Dynamic network analysis of North American financial institutions

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Abstract

We propose a state-space model to estimate the dynamic network structures among 67 financial institutions selected from $STOXX$ 600 North America in the period January 2005 to May 2020. We measure the network strength and find that the spillover effect increases significantly during the period of the latest two crises: the 2008 financial crisis and the coronavirus pandemic. Using weekly updates of the weight matrix, we detect four time-varying communities using the Louvain approach. Three communities mostly include companies of the financial supersectors (banks, financial services and insurance), while the remaining one includes mostly Canadian companies. Furthermore, we notice that communities centralities are peaking during 2008 financial crisis, while during the COVID-19 period lower values are estimated.

1 Introduction

Recent crises have shown that knowing the financial market network structure is of paramount importance to understand potential spillover effects across the system as well as the role of single institutions. Furthermore, detecting the potential presence of communities can provide more insight on the channels of propagations of shocks, and on which target groups to focus on to prevent potential damages to the entire system.

So far, a variety of methods have been proposed for estimating financial networks. One group of methods construct the network by measuring the bilateral risk exposures, e.g., Granger-causality (Billio et al., 2012), CoVaR (Adrian and Brunnermeier, 2011) or copula (Li et al., 2018). Another popular group of methods focuses on matrices related to the underlying network, e.g., the inverse covariance (Friedman et al., 2008; Torri et al., 2018) or weight matrix in a SAR model (Meen, 1996; Bhattacharjee and Jensen-Butler, 2013). Given that financial networks are inherently dynamic, when considering time-varying networks, the most common way is to adopt a moving-window approach. If the network relationships are assumed to be cross-lagged, one could also apply time-varying VAR (Kimura et al., 2003).

A different strand of the financial literature shows that big public health events might cause strain on the financial market (Gong et al., 2020; Leoni, 2013). In particular, the potential effects of COVID-19 on stock markets are very much under scrutiny, as the pandemic could have consequences on the entire financial system (Goodell, 2020). Several recent papers investigate the impact of the pandemic on the US stock market volatility (Albulescu, 2020; Baker et al., 2020), but to our knowledge, only a handful of papers examine the impact from a systemic risk angle. One such example is Rizwan et al. (2020), the authors study the stock market in eight countries which are affected the most by the coronavirus, and shows that the systemic risk increases significantly in the pandemic period.

In this paper, we make a step forward and propose the use of a state-space model to estimate the weekly evolution of the network across financial institutions listed in the STOXX 600 North America index. Further, we detect communities and study network strength and centrality during crisis periods. Empirical results show that the network strength has a steep upraise during both the 2008 financial crisis and the COVID-19 pandemic crisis. In the meanwhile, the network centralities of the identified groups peak in 2008 and decrease afterwards.

2 Model Description

In a spatial autoregressive model (SAR), the weight matrix captures the relationship among subjects or different entities. If the number of subjects is D, the simplest form of SAR is,

$$y_t = \rho \tilde{W} y_t + \epsilon_t, \epsilon_t \sim N(0, \sigma_\epsilon^2 I_D) \tag{1}$$

where y_t is the vector containing the log returns of D companies at week t, and $\tilde{W}$ is the $D \times D$ weight matrix, representing the relationships among entities. $\tilde{W}$ is usually row-normalized with zero diagonal elements. Depending on the model specification, ρ can be a diagonal matrix with distinct or equal entries (Caporin and Paruolo, 2015). The latter case is here adopted, and the scalar coefficient ρ quantifies the overall network strength.

To obtain a time-varying network structure, we introduce the following state-space model,

$$\begin{cases} y_t = \mathbf{A}_t y_{t-1} + (W_t + W_t^2) y_t + \epsilon_t, & \epsilon_t \sim N(0, \sigma_\epsilon^2 I_D), \\ x_t = x_{t-1} + \eta_t, & \eta_t \sim N(0, \sigma_\eta^2 I_{D_x}). \end{cases} \tag{2}$$

The first equation (the observation equation) includes three elements: the time lag $\mathbf{A}_t y_{t-1}$, the spatial lag $(W_t + W_t^2) y_t$ and a white noise ϵ_t. $\mathbf{A}_t$ is a diagonal matrix capturing the serial dependence, and we define $W_t = \rho_t \tilde{W}_t$. Moreover, $\tilde{W}$ is assumed to be max-row normalized, similarly to Billio et al. (2017), thus allowing to recover ρ_t from the sequence of W_t. We treat the diagonal of $\mathbf{A}_t$ and the off-diagonal elements of W_t as hidden states. Thus, the state vector x_t has dimension $D_x = D^2$. The second equation (the state equation) in (2) allows x_t to evolve stochastically.

Different from the conventional SAR, whereas the weight matrix is usually pre-specified, W_t in (2) evolves according to a multivariate regression scheme, and in order to address the second order of spillover effects, W_t^2 is included. Notice that higher orders (larger than 2) of W_t can be easily included in the model (2), but we find that the current form delivers the best results. The possible reason is that higher orders of the weight matrix introduce limited information, which is largely offset by the extra noise they bring. Considering the observation equation is nonlinear, the ensemble Kalman filter (Evensen, 1994) is applied for the state estimation.

3 Empirical Results

We focus on $D = 67$ financial companies listed in $STOXX$ 600 North America, selected from three supersectors, banks, financial services and insurance; Appendix A lists the companies' ticker symbols. We consider the stock log-returns in the period from January 5, 2001 to May 8, 2020, for a total of $T = 1010$ weekly observations. The first 209 observations (4 years) are used for warm-up, as in high dimension (in our case $D_x = 4489$) the filter needs several steps to converge. Moreover, the observation variance σ_ϵ^2 is calculated from a 26-week moving window, while the state variance σ_η^2 is set differently for $\mathbf{A}_t$ and W_t: the variance of $\mathbf{A}_t$ is 0.1^2 and the variance of W_t is 0.001^2. The initial guess for the states is sampled from a $N(0.01, 0.05^2)$. Empirical results are then reported starting from January 2005. Robustness tests with different starting points over the available data and different window lengths provide qualitatively similar results and are not reported.

Network strength and the COVID-19 crisis

Given the weekly full weight matrices W_t obtained from the model estimation, we first calculate the dynamic network strength ρ_t and plot in Figure 1 (a). The curve shows ρ_t rises steeply during the periods of the 2008 financial crisis and the recent pandemic crisis. The evidence implies that during the pandemic crisis the spillover effect plays a bigger role in the stock price movement. Further, Figure 1 (b) compares the movement of ρ_t with the daily confirmed COVID-19 cases in the US and in the 5 most affected European countries (Italy, France, Germany, Spain and UK).[1] It's clear that the blue line echoes the upraise of the red lines, which confirms the relation between the pandemic and the network strength.

Communities Detection

Louvain algorithm is applied to the weekly weight matrices to identify network partitions. Figure 2 reports the detected communities across the 67 companies (columns), whose names are colored according to their supersectors: blue for banks, red for financial services, black for insurance companies. In each week (row), the companies that belong to the same group have the same color. In total, four stable communities are detected. We notice that, with few exceptions, the detected communities are coherent with the supersectors. Specifically, group 1, 2 and 4 correspond to the supersectors banks, financial services and insurance, respectively. Differently, group 3 (in orange) includes all the Canadian companies.

We further calculate the centrality for each group by averaging the closeness centralities of the group members. Figure 3 compares the centralities of the four detected groups. We see that all groups achieve the highest centrality during the 2008 crisis and diminish slightly during the post-crisis period. In general, the banks group and the financial services group have higher centrality than the insurance group. As for the period of the recent pandemic (in a black box), we observe that the insurances group starts to show a steady upward trend.

[1] The COVID-19 data have been downloaded from the online data repository provided by Johns Hopkins University at https://github.com/CSSEGISandData/COVID-19.

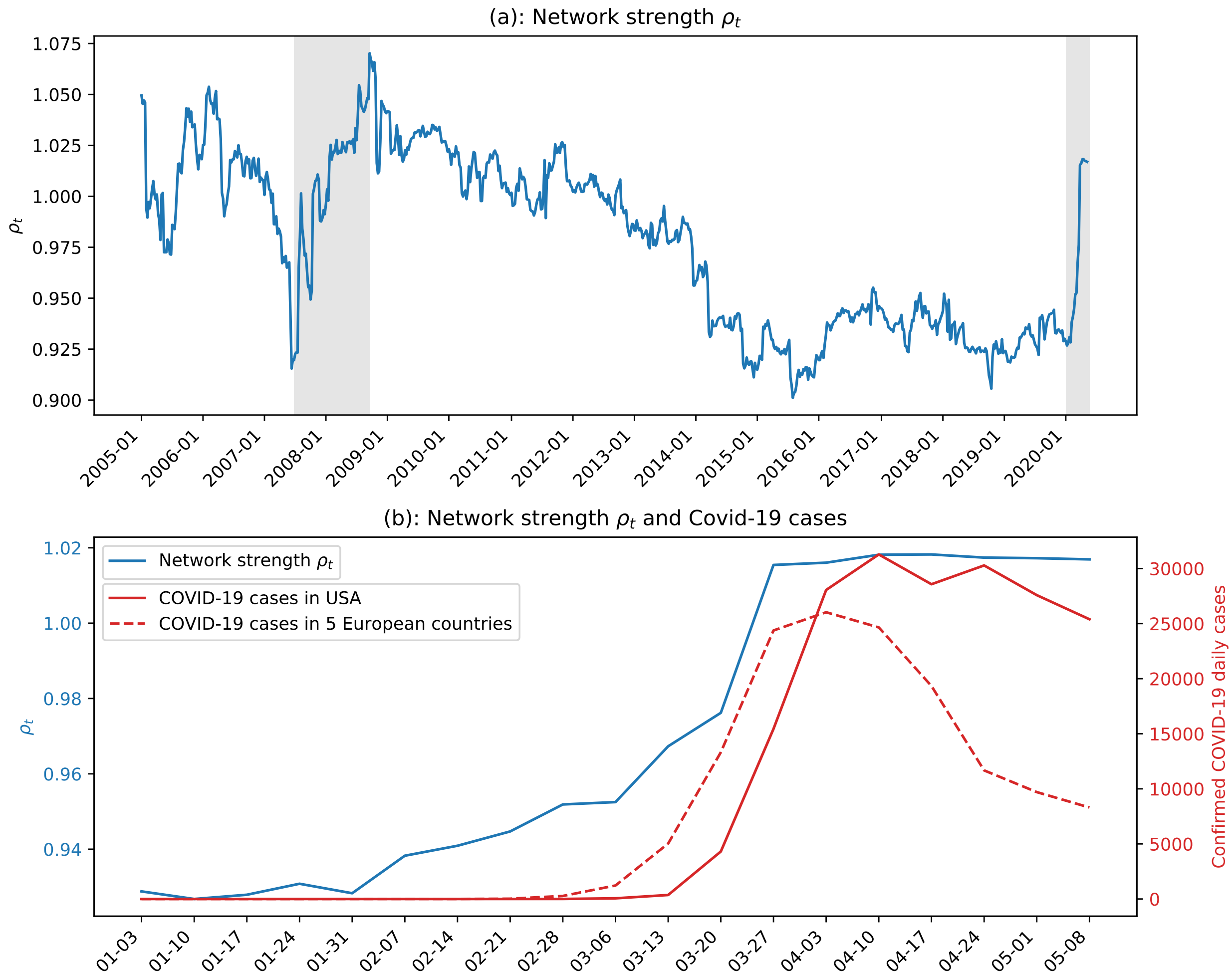

Figure 1: (a) ρ_t, from January 2005 to May 2020. The grey shaded bars indicate the periods of two latest crises: the 2008 financial crisis and the COVID-19 pandemic crisis. (b) ρ_t and confirmed COVID-19 cases since 2020. The red dashed line is the sum of the confirmed daily COVID-19 cases in 5 European counties: Italy, Germany, Spain, France and UK.

A possible explanation is that the insurance companies are expected to deal with much more reimbursements during the post-pandemic period.

4 Conclusion

In this article, we use a state-space model to estimate the dynamic network structures for US financial market. The steep raises of the network strength shows the spillover effect is

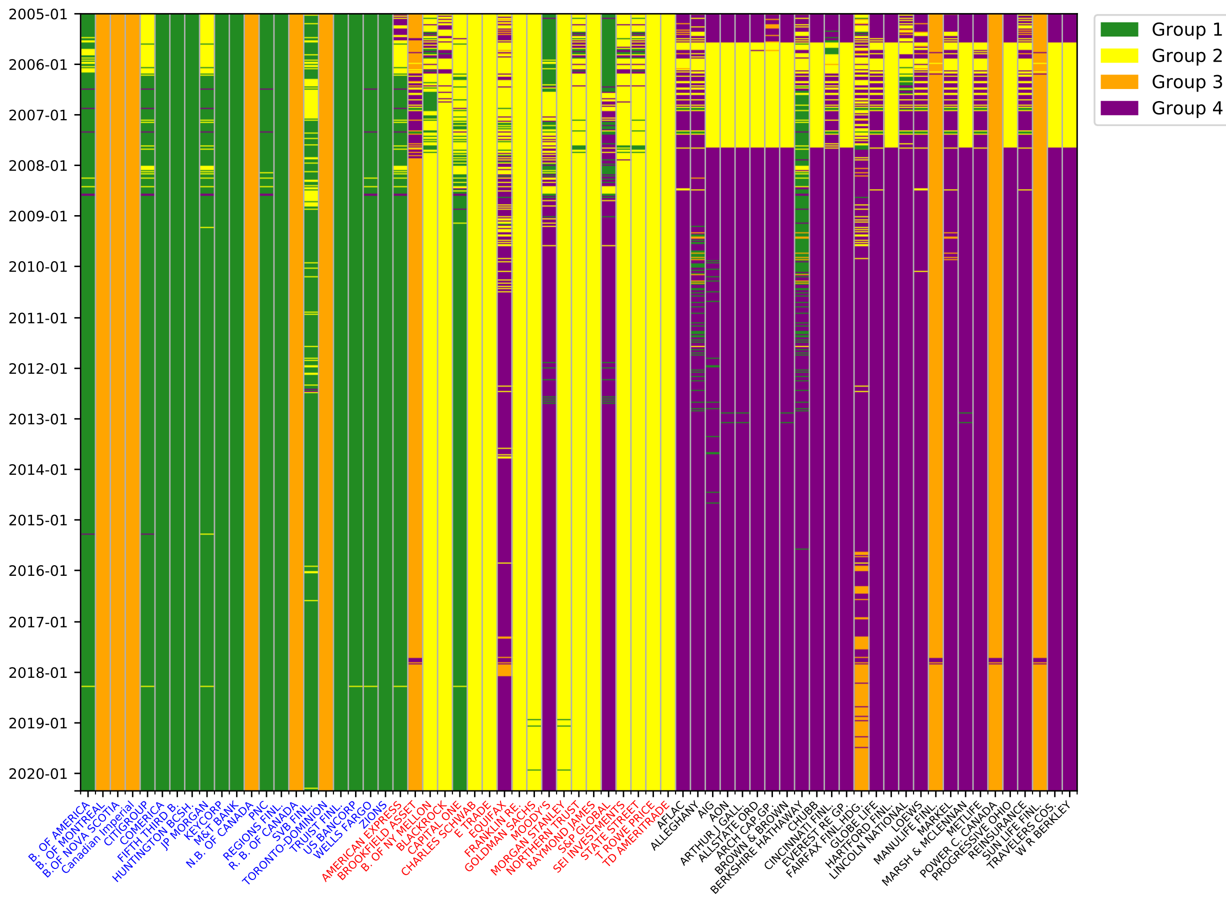

Figure 2: Community detection. Each company corresponds to one column, the color of which indicates the weekly detected groups for this company. The company name at the bottom is colored by supersectors (from STOXX): blue for banks, red for financial services and black for insurance companies.

much higher during both the 2008 crisis and the COVID-19 pandemic. We identify four stable groups and show how their centralities vary across the study period. Our work provides some new evidence showing that the financial network can be subject to change as a consequence of a pandemic crisis.

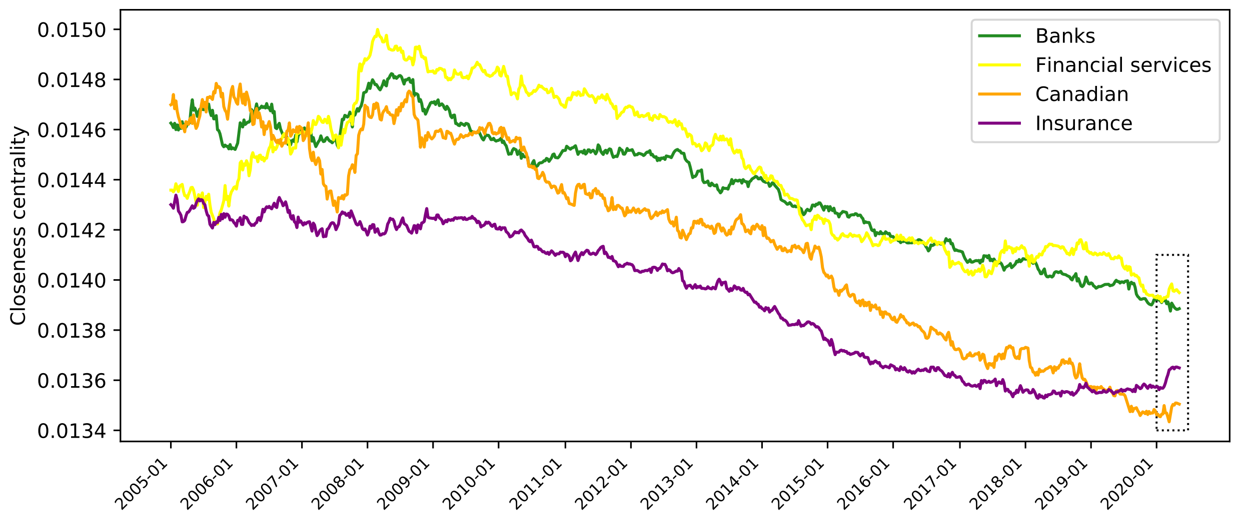

Figure 3: Group centralities, from January 2005 to May 2020. The recent pandemic period is outlined in a black box.

Appendices

A Tickers of 67 financial companies

Supersector	Stock ticker symbol
Banks	BAC, BOM, BNS, CM, C, CMA, FITB, HBAN, JPM, KEY, MTB, NTIOF, PNC, RF, RY, SIVB, TD, TFC, USB, WFC, ZION
Financial Services	AXP, BAM, BK, BLK, COF, SCHW, ETFC, EFX, BEN, GS, MCO, MS, NTRS, RJF, SPGI, SEIC, STT, TROW, AMTD
Insurance	AFL, Y, AIG, AON, AJG, ALL, ACGL, BRO, BRK.B, CB, CINF, RE, FRFHF, GL, HIG, LNC, L, MFC, MKL, MMC, MET, POW, PGR, RGA, SLF, TRV, WRB

References

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

Albulescu, C. T. (2020). COVID-19 and the United States financial markets volatility. *Finance Research Letters*, page 101699.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., and Viratyosin, T. (2020). The unprecedented stock market impact of COVID-19. Technical report, National Bureau of Economic Research.

Bhattacharjee, A. and Jensen-Butler, C. (2013). Estimation of the spatial weights matrix under structural constraints. *Regional Science and Urban Economics*, 43(4):617–634.

Billio, M., Caporin, M., Panzica, R., and Pelizzon, L. (2017). The impact of network connectivity on factor exposures, asset pricing and portfolio diversification. Technical report, Leibniz Institute for Financial Research SAFE, SAFE Working Paper Series n. 166.

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.

Caporin, M. and Paruolo, P. (2015). Proximity-structured multivariate volatility models. *Econometric Reviews*, 34(5):559–593.

Evensen, G. (1994). Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. Technical Report C5.

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

Gong, D., Jiang, T., and Lu, L. (2020). Pandemic and bank Lending: Evidence from the 2009 H1N1 pandemic. *Finance Research Letters*, page 101627.

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, page 101512.

Kimura, T., Kobayashi, H., Muranaga, J., Ugai, H., et al. (2003). The effect of the increase in the monetary base on Japans economy at zero interest rates: An empirical analysis. In *Monetary Policy in a Changing Environment, Bank for International Settlements Conference Series*, volume 19, pages 276–312.

Leoni, P. L. (2013). HIV/AIDS and banking stability in developing countries. *Bulletin of Economic Research*, 65(3):225–237.

Li, W., Hommel, U., and Paterlini, S. (2018). Network topology and systemic risk: Evidence from the Euro Stoxx market. *Finance Research Letters*, 27:105–112.

Meen, G. (1996). Spatial aggregation, spatial dependence and predictability in the UK housing market. *Housing studies*, 11(3):345–372.

Rizwan, M. S., Ahmad, G., and Ashraf, D. (2020). Systemic risk: The impact of COVID-19. *Finance Research Letters*, page 101682.

Torri, G., Giacometti, R., and Paterlini, S. (2018). Robust and sparse banking network estimation. *European Journal of Operational Research*, 270(1):51–65.