Financial network estimation for measuring bank interconnectedness

Aron Denes Hartvig and Aron Pap

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1 Introduction

Both the financial crisis of 2007-08 and the COVID-19 shock in 2020 demonstrated that global interconnectedness of the financial system is a double-edged sword. Interconnectedness adds flexibility to investment and to the financing of the economy, however, at times of crisis it may contribute to propagating contagion through the system. Also, high interdependence promotes sudden transformation of the network architecture. Unregularized high frequency trading in 2010 or the recent GameStop craze showed that stock market may experience sudden, even intraday changes. These events make clear that financial system can be hit by a great variety of shocks. Thus, continuous monitoring of the whole financial network is essential to identify shocks impacting the system. Nevertheless, financial interconnectedness remained a rather elusive concept.

Interconnectedness is an inherent characteristic of developed financial systems. Increased interdependence arises between institutions that hold each other's shares, debts, and other obligations or invest in assets with correlated payoffs. Financial network analysis is a prominent topic, several articles appeared on both theoretical and empirical side. 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.

On the empirical side several methods were built to estimate financial connections based on publicly available data. Nevertheless, most methods are not capable of monitoring the financial system on a daily basis or scaling of the analysis may be complicated. The most widely used methods to estimate financial networks are Granger causality (Billio et al., 2012), ΔCoVar (Adrian and Brunnermeier, 2016), SES (Acharya et al., 2017) and DY connectedness (Diebold and Yılmaz, 2014). ΔCoVaR and SES relies on balance sheet data therefore they can be only calculated on a quarterly basis. In addition, high-dimensional analysis, that is crucial in the financial system, is troublesome in these frameworks due to data limitations. Granger causality or Diebold-Yilmaz (DY) connectedness frameworks rely on daily stock prices that are easily available. Still, Granger causality network has unweighted edges that limits the analysis to the existence of relationships. DY connectedness is a simple method which estimates weighted linkages relying on daily, or even high frequency data. Due to this favourable property it can promptly adopt to changes in the network.

However, there are other techniques to quantify interdependence that are prominent in other domains like biology or traffic. These models are designed for high dimensional an high frequency analysis. Graphical lasso (Hallac et al., 2017; Arbia et al., 2018; Lee and Seregina, 2020), SPACE (Millington and Niranjan, 2019), neighborhood selection or Bayesian network (Sanford and Moosa, 2012) has already been tested in financial network analysis but they are not yet widespread.

In this paper we compare Diebold-Yilmaz connectedness, neighborhood selection, graphical lasso, SPACE and sparse Bayesian network methods with the analytical purpose to test which one describes high dimensional financial networks the best. We look at log returns of 76 financial institutions from 21 countries and estimate these networks based on that empirical data throughout 2020. Through snapshots of the financial network we shed light on the transformation of the financial network during the observed interval by visualisation, centrality measures and Kendall tau rank correlation coefficient.

Our contribution to the financial network literature is three-fold. First, we show that graphical lasso is a powerful tool to estimate financial linkages. It represents an optimal trade-off between flexibility and robustness. Also, in SPACE networks geographical clusters are outlined. Second, a new centrality rank measure is introduced. We rank the financial institutions based on their centrality to determine which are the systemically most important ones. The identification of Systemically Important Financial Institutions (SIFIs) is a key regulatory issue since the failure of Lehman Brothers. Still, as the architecture of financial network may change rapidly, centrality ranking can support prompt regulatory decisions. Finally, we closely examine the financial during a highly volatile period. During the observed time period the United Kingdom left the European Union, curfews have been implemented globally due to the pandemic and in November the U.S. elections was held.

The article proceeds as follows. In Section 2 we briefly summarise the relevant literature and the applied methods. Then, in Section 3 we present our data and in Section 4 we compare the proposed networks. Finally, in Section 5 we conclude.

2 Literature review

2.1 Financial contagion

Since the financial crisis of 2007-08 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.

On the theoretical side (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.

Acemoglu et al. (2015) demonstrated that financial interconnectedness enhances stability if the magnitude and the number of the shocks remains below a certain threshold. Still, if the shocks exceed this threshold the effect is the opposite, interconnectedness makes the system more sensitive and more prone to contagion.

Numerous articles appeared on the empirical side as well. Bisias et al. (2012) in their survey identified 31 quantitative measures of systemic risk in economics and finance literature. Since tracking the linkages between financial institutions is highly complex most methods estimates interconnectedness from stock prices or balance sheet data. These methods estimate the associations between the individual financial institutions and the whole market (ΔCoVaR of Adrian and Brunnermeier (2016), SES of Acharya et al. (2017)) or association between individual financial institutions (Granger causality of Billio et al. (2012), spillover indices of Diebold and Yilmaz (2012)).

No extensive comparison has been done Most methods uses balance sheet data -¿ quarterly available Check which methods can be regularized. Balance sheet - daily stock price Regularized - non-regularized

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 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 outper-

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

forms 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, 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,

[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.

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

[4]Which are undirected/symmetrical.

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.

3 Data

We study daily stock returns of 76 financial institutions from 28 economies downloaded from Yahoo Finance, from June 6, 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

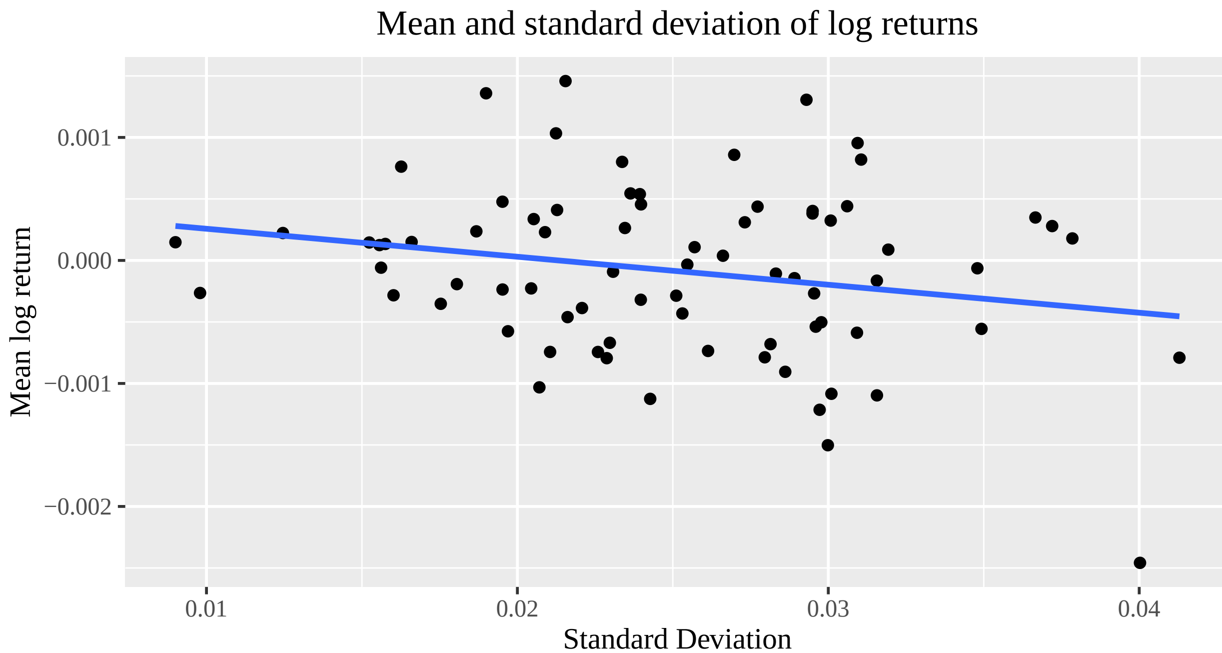
To get a broad picture of the financial system during the observed time interval we take a closer look on the descriptive statistics of the stock prices. On Figure 1 we present the mean and the standard deviation of the stock prices included in our analysis. Intriguingly, contrary to our expectations we can see a downtrend on the figure thus riskier stocks performed worse during the observed period. This reveals how severe was the COVID-19 shock in the financial system. In our sample 40 out of 76 financial institutions experienced negative mean return. The largest losses occurred to Banco de Sabadell in Spain with -0.0025 average log return.

To further examine our data in Table 1 we present the average descriptive statistics of the countries included. The average log return was the highest in Russia and Turkey while the lowest in Spain and Denmark. The two important financial hubs, U.S. and U.K., show different impacts. Mean log return in the U.S. was positive and standard deviation was high, in the U.K. mean was negative and standard deviation was also lower. Germany and France, the two largest economies of the European Union had positive mean log return, but negative median values. The developing countries like Brazil, India and South Africa were all hit negatively by the shock.

Table 1: Average descriptive statistics of the countries' financial institutions' stock prices between June 6, 2019 and December 31, 2020

Country	Mean	Median	Std	Min	Max
Australia	-0.00029	0.00042	0.02278	-0.13278	0.10417
Austria	-0.00079	-0.00015	0.02796	-0.13203	0.12851
Belgium	-0.00054	0.00022	0.02960	-0.21246	0.13159
Brazil	-0.00082	-0.00060	0.02751	-0.12869	0.13038
Canada	0.00034	0.00076	0.02146	-0.15619	0.16135
Denmark	-0.00113	-0.00048	0.02427	-0.12046	0.10262
France	0.00015	-0.00011	0.02891	-0.16498	0.14673
Germany	0.00020	-0.00039	0.03293	-0.22111	0.13216
India	-0.00082	0.00110	0.02945	-0.15320	0.13620
Ireland	-0.00079	-0.00270	0.04129	-0.17096	0.14374
Italy	-0.00009	-0.00010	0.02697	-0.19611	0.15492
Netherlands	-0.00016	-0.00029	0.03156	-0.21532	0.18645
Norway	0.00046	0.00036	0.02398	-0.13440	0.12632
Russia	0.00136	0.00071	0.01899	-0.10061	0.12132
Singapore	0.00013	0.00024	0.01566	-0.08000	0.07584
South Africa	-0.00091	-0.00223	0.02862	-0.13647	0.11701
Spain	-0.00138	-0.00203	0.03368	-0.18086	0.18324
Switzerland	0.00042	-0.00060	0.02499	-0.15815	0.12863
Turkey	0.00103	0.00044	0.02124	-0.07152	0.09575
UK	-0.00050	-0.00048	0.02640	-0.13746	0.12983
US	0.00025	0.00012	0.03140	-0.18652	0.16390

Figure 1: Mean and standard deviation of the observed banks' stock price log returns between June 6, 2019 and December 31, 2020



4 Empirical results

In applications we base connectedness assessment on the methods described in Section 2.2. 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 five 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

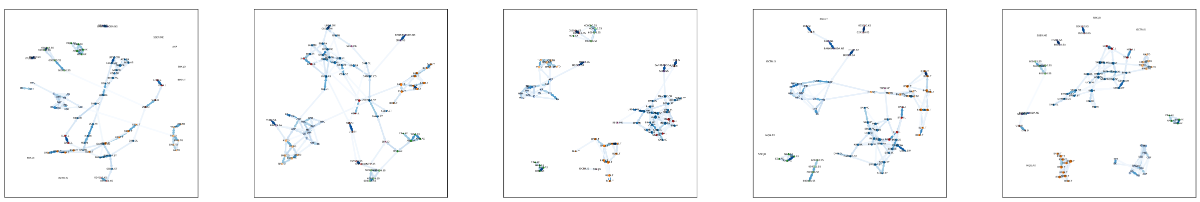
First, we estimate the networks for the end-quarter dates between December 31, 2019 and December 31, 2020. For all the figures in this section:

- Nodes represent individual financial institutions, while the directed edges between them represent the interconnectedness values
- Node size represents the average of out- and indegree
- Node color represents the region of the financial institution
- Node link width and color hue represent the weight of the connection
- The position of the nodes on the figures is determined using the Fruchterman-Reingold force-directed algorithm

4.1.1 Neighborhood Selection Graphs

On Figure 2 we present the five networks that are estimated with the Neighborhood Selection method. As it is evident to see from the figure, the number of edges is quite stable over time, however some of those edges are always "rewired" meaning that some financial institutions increase, while others decrease their out-/indegrees in these networks. One can also clearly see from the figures that there are strong clustering effects in these networks and that they coincide with regional groups in most cases. This seems obvious given the potential effect of local economic conditions and is also a stylized fact in the literature. However, one can make another interesting observation here since the time zones could also influence the results since for instance Asian markets cannot react to US intraday news in real-time, which might also contribute to these emerging regional clusters.

Figure 2: 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

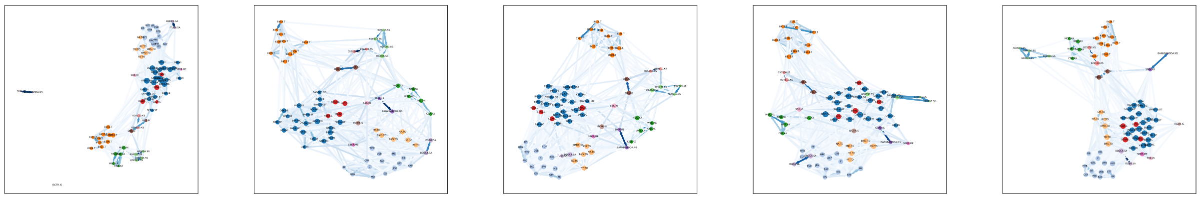
On Figure 3 we present the five networks that are estimated with the GLASSO method. It is evident to see from this figure that the interconnectedness is quite high in this network, but still one can observe outlier groups, notably some Indian banks in this particular case. The regional groups are also clearly recognizable from these networks, however the structure does seem to change over time. During the peak of the COVID-19 crisis on the stock markets in March 2020, the connectedness between financial institutions in different regional clusters seem to be increasing (and therefore intra-cluster connectedness seem to weaken slightly in relative terms) which seems plausible since during crisis times these networks tend to become more connected. Then in the later quarters of 2020 these clusters "pull together" more strongly once again.

4.1.3 SPACE Graphs

On Figure 4 we present the five networks that are estimated with the SPACE method. One can observe regional clusters similar to the ones we documented in previous sections, however the structure of the network does change substantially throughout the considered quarters. It is also interesting to observe[5] that commercial banks tend to be more "sensitive" during

[5] Although it is a bit cumbersome to deduct it from the presented figure.

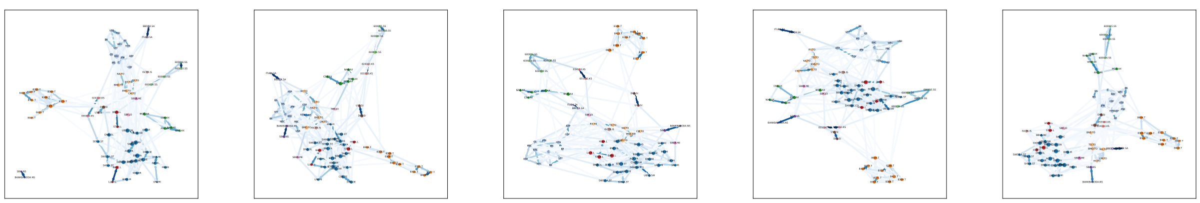
Figure 3: Financial networks estimated with GLASSO method at different quarters



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

the COVID-19 crisis than the commercial banks. A higher share of their connections are rewired and their local cluster structures change more abruptly.

Figure 4: Financial networks estimated with SPACE method at different quarters

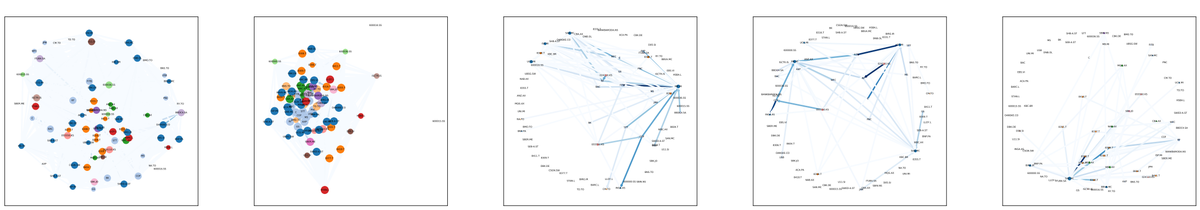


2019-12-31 2020-03-31 2020-06-30 2020-09-30 2020-12-31

4.1.4 Diebold-Yilmaz Graphs

On Figure 5 we present the five networks that are estimated with the Diebold-Yilmaz method. As it is evident to see from the figures, there is a structural change after the peak of the COVID-19 crisis, when the estimated network "falls apart" and the sparsity increases significantly. Also, it is interesting to note here that these networks have less regional clustering than those estimated with other methods. The network becomes especially "crowded" and intertwined during Q1 2020.

Figure 5: Financial networks estimated with Diebold-Yilmaz method at different quarters

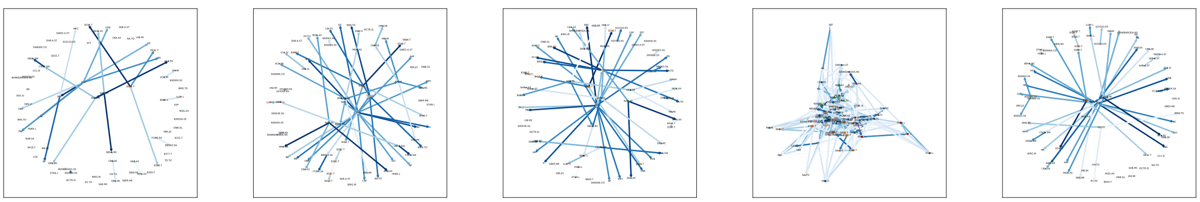


2019-12-31 2020-03-31 2020-06-30 2020-09-30 2020-12-31

4.1.5 Sparse Bayesian Graphs

On Figure 6 we present the five networks that are estimated with the Directed Acyclic Graph method. One can observe that the number of edges is significantly lower than with the other estimated methods, the DAG method returns the sparsest networks. However the edges found have quite large weights, but they can change abruptly over time as it is evident to see from the figures. It is also important to point out that the networks from DAG will be inherently asymmetric due to its acyclical property, whereas Neighborhoud Selection, SPACE and GLASSO will always return symmetric interconnectedness networks, since they are estimating partial correlation matrices.

Figure 6: 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

In Table 2a we summarise some descriptive statistics of the studied networks. The results highlight what we already documented about DAG estimating the sparsest networks whereas GLASSO estimating the most edges, but with lower weights on average than the others. The GLASSO and SPACE networks are fully connected, whereas DY and DAG do not have strongly connected components. Neighborhood Selection provides a "middle-ground" since its estimated network has 11 components, with the largest having 32 members.

Table 2: Summary statistics and general characteristics of the studied networks with data at 2020-12-31

	NS	**GLASSO**	**SPACE**	**DY**	**DAG**
Number of nodes	76	76	76	76	76
Number of edges	254	1482	584	54	50
*Number of components**	11	1	1	76	76
Size of giant component	32	76	76	1	1
Max edge weight	0.67	0.46	0.74	0.06	0.94
Average degree	3.34	19.5	7.68	0.71	0.66

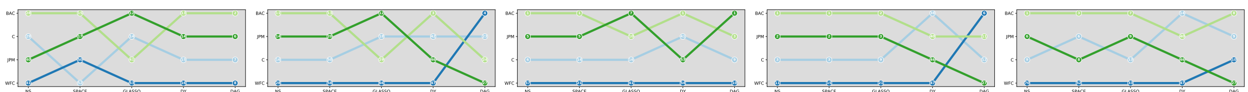
(a) *By components we mean strongly connected components here

On Figure 7 we report results from a centrality ranking exercise, which works as follows:

1. We estimate the networks with the different methods for a specific point in time
2. Then we calculate a specific centrality ranking for those estimated networks
3. We compare the centrality ranking of a set of selected financial institutions for the different estimaton methods

The figures shows that the centrality rank of the same financial institutions is somewhat similar in the estimated networks, however there are substantial differences when we consider different types of centrality measures.

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

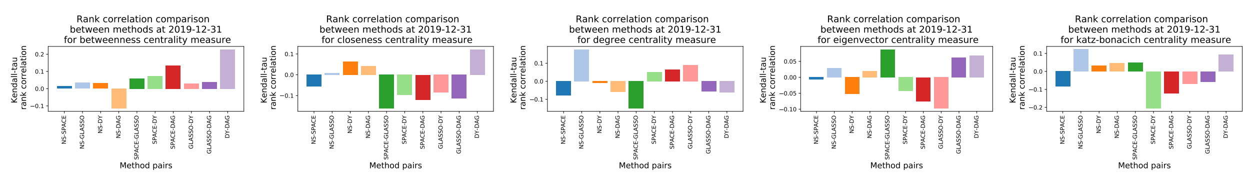


Betweenness Closeness Degree Eigenvector Katz-Bonacich

Network estimated with data at 2019-12-31

On Figure 8 it is evident to see that the Kendall-Tau rank correlation between the centrality rankings of the different methods is quite weak and seem to be distributed around zero. The method pairs with the highest positive correlation seem to be {Neighborhood Selection, GLASSO} and {DY, DAG}.

Figure 8: Correlation of the rankings for different estimation method pairs with different centrality measures



Betweenness Closeness Degree Eigenvector Katz-Bonacich

Network estimated with data at 2019-12-31

4.1.7 Effect of Brexit on UK financial institutions

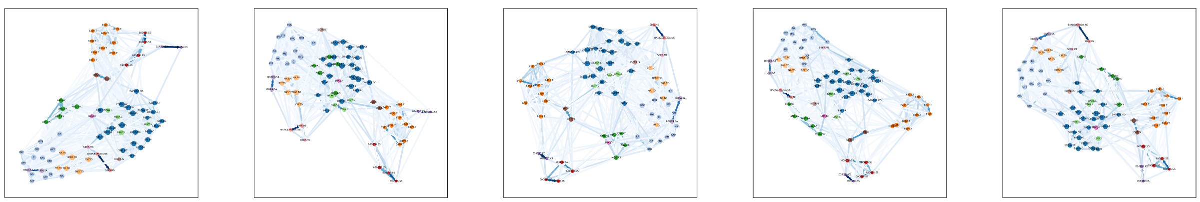
It is also interesting to analyse in the estimated networks whether the impact of Brexit "manifests" in the interconnectedness of the UK financial institutions. Our results suggest that they do not yet, since financial institutions from the UK are clearly still part of the European cluster over the course of 2020 as it is depicted on Figure 3 for instance[6].

[6] Financial institutions from the UK have red color on the figure.

4.1.8 COVID-19 shock analysis

On Figure 9 we analyse the week during which the volatility due to the COVID-19 crisis was highest on the financial markets. We re-estimate the networks every day as new returns data come in[7] and the results suggest that networks do change quite substantially during this time of increased volatility. This exercise showcases that our estimation methods which can incorporate daily or even more frequent observations might provide an advantage over methods that can be updated less frequently.

Figure 9: Financial networks estimated with GLASSO method during the peak of the COVID-19 crisis



2020-03-16 2020-03-17 2020-03-18 2020-03-19 2020-03-20

4.2 Network dynamics

On Figure 10 it is evident to see that some of the network estimation methods are more robust to changes in the data over time, whereas others are more flexible. Here we are reporting the temporal deviation ratio, which is defined as the Frobenius-norm of the difference of the estimated adjacency matrices at consecutive quarters. The same metric is used in (Hallac et al., 2017), where the authors introduce a time-varying GLASSO formulation, which could be an interesting avenue of future research for us as well.

It is clear to see that the DY method is the least flexible whereas DAG is the least robust with huge changes in the estimated network. The optimal robustness/flexibility is probably somewhere in the middle, not in the extremes. Also, it is interesting to see that the largest changes in all estimated networks occur in Q1 2020 and Q4 2020, which could be due to the initial COVID-19 crisis and the US Presidential election respectively, which caused substantial shocks in the financial markets, during which times the interconnectness between certain financial institutions might have changed abruptly.

4.3 Sensitivity analysis

To check the sensitivity of our results with respect to the estimation window size used we run the models with both a 100-days and a a 150-days window as well and compare the estimated networks. On Figure 11 we show these networks for the GLASSO method and the figures suggests that the estimated networks are robust with respect to the window size,

[7]But the window size is still 150 days.

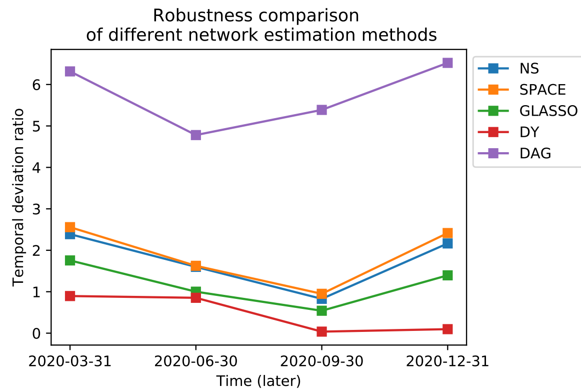
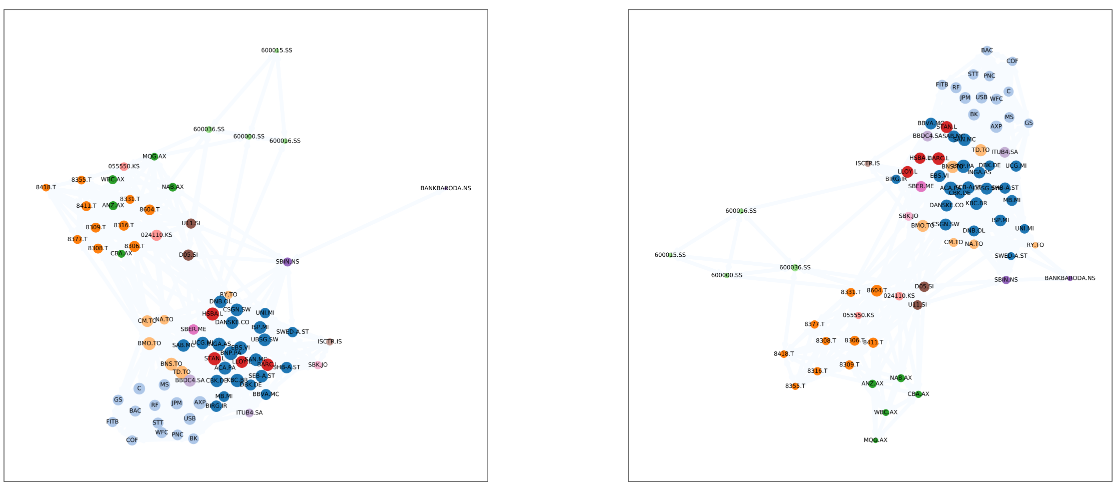


Figure 10: Network estimation robustness dynamics

since we only see small variation in the network structure.
The rest of the methods are shown on Figure 14 in Section A.1 of the Appendix.



(a) Window size: 150

(b) Window size: 100

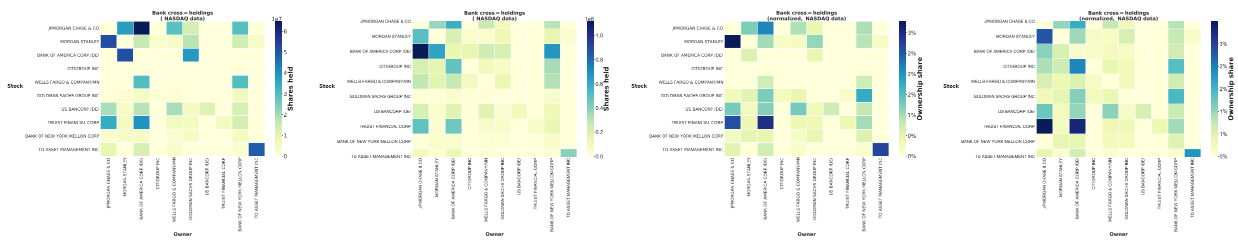
Figure 11: Financial networks estimated with different window sizes (using GLASSO method)

We also provide numerical measures of this sensitivity in Table 3.

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 12 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.

Figure 12: Cross holdings networks of selected US financial institutions



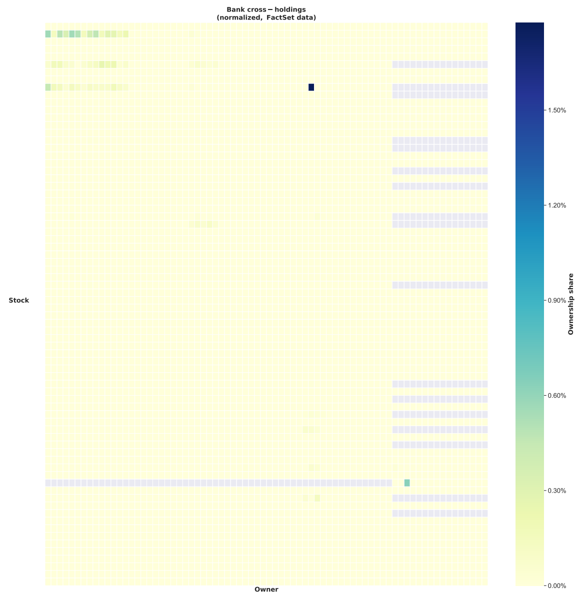
Absolute cross-holdings values at 2020-06-30 | Absolute cross-holdings values at 2020-09-30 | Relative cross-holdings values at 2020-06-30 | Relative cross-holdings values at 2020-09-30

Data from NASDAQ

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 13, 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 13: Cross holdings networks of all considered financial institutions



Data from FactSet

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

5 Conclusions and ideas for further research

In this article we analyse interconnectedness among financial institutions via estimating their networks of relationships. More specifically, we look at historical data of stock price log returns of these banks and estimate these networks based on that empirical data throughout 2019 and 2020. We compare several estimation methods for this purpose, from which some are well-known in the financial literature and some potential ones which seem "underutilized" in financial applications, nevertheless being prominent in other domains. We document for instance that the *graphical lasso* method seems to strike a good balance between robustness and flexibility, since its estimated networks adapt to changing market structure but still seem to remain persistent against small market disturbances or noisy signals. The *SPACE* method gives similarly appealing results as the *graphical lasso*, therefore we expect that these estimation methods might become more pervasive in the financial econometrics literature. We also document the regional clustering patterns in these networks and analyse the changes over time. This analysis helps us to shed some light on how the position of UK's financial institutions vary in the European cluster as the Brexit negotiations proceed and also whether time zone differences between Asian and US markets might influence our results. We also compute and compare network centrality of nodes with different approaches which gives intriguing insights about the structure of financial interconnectedness and highlights the key global players. This can provide additional tools for financial regulatory bodies for identifying systematically important financial institutions[8] which has been a really prominent topic recently. Another exercise that we carry out in this article is to compare the estimated financial interconnectedness networks with empirical cross-holdings among these banks. For the US we have extensive data and we can reach reasonable results, however when we apply the same framework globally, we run into data quality issues and therefore a potential extension of our project could be to analyse these cross-holdings networks on a global scale with appropriate prior data collection and quality check exercises.

Our study also opens up several other "avenues" for future research. We dynamically analyse the interconnectedness networks and estimate them with regularisation, however these regularisation penalty terms do not take the temporal aspect into account, therefore a time-varying graphical lasso approach as in Hallac et al. (2017) might be an interesting addition for our project. Moreover, recent stock market events (e.g. GameStop rally and the subsequent temporary liquidity shortages at Robinhood) highlight the importance of being able to offer almost real-time measures of financial connectivity. Therefore another future research direction could be to work with even more granular data sources to be able to carry out financial network estimation for a large set of market participants *intraday* as well. Another potential project extension where we anticipate numerous practical applications is using the discussed network estimation methods for *scenario analysis* in general and for stress tests in particular. The outcomes of these studies with the different methods might lead to a superior "ensemble" for inferring what might happen in the considered scenarios.

[8]Also called SIFIs as an abbreviation

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A Appendix

A.1 Sensitivity analysis results

On Figure 14 it is straightforward to see that most network estimation methods are rather insensitive to changing the window size for estimation.

A.2 Small network analysis

On Figure 15 the interconnectedness networks of 10 large financial institutions from the US are shown with a *Chord diagram visualisation*.

On Figure 16 it is evident to see that the centrality rank of most financial institutions is robust across different centrality measures and network estimation methods, but there are a few large changes as well (e.g. *Goldman Sachs*).

On Figure 17 the interconnectedness networks of 10 large financial institutions from the US are shown with a *Chord diagram visualisation*. This is the same analysis as before, just for a different date.

On Figure 18 it is evident to see that the centrality rank of most financial institutions is robust across different centrality measures and network estimation methods, but there are a few large changes as well (e.g. *Goldman Sachs*). This is the same analysis as before, just for a different date.

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	-0.0818	-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
Banco Bradesco	BBDC4.SA	-0.0202	-0.3331	-0.4434	-0.3642	0.0522
Deutsche Bank	DBK.DE	0.0127	-0.1556	0.2024	0.1704	0.0783
Commerzbank	CBK.DE	-0.1009	-0.3234	-0.19	-0.0768	0.1964
Bank of Ireland	BIRG.IR	0.0098	-0.4795	-0.5433	-0.4193	0.3995
State Bank of India	SBIN.NS	0.022	-0.3132	-0.3829	-0.2122	0.3374
Bank of Baroda	BANKBARODA.NS	-0.1956	-0.4411	-0.3424	-0.2659	0.2213
DBS Group Holdings	D05.SI	0.0471	-0.1809	-0.0952	-0.1067	0.0689
United Overseas Bank	U11.SI	-0.0889	-0.2097	-0.0275	0.0595	0.1369
Erste Group Bank	EBS.VI	0.0972	-0.3255	-0.3085	-0.3846	-0.012
Danske Bank	DANSKE.CO	-0.0223	0.01	-0.1735	-0.3712	-0.0147
ING Groep	INGA.AS	0.0715	-0.4088	-0.2971	-0.1038	0.1879
DNB ASA	DNB.OL	0.0752	-0.1377	-0.0559	-0.0921	0.1125
Sberbank Rossii	SBER.ME	0.0788	-0.0596	0.0901	0.1938	0.2505
Turkiye Is Bankasi	ISCTR.IS	0.1868	-0.1314	-0.0708	-0.0583	0.2632
Standard Bank Group	SBK.JO	-0.1248	-0.3647	-0.2288	-0.143	0.0616

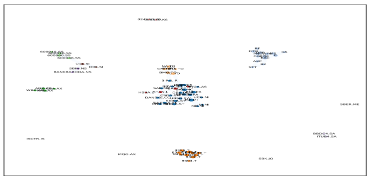
Table A.2: U.S. Financial institutions, tickers and quarterly median of returns between Q4 2019 and Q4 2020.

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
Itau Unibanco Holding	ITUB4.SA	-0.0552	-0.3001	-0.4266	-0.0956	0.0331
Banco Bradesco	BBDC4.SA	-0.0753	-0.1266	-0.4373	-0.1003	0.0234
Deutsche Bank	DBK.DE	0.0748	-0.104	-0.0339	-0.0539	-0.1891
Commerzbank	CBK.DE	-0.0307	-0.0526	-0.0153	-0.0596	-0.0133
Bank of Ireland	BIRG.IR	-0.156	-0.1019	-0.4094	-0.7125	0.007
State Bank of India	SBIN.NS	0.2382	0.0893	-0.1997	0.0261	0.3476
Bank of Baroda	BANKBARODA.NS	-0.1021	-0.0513	0.0314	0.1003	0.1529
DBS Group Holdings	D05.SI	0.116	0.0192	-0.0785	-0.2504	0.0563
United Overseas Bank	U11.SI	0.0581	-0.005	-0.0025	0	0.0518
Erste Group Bank	EBS.VI	0.2067	0.1004	-0.0297	-0.3551	-0.1812
Danske Bank	DANSKE.CO	-0.0107	0.0943	0.1596	-0.1865	-0.0945
ING Groep	INGA.AS	-0.029	-0.0616	-0.0037	0.0322	0.03
DNB ASA	DNB.OL	0.0492	0.0299	0.0587	0.018	0.0375
Sberbank Rossii	SBER.ME	0.0709	0.0709	0.0709	0.0709	0.0709
Turkiye Is Bankasi	ISCTR.IS	0	0	0.0221	0.0441	0.0441
Standard Bank Group	SBK.JO	-0.2853	-0.0822	-0.0822	-0.4509	-0.2225

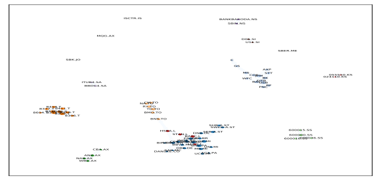
Table A.3: U.S. Financial institutions, tickers and quarterly standard deviation of returns between Q4 2019 and Q4 2020.

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
Itau Unibanco Holding	ITUB4.SA	1.4809	2.6504	3.4153	3.5516	2.2977
Banco Bradesco	BBDC4.SA	1.5242	3.4839	4.1642	4.2688	2.4952
Deutsche Bank	DBK.DE	2.1798	3.4137	4.3012	4.1441	2.186
Commerzbank	CBK.DE	2.2619	3.7721	4.5819	4.6367	3.2783
Bank of Ireland	BIRG.IR	2.8803	3.9727	5.2748	5.51	3.8821
State Bank of India	SBIN.NS	2.3319	3.5162	3.6516	3.6673	2.3679
Bank of Baroda	BANKBARODA.NS	2.3399	3.3423	3.664	3.707	2.764
DBS Group Holdings	D05.SI	0.8366	1.7095	2.1014	2.1827	1.4027
United Overseas Bank	U11.SI	1.1071	1.7194	2.1608	2.1926	1.2002
Erste Group Bank	EBS.VI	1.3946	2.8573	3.8419	3.9483	2.5368
Danske Bank	DANSKE.CO	1.756	2.6004	3.2132	3.201	1.9562
ING Groep	INGA.AS	1.5001	3.5277	4.3157	4.462	2.9048
DNB ASA	DNB.OL	1.5783	2.6945	3.1895	3.2784	2.0004
Sberbank Rossii	SBER.ME	1.0405	2.1941	2.5213	2.6445	1.6681
Turkiye Is Bankasi	ISCTR.IS	1.9304	2.182	2.0828	2.0483	2.1881
Standard Bank Group	SBK.JO	1.5372	2.9354	3.7273	3.9684	2.7175

Figure 14: Financial networks estimated with different window size

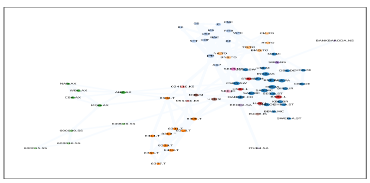


(a) Window size: 150

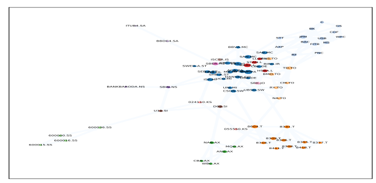


(b) Window size: 100

Neighborhood Selection method

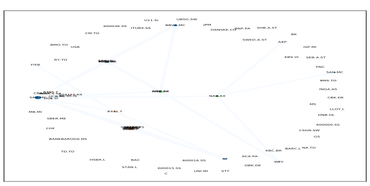


(c) Window size: 150

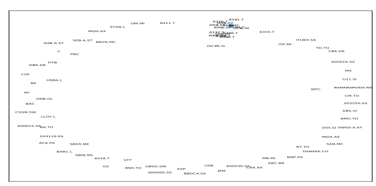


(d) Window size: 100

SPACE method

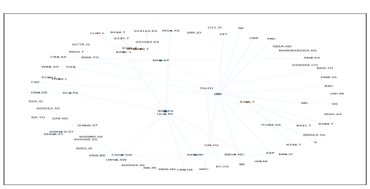


(e) Window size: 150

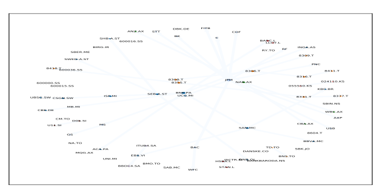


(f) Window size: 100

DY method



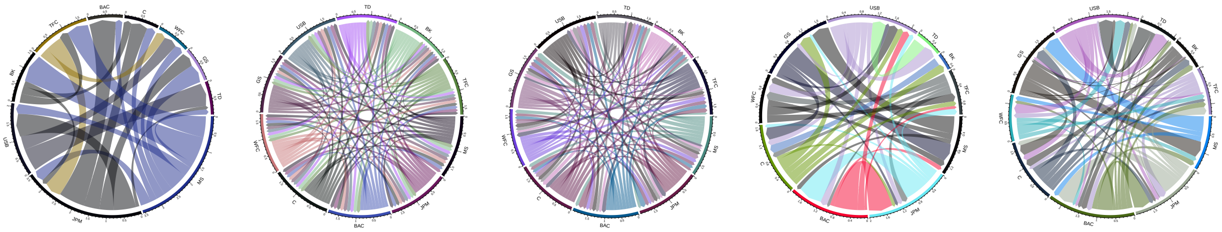
(g) Window size: 150



(h) Window size: 100

DAG method

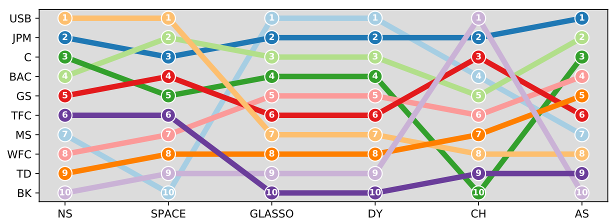
Figure 15: Financial networks estimated with different models



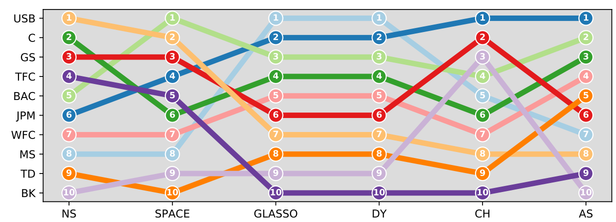
(a) DAG (b) DY (c) GLASSO (d) NS (e) SPACE

Data at 2020-03-16

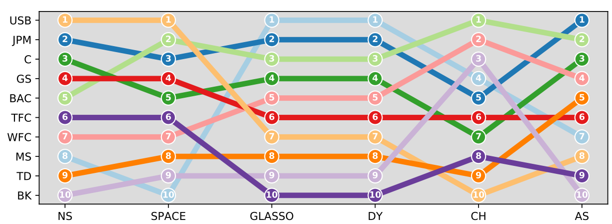
Figure 16: Ranking of financial institutions according to varying network estimation methods and centrality measure



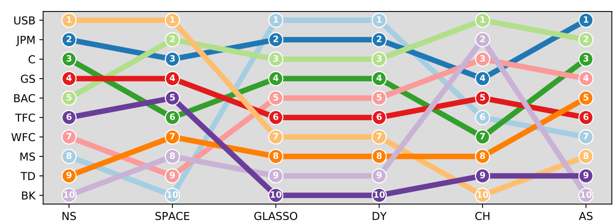
(a) Degree centrality



(b) Betweenness centrality



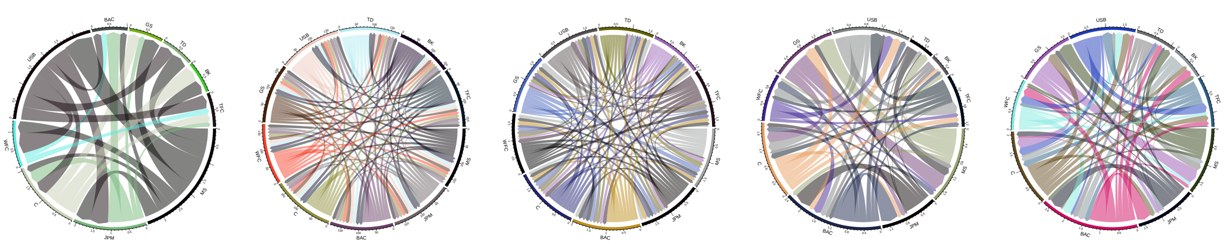
(c) Closeness centrality



(d) Eigenvector centrality

Data at 2020-03-16

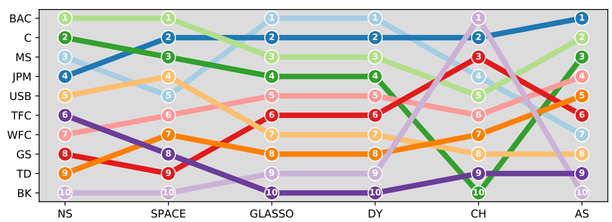
Figure 17: Financial networks estimated with different models



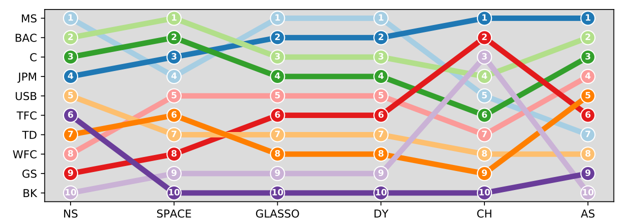
(a) DAG (b) DY (c) GLASSO (d) NS (e) SPACE

Data at 2020-06-30

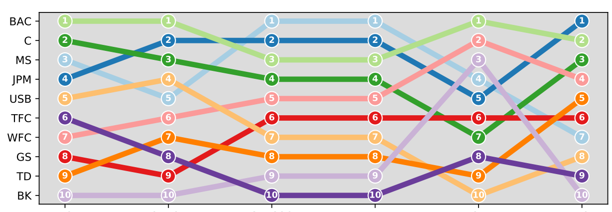
Figure 18: Ranking of financial institutions according to varying network estimation methods and centrality measure



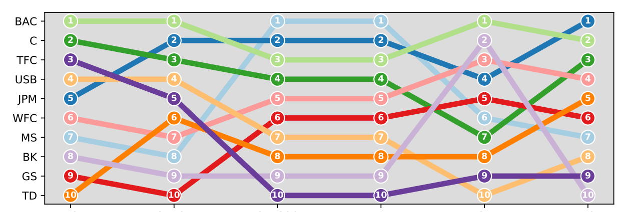
(a) Degree centrality



(b) Betweenness centrality



(c) Closeness centrality



(d) Eigenvector centrality

Data at 2020-06-30