
Industrial Bank of Korea	024110.KS	-0.0848	-0.2267	-0.2075	-0.1223	-0.029
UBS	UBSG.SW	0.007	-0.0988	0.1465	0.1814	0.0879
Credit Suisse Group	CSGN.SW	0.0603	-0.2518	-0.1312	-0.0458	0.1067
KBC Groupe	KBC.BR	0.0772	-0.1464	-0.1971	-0.3432	-0.0246
Itau Unibanco Holding	ITUB4.SA	-0.0312	-0.2872	-0.2655	-0.2182	0.0829

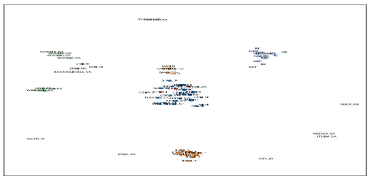
Table A.2: U.S. Financial institutions, tickers and quarterly median of returns between Q4 2019 and Q4 2020.

Financial institution	Ticker	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020
JPMorgan Chase	Co	JPM	0.2244	0.0407	-0.0146	-0.1192
-0.0688						
Bank of America	BAC	0.1999	0.0906	0.0441	0.0988	0.1107
Citigroup	C	0.2002	-0.0694	-0.1598	-0.3139	0
Wells Fargo	WFC	0.1222	-0.0577	-0.3721	-0.2679	-0.0853
Goldman Sachs Group	GS	0.0934	-0.0107	0.0421	0.0786	0.1441
Morgan Stanley	MS	0.1734	0.0799	0.0782	-0.09	0.1924
Bank of New York Mellon	BK	0.1767	0.0218	-0.0348	-0.0696	0.0252
U.S. Bancorp	USB	0.1084	-0.0963	-0.2006	-0.2316	-0.1316
PNC Financial Services Group	PNC	0.1762	0.1034	-0.1413	-0.2126	-0.0997
Capital One Financial	COF	0.0743	-0.0146	-0.0146	-0.5125	-0.1948
State Street Corporation	STT	0.2021	0.2581	0.2223	0.1371	0.0715
American Express	AXP	0.1107	0.1289	0.1903	-0.147	-0.0191
Fifth Third Bancorp	FITB	0.0522	-0.0817	-0.0816	0.1019	-0.0518
Regions Financial	RF	0.1544	-0.1842	-0.2436	-0.2622	-0.1046
Mitsubishi UFJ Financial Group	X8306.T	-0.0194	-0.128	-0.3092	-0.1754	-0.0704
Mizuho Financial Group	X8411.T	0	0	-0.0776	-0.0019	-0.1473
Sumitomo Mitsui Financial Group	X8316.T	0.0515	-0.0885	-0.2606	-0.0963	-0.0963
Resona Holdings	X8308.T	-0.007	-0.2343	-0.2521	-0.0154	-0.0819
Nomura Holdings	X8604.T	-0.0329	0.0022	-0.0498	0.0296	-0.0092
Sumitomo Mitsui Trust Holdings	X8309.T	0.0245	-0.0842	-0.2952	-0.0342	-6.00E-04
Chiba Bank	X8331.T	0	-0.0238	-0.204	0.1054	-0.1691
Hokuhoku Financial Group	X8377.T	0	0	-0.1101	0.102	0
Shizuoka Bank	X8355.T	0.0475	-0.1203	-0.1586	0	0
Yamaguchi Financial Group	X8418.T	0.0606	0	-0.1488	0.1688	-0.0639
Toronto-Dominion Bank	TD.TO	0.0854	0.0448	0.0352	0.0466	-0.0071
Royal Bank of Canada	RY.TO	0.0301	0.0748	0.005	0.0769	0.0741
Bank of Nova Scotia	BNS.TO	0.0614	0	-0.0744	-0.0109	0.0986
Bank of Montreal	BMO.TO	0.1295	0.0975	-0.0273	0.0591	0.1165
Canadian Imperial Bank of Commerce	CM.TO	0.072	0.036	-0.0199	0.1009	0.1155
National Bank of Canada	NA.TO	0.1236	0.1128	0.048	0.1328	0.138
Unicredit	UCG.MI	0.0342	-0.128	-0.1562	-0.308	-0.1811
Intesa Sanpaolo	ISP.MI	0.1096	0.1037	0.1173	-0.2126	-0.0409
Unipol Gruppo Finanziario	UNI.MI	0.1102	0.0142	-0.0703	0	0.0745
Mediobanca Banca di Credito Finanziario	MB.MI	0.1717	-0.0951	-0.3721	-0.1412	0.0219
National Australia Bank	NAB.AX	0	0.0026	0	-0.3884	-0.026
Commonwealth Bank of Australia	CBA.AX	0.102	0.0189	-0.1519	-0.4638	-0.1086
Australia and New Zealand Banking Group	ANZ.AX	0.0402	0.0955	0.0704	-0.1435	-0.092
Westpac Banking	WBC.AX	0.0867	-0.0375	0.0848	-0.1459	-0.0784
Macquarie Group	MQG.AX	0.1308	0.1608	0.1674	0.2647	0.0578
China Merchants Bank	X600036.SS	-0.0933	-0.1604	-0.1604	-0.2036	0.1123
Shanghai Pudong Development Bank	X600000.SS	0.0824	0.0806	0.0816	-0.1992	-0.1505
China Minsheng Banking Corp	X600016.SS	0	0	0	-0.1738	0
Hua Xia Bank	X600015.SS	0.0642	0	-0.1302	-0.1566	-0.063
HSBC Holdings	HSBA.L	0.025	0	-0.1086	-0.385	-0.1648
Barclays	BARC.L	0.0273	0.0146	-0.1035	0.0119	0.0975
Lloyds Banking Group	LLOY.L	-0.0971	-0.2324	-0.2812	-0.3483	-0.0324
Standard Chartered	STAN.L	-0.0431	-0.1569	-0.1728	-0.2789	0.1337
Banco Santander	SAN.MC	-0.1637	-0.1454	-0.3838	-0.8715	-0.4272
Banco Bilbao Vizcaya Argentaria	BBVA.MC	-0.12	-0.104	-0.163	-0.3104	-0.0245
Banco de Sabadell	SAB.MC	0.0694	0.0116	-0.2912	-0.6575	-0.3907
Svenska Handelsbanken	SHB.A.ST	-0.0217	-0.1105	-0.1498	-0.2809	-0.1732
Skandinaviska Enskilda Banken	SEB.A.ST	-0.0826	0.0311	0.0501	-0.1845	-0.0795
Swedbank	SWED.A.ST	-0.0351	0.0923	0.1517	-0.0618	-0.0731
BNP Paribas	BNP.PA	0.0211	-0.0211	-0.0674	-0.3951	-0.2309
Credit Agricole	ACA.PA	0.1163	0.0192	-0.0949	-0.4351	0.0358
Shinhan Financial Group	X055550.KS	0.1145	0.1145	-0.3206	-0.3269	0
Industrial Bank of Korea	X024110.KS	0	0	-0.2915	-0.1827	0
UBS	UBSG.SW	-0.1254	-0.0418	-0.0237	-0.0331	-0.1296
Credit Suisse Group	CSGN.SW	-0.0398	-0.0197	-0.104	-0.2587	-0.0321
KBC Groupe	KBC.BR	-0.0172	0.0751	0.0102	-0.0601	0.0361

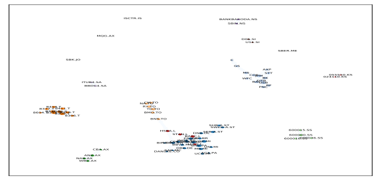
Table A.3: U.S. Financial institutions, tickers and quarterly standard deviation of returns between Q4 2019 and Q4 2020.

Financial institution	Ticker	Q4 2019	Q1 2020	Q2 2020	Q3 2020	Q4 2020
JPMorgan Chase	Co	JPM	1.1372	3.3286	4.0414	4.059
2.2288						
Bank of America	BAC	1.3402	3.5237	4.3589	4.3759	2.4804
Citigroup	C	1.4417	4.0266	5.1496	5.212	2.8053
Wells Fargo	WFC	1.3067	3.4335	4.5094	4.6467	2.8191
Goldman Sachs Group	GS	1.3263	3.2984	3.9628	3.9857	2.1132
Morgan Stanley	MS	1.3213	3.688	4.3239	4.2873	2.1014
Bank of New York Mellon	BK	1.3682	3.1237	3.5148	3.5142	2.1882
U.S. Bancorp	USB	1.0442	3.2376	4.2857	4.4133	2.5293
PNC Financial Services Group	PNC	1.1834	3.4244	4.3216	4.3386	2.3962
Capital One Financial	COF	1.4227	4.1579	5.4639	5.6224	2.9664
State Street Corporation	STT	1.8544	3.7876	4.3297	4.3902	2.4779
American Express	AXP	1.1148	3.737	4.6452	4.6148	2.5583
Fifth Third Bancorp	FITB	1.4648	4.3361	5.5744	5.6934	3.0753
Regions Financial	RF	1.5828	4.0674	5.2033	5.3399	3.1678
Mitsubishi UFJ Financial Group	X8306.T	0.98	1.858	2.215	2.3421	1.5665
Mizuho Financial Group	X8411.T	0.7647	1.7903	2.1319	2.3393	1.5775
Sumitomo Mitsui Financial Group	X8316.T	0.8354	1.6896	2.0919	2.2032	1.5229
Resona Holdings	X8308.T	1.1556	1.9665	2.3466	2.4891	1.6841
Nomura Holdings	X8604.T	1.8472	2.3585	2.7018	2.6807	1.6713
Sumitomo Mitsui Trust Holdings	X8309.T	1.0896	2.0044	2.2674	2.3994	1.7127
Chiba Bank	X8331.T	1.4651	2.0943	2.456	2.5046	1.7913
Hokuhoku Financial Group	X8377.T	1.4221	1.9254	2.4013	2.6169	1.8742
Shizuoka Bank	X8355.T	1.0978	1.7347	1.923	2.0391	1.3658
Yamaguchi Financial Group	X8418.T	1.6787	2.1218	2.4133	2.4655	1.8031
Toronto-Dominion Bank	TD.TO	0.7764	2.8308	3.2168	3.2375	1.2819
Royal Bank of Canada	RY.TO	0.6007	2.6028	2.9272	2.9331	0.9993
Bank of Nova Scotia	BNS.TO	0.5344	2.831	3.2061	3.2458	1.1914
Bank of Montreal	BMO.TO	0.6944	3.1992	3.6164	3.6899	1.4472
Canadian Imperial Bank of Commerce	CM.TO	0.7826	3.0438	3.3867	3.3657	0.933
National Bank of Canada	NA.TO	0.5593	3.3632	3.8259	3.8605	1.1054
Unicredit	UCG.MI	1.9374	3.3432	3.8672	3.8903	2.7199
Intesa Sanpaolo	ISP.MI	1.2323	2.7472	3.6476	3.6817	2.0488
Unipol Gruppo Finanziario	UNI.MI	1.2602	3.0994	3.4994	3.5142	2.0462
Mediobanca Banca di Credito Finanziario	MB.MI	1.11	3.1918	3.7791	4.0311	2.4734
National Australia Bank	NAB.AX	0.9512	2.7879	3.3193	3.4602	1.8516
Commonwealth Bank of Australia	CBA.AX	0.8963	2.6761	3.0193	3.0658	1.4441
Australia and New Zealand Banking Group	ANZ.AX	0.9055	3.0056	3.5422	3.6748	1.8289
Westpac Banking	WBC.AX	0.9394	2.7351	3.3243	3.5043	1.8344
Macquarie Group	MQG.AX	1.048	3.122	3.5848	3.6183	1.5143
China Merchants Bank	X600036.SS	1.3287	1.5108	1.5449	1.9671	1.8368
Shanghai Pudong Development Bank	X600000.SS	1.0998	1.2319	1.2518	1.4717	1.3021
China Minsheng Banking Corp	X600016.SS	0.6658	0.8599	0.8417	1.0694	1.0672
Hua Xia Bank	X600015.SS	0.71	0.867	0.7977	1.2412	1.2523
HSBC Holdings	HSBA.L	1.0298	1.7757	2.408	2.7119	2.4227
Barclays	BARC.L	1.5692	3.2647	4.15	4.2316	2.8339
Lloyds Banking Group	LLOY.L	1.8484	2.873	3.5191	3.641	2.8213
Standard Chartered	STAN.L	1.4585	2.2767	3.2082	3.4533	2.8038
Banco Santander	SAN.MC	1.5854	3.0389	3.6689	3.9472	3.3828
Banco Bilbao Vizcaya Argentaria	BBVA.MC	1.5155	3.0115	3.8315	4.1386	3.3234
Banco de Sabadell	SAB.MC	2.267	3.916	4.6908	5.0072	4.5006
Svenska Handelsbanken	SHB.A.ST	1.3394	2.4417	2.9368	2.9881	1.8633
Skandinaviska Enskilda Banken	SEB.A.ST	1.6052	2.7855	3.1105	3.1996	1.8241
Swedbank	SWED.A.ST	1.561	2.5264	2.9106	2.9942	1.8477
BNP Paribas	BNP.PA	1.3593	3.008	3.9516	4.0804	2.8371
Credit Agricole	ACA.PA	1.3866	3.1625	3.8496	3.9503	2.5953
Shinhan Financial Group	X055550.KS	1.4126	2.5768	3.0797	3.1131	2.0043
Industrial Bank of Korea	X024110.KS	1.2944	2.6382	2.998	2.9619	1.6345
UBS	UBSG.SW	1.3035	2.6138	3.2802	3.3169	1.8075
Credit Suisse Group	CSGN.SW	1.4266	3.1205	3.7511	3.7911	2.0964
KBC Groupe	KBC.BR	1.3552	3.2528	4.1359	4.2484	2.4628

Figure 12: Financial networks estimated with different window size

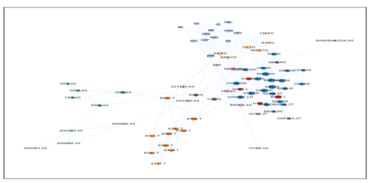


(a) Window size: 150

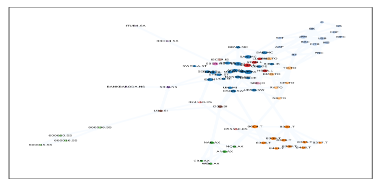


(b) Window size: 100

Neighborhood Selection method

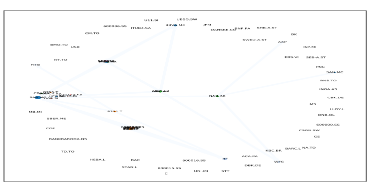


(c) Window size: 150

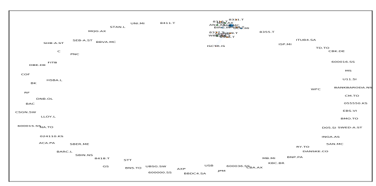


(d) Window size: 100

SPACE method

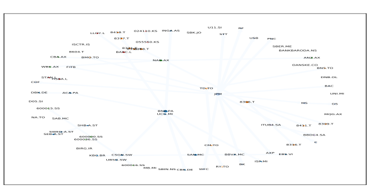


(e) Window size: 150

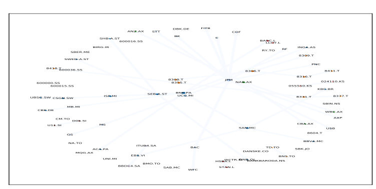


(f) Window size: 100

DY method



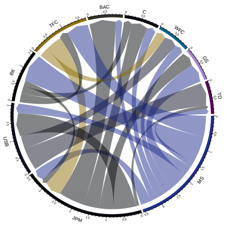
(g) Window size: 150

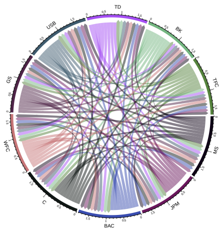


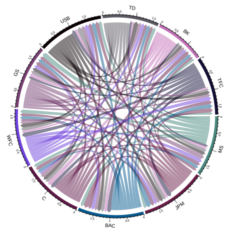
(h) Window size: 100

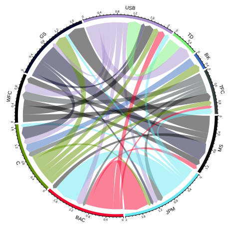
DAG method

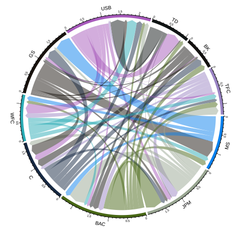
Figure 13: Financial networks estimated with different models


(a) DAG


(b) DY

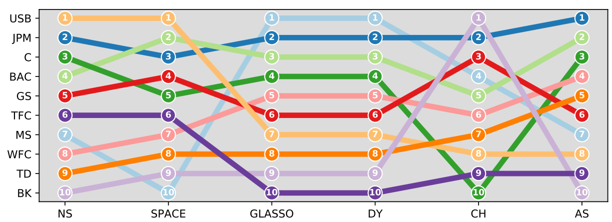

(c) GLASSO


(d) NS

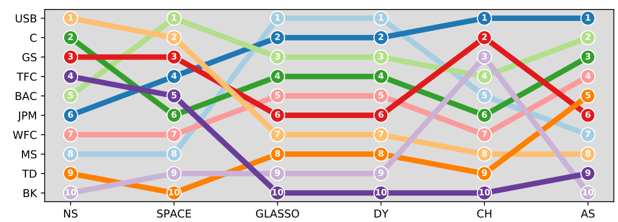

(e) SPACE

Data at 2020-03-16

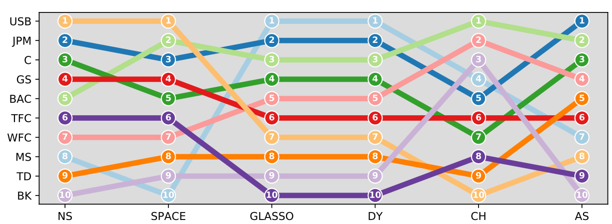
Figure 14: Ranking of financial institutions according to varying network estimation methods and centrality measure



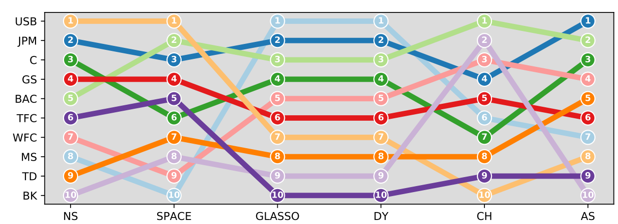
(a) Degree centrality



(b) Betweenness centrality



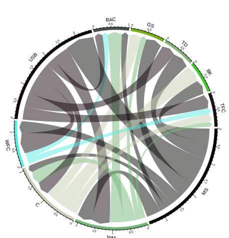
(c) Closeness centrality

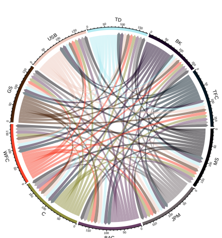


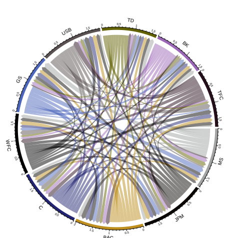
(d) Eigenvector centrality

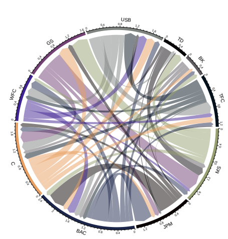
Data at 2020-03-16

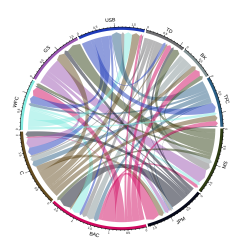
Figure 15: Financial networks estimated with different models


(a) DAG


(b) DY

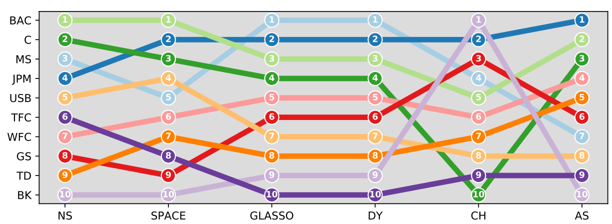

(c) GLASSO


(d) NS

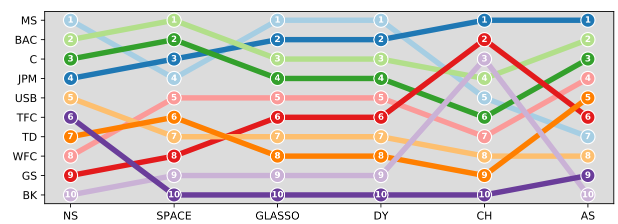

(e) SPACE

Data at 2020-06-30

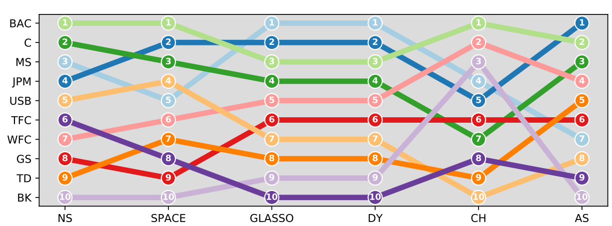
Figure 16: Ranking of financial institutions according to varying network estimation methods and centrality measure



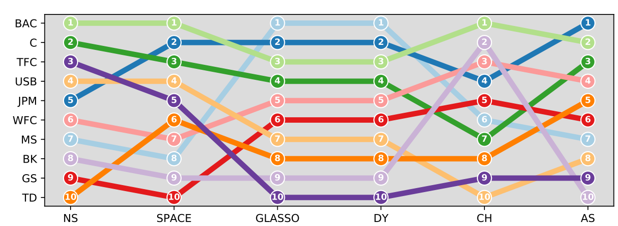
(a) Degree centrality



(b) Betweenness centrality



(c) Closeness centrality



(d) Eigenvector centrality

Data at 2020-06-30