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Global Realignment in Financial Market Dynamics: Evidence from ETF Networks

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Abstract

The centrality of the United States in the global financial system is taken for granted, but its response to recent political and epidemiological events has suggested that China now holds a comparable position. Using minute-by-minute data from 2012 to 2020 on the financial performance of twelve country-specific exchange-traded funds, we construct daily snapshots of the global financial network and analyze them for the centrality and connectedness of each country in our sample. We find evidence that the U.S. was central to the global financial system into 2018, but that the U.S.-China trade war of 2018–2019 diminished its centrality, and the Covid-19 outbreak of 2019–2020 increased the centrality of China. These indicators may be the first signals that the global financial system is moving from a unipolar to a bipolar world.

Keywords: Network theory; Centrality; High Frequency Data; ETFs; Financial Crises; Covid-19; International Finance;

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1. Introduction

The United States is usually considered the center of the world's financial system. This was made dramatically clear during the financial crisis of 2008–2009, which originated in the U.S., transmitting itself to other countries from there. Yet the centrality of the U.S. in the global financial system is not limited to disruptive financial contagion. Returns to U.S. stocks have led those of other advanced economies for the last forty years, with shocks to returns in the U.S. predicting lagged returns in other countries, but not vice versa (Rapach, Strauss, and Zhou, 2013; Cieslak, Morse, and Vissing-Jorgensen, 2019).

Very recent financial data, however, indicates that the world has started to move from a unipolar to a bipolar system. Specific political and epidemiological forces, namely, the U.S.–China trade wars and the outbreak of Covid-19, have coupled China and the U.S. together in the global financial system (Acharya, Jiang, Richmond, and von Thadden, 2020; Antràs, Redding, and Rossi-Hansberg, 2020; Ossa, 2014; McKibbin and Fernando, 2020). These forces have made the international market system measurably less centered on the U.S.

High-frequency data is able to capture previously unrecognized patterns in the real-time dynamics of the market. It also makes it possible to calculate the origin and spread of informational and financial contagion from an individual financial market or specific financial instruments to the financial system as a whole (Gao, Han, Li, and Zhou, 2018; Hasbrouck, 1995). Using high-frequency intraday data, we can thus determine the network structure of the global financial system at any given moment, including the relative centrality of countries within it, and visualize the system's response to "innovations" such as trade wars and Covid-19. This network approach has been applied to economic and sociological analysis (Battiston, Farmer, Flache, Garlaschelli, Haldane, Heesterbeek, Hommes, Jaeger, May, and Scheffer, 2016; Diebold and Yılmaz, 2014; Jackson, 2014; LeBaron and Tesfatsion, 2008; Mantegna and Stanley, 1995).

We focus our analysis on twelve country-specific exchange-traded funds (ETFs) for

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Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, China, and the U.S. Our minute-by-minute high-frequency data comes from the New York Stock Exchange's Trade and Quote dataset from January 3, 2012 to May 29, 2020. Ernst (2020) concludes that ETFs can provide single-stock price discovery. Moreover, since all ETFs used in the analysis are traded on US exchanges, there is no need for timing synchronization which is imperative when comparing individual country stocks or indices.

The first attempt to estimate financial interconnectedness by examining the lead-lag relationship (Granger causality) between stock returns was proposed by (Billio, Getmansky, Lo, and Pelizzon, 2012); however, the authors used only lower frequency (i.e., monthly) returns in their analysis. Other proposed methods include using a multiplex financial network (Battiston et al., 2016), an agent-based network (LeBaron and Tesfatsion, 2008), production-based network (Gofman, Segal, and Wu, Forthcoming), an approach combining variance-decomposition and network topology theories (Diebold and Yılmaz, 2014), and a network based on intersectoral input-output linkages (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012).

We use three methods to quantify the contagion between international markets: (i) vector autoregression (VAR) estimation; (ii) the machine-learning technique of least absolute shrinkage and selection operator (LASSO) estimation (Gu, Kelly, and Xiu, 2020); and (iii) variance decomposition (Diebold and Yılmaz (2014)). Each method allows us to construct a mathematical snapshot of the connections between the country-specific ETFs for each day in our dataset. From these snapshots, we are able to compute three network measures over time. Specifically we compute degree centrality from VAR estimation, Katz centrality from LASSO estimation, and net total directional connectedness from variance decomposition estimation.

All three methods depict a pattern of declining centrality for the U.S. and an increase in the centrality of China at the start of the trade war between the two countries, begin-

ning with the U.S. implementation of global safeguard tariffs on February 7, 2018, and a memorandum to impose tariffs on Chinese products on March 22, 2018 (the initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018). We also capture a similar pattern leading up to the World Health Organization's announcement of the global Covid-19 pandemic on March 11, 2020. Our high-frequency financial data shows that China became central well *before* the announcement of tariffs or the pandemic.

The timing of the rise of the centrality of China and the outbreak of Covid-19 leads to the natural question of the relationship between network measures and the spread of the virus. We analyze the relationship between network measures (centrality and net total directional connectedness) to the daily increase in the number of Covid-19 cases in each individual country as reported by the World Health Organization (WHO-Report, 2020) by using a pooled regression approach. We find that there is a significant relationship between the number of new Covid-19 cases and our measures of centrality and net total directional connectedness. We therefore conclude that financial markets incorporate information from the epidemiological data.

When instead of using high-frequency ETF returns, we use daily returns data for stock indices and ETFs, no clear patterns emerge among country indexes even after accounting for timing synchronization. High-frequency data is forward-looking in capturing the rise of centrality of China. We show that since 2018, China has held a comparable position to the U.S. suggesting that the world has started to move from a unipolar to bipolar system.

The paper is organized as follows. Section 2 describes data and summary statistics. Section 3 describes methodology for contagion models and network measures. Section 4 provides results for these network measures. Section 5 provides results for Covid-19 analysis. Section 6 provides additional analysis and robustness results and we conclude in Section 7.

2. Data and Summary statistics

2.1. Exchange Traded Funds (ETF) List

We focus on 12 country ETFs listed in Table 1. These countries encompass the 11 industrial countries examined in Rapach et al. (2013) and iShares MSCI China ETF. The iShares country ETFs, managed by BlackRock, have exposure to large and mid-sized companies in each country available to international investors, and thus are representative of each country's economy.[1] These companies should be available to international investors and are included in corresponding country ETFs. We choose SPDR S&P 500 ETF Trust as the US ETF. This ETF follows the S&P 500 stock market index. Table 1 presents the ETF list.

Table 1: ETF List

The list of 12 country ETFs. This list comes from 11 industrial countries in Rapach et al. (2013) and iShares MSCI China ETF. The iShares MSCI ETF for each country exhibits exposure to large and mid-sized companies in their corresponding countries. These companies should be available to international investors for investment.

	Name	Ticker	Country	Inception Date
1	iShares MSCI Australia ETF	EWA	Australia	March 12, 1996
2	iShares MSCI Canada ETF	EWC	Canada	March 12, 1996
3	iShares MSCI France ETF	EWQ	France	March 12, 1996
4	iShares MSCI Germany ETF	EWG	Germany	March 12, 1996
5	iShares MSCI Italy ETF	EWI	Italy	March 12, 1996
6	iShares MSCI Japan ETF	EWJ	Japan	March 12, 1996
7	iShares MSCI Netherlands ETF	EWN	Netherlands	March 12, 1996
8	iShares MSCI Sweden ETF	EWD	Sweden	March 12, 1996
9	iShares MSCI Switzerland ETF	EWL	Switzerland	March 12, 1996
10	iShares MSCI United Kingdom ETF	EWU	United Kingdom	March 12, 1996
11	iShares MSCI China ETF	MCHI	China	March 29, 2011
12	SPDR S&P 500 ETF Trust	SPDR	USA	January 22, 1993

2.2. Minute-by-minute returns

Our high frequency data comes from the TAQ (Trade and Quote Database) dataset from January 3, 2012 to May 29, 2020. We choose January 2012 as the start date, since this is the earliest year for which data for all ETFs are available. The earliest date that all the ETF data is available is March 29, 2011, the inception date of the China ETF (MCHI).

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[1]For example, the iShares MSCI China ETF on May 19 2020 has 17.73% invested in Alibaba Group, 14.95% in Tencent Holdings, and 3.62% in China Construction Bank Corp.

The data is filtered following the steps in Holden and Jacobsen (2014). We remove quotes with abnormal quote conditions (mode value in TAQ equal to 4, 7, 9, 11, 13, 14, 15, 19, 20, 27, 28), cross quotes on the same exchange (cross quotes are quotes from the same exchange that are both positive and the bid is higher than the ask), one-sided bid and ask quotes (for one-sided bid quotes, where the bid is positive and the ask is zero, we set the ask to an extreme value so it does not enter the NBO; for one-sided ask quotes, where the ask is positive and the bid is zero, we do not apply any adjustment), quotes with abnormally large spreads (positive quotes with spreads higher than $5) and withdrawn quotes (when price or depth fields are less than zero or equal to '.', we set the quotes equal to extreme values, e.g. $1 million).

We compute and assign the average best bid-ask quote midpoint in each minute as the quote price of each minute. To avoid distortions in prices, we drop the first and last minute of each trading day in our sample. As a result, every day our minute-by-minute prices are observed from 9:31 A.M. to 3:59 P.M. leading to 389 daily price observations per ETF. For missing observations, we replace the missing return for any ETF in each minute by the average return in the cross-section in that minute. Our ETFs are traded in the United States market and are traded in the same time zone. Therefore, no time adjustment is needed for our VAR and LASSO lead-lag estimations.

Descriptive statistics for minute-by-minute returns (in basis points) for all country ETFs are reported in Table 2.

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Table 2: Descriptive statistics of ETF minute-by-minute returns

Summary statistics for the minute-by-minute returns from mid-point prices for each country-specific ETF. The ETF list is reported in Table 1. The minute-by-minute returns are in basis points. The sample is from January 3, 2012 to May 29, 2020.

Num.	Country	Mean	Std	Skewness	Kurtosis	Min	Max
1	Australia	0.014	3.236	0.221	24.932	-71.497	87.575
2	Canada	0.006	3.424	0.587	48.500	-133.674	181.037
3	France	0.014	3.352	0.100	20.578	-82.465	80.865
4	Germany	0.013	3.354	0.058	20.945	-78.889	77.496
5	Italy	0.007	3.943	-0.012	19.636	-98.427	107.738
6	Japan	0.013	2.707	-0.012	23.959	-93.233	63.528
7	Netherlands	0.011	3.129	0.213	40.005	-128.144	119.807
8	Sweden	0.014	3.302	0.200	25.764	-90.871	92.334
9	Switzerland	0.013	2.634	0.125	32.108	-89.974	87.040
10	United Kingdom	0.011	2.997	0.097	18.838	-60.390	66.93
11	China	0.008	3.366	0.227	17.926	-64.297	90.382
12	USA	0.010	3.320	0.878	74.060	-81.782	226.983

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3. Contagion models and network measures

We use three methods to quantify the contagion between international markets: (i) vector autoregression (VAR) estimation; (ii) the machine-learning technique of least absolute shrinkage and selection operator (LASSO) estimation; and (iii) variance decomposition. Each method allows us to construct a mathematical snapshot of the connections between the country-specific ETFs for each day in our dataset. From these snapshots, we are able to compute three network measures over time. Specifically we compute degree centrality from VAR estimation, Katz centrality from LASSO estimation, and net total directional connectedness from variance decomposition estimation. This section describes in detail all three methods and construction of three network measures.

3.1. Vector Autoregression (VAR) Estimation

Using the standard VAR method, we consider the following basic linear data-generating process for the market returns for each country ETF:

$$r_{i,t} = a_i + \sum_{j=1}^{N} b_{i,j} r_{j,t-1} + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return for country i at time t, and $\epsilon_{i,t}$ is the noise term with $E[\epsilon_{i,t}] = 0$ and $Var[\epsilon_{i,t}] = \sigma_\epsilon^2$. We use the Akaike information criterion (AIC) with one-day minute-by-minute returns to check for the minimum number of lags in the VAR model, finding that one lag gives the lowest AIC value.

We estimate the above VAR(1) model for each country ETF in a rolling daily window to document any lead-lags in our data. This procedure generates a 12×12 set of coefficient estimates of $b_{i,j}$. Next, we build the adjacency matrix, B, using these estimated $b_{i,j}$ values. In this adjacency matrix, the element $B_{i,j}$ measures the impact of asset j's lagged return on asset i's.

$$B = \begin{pmatrix} b_{1,1} & b_{1,2} & \cdots & b_{1,N} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{N,1} & b_{N,2} & \cdots & B_{N,N} \end{pmatrix} \quad (2)$$

The matrix B can be interpreted as a directed weighted network between countries, and the magnitude of each element as the strength of the connection. To measure the overall impact of lagged values of country j on other countries, we define the degree centrality of country i as:

$$Degree - centrality_j = \sum_{i=1}^{N} b_{i,j} \quad (3)$$

The higher the degree centrality of a country ETF, the greater its leading position. Although this definition of degree centrality may lead to negative values, our results are qualitatively the same when using squared coefficients.

We also estimate the Katz centrality:

$$Katz - centrality_j = [(I - B')^{-1}.\mathbf{1}]_{j,1} \quad (4)$$

to capture higher-order relations between countries in the lead-lag network, similar to measures of the level of influence of a publication in a citation network.

3.2. LASSO Estimation

Motivated by the empirical fact that only a sparse set of predictors is important at any one time, we use the machine-learning technique of LASSO — a penalized regression algorithm — to estimate the lead-lag network (Chinco, Clark-Joseph, and Ye, 2019). For example, it is very rare that all twelve countries in our data set have commensurate effects on stock returns. Using the data-generating process in Equation (1) and a rolling daily

window to document lead-lags among country ETFs, we apply LASSO to our dataset. LASSO works by formulating the regression as a convex optimization problem with a penalty parameter:

$$arg \min_{a_i, b_{i,j}} \{\frac{1}{T} \sum_{t=2}^{T} (r_{i,t} - a_i - \sum_{j=1}^{N} b_{i,j} r_{j,t-1})^2 + \lambda_i (\sum_{j=1}^{N} |b_{i,j}|)\} \tag{5}$$

where λ_i is the penalty parameter, setting all ordinary least squares coefficients smaller than itself to be zero. We estimate λ_i using 10-fold cross-validation (Hastie, Tibshirani, and Friedman, 2001). Because LASSO is convexified and drops weak coefficients, we can estimate strong connections in a network using far fewer observations than the standard VAR method described earlier. We additionally no longer have the computational roadblock of applying an informational criterion to our data.

3.3. Variance Decomposition Estimation

We use variance decomposition approach to calculate the net total directional connectedness between country ETFs. In variance decomposition, rather than determining the pairwise strength of connection between the performances of country ETFs, the forecast error variance of a given country variable is decomposed into parts that are attributable to other variables (Diebold and Yılmaz (2014)). This approach measures the variation due to shocks from other parts of the overall system, and therefore is also useful in determining the directionality of a network.

Using Equation 1, we estimate $\mathbf{r}_t$ by reinterpreting the error term vector as a shock vector. In operator notation, this becomes:

$$\mathbf{r}_t = \Omega(L)\epsilon_t \tag{6}$$

where $\Omega(L) = (I - BL)^{-1}$, and I is the identity matrix. We can then calculate the forecast error variance decomposition of an innovation shock of one standard deviation

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as follows:

$$\gamma_{kj}^{H} = \frac{\sum_{t=0}^{H-1}(e_{k}^{'}C_{t}e_{j})^{2}}{\sum_{t=0}^{H-1}(e_{k}^{'}\Omega_{t}\Sigma\Omega_{t}^{'}e_{k})} \tag{7}$$

where γ_{kj}^{H} is the variance decomposition component of variable k due to shocks in variable j forecast H time steps ahead, and e_{j} is a selection vector in which element j is equal to unity and all other elements are zeros. When the shocks are orthogonal, Σ is automatically equal to Ω_{t}. However, this is typically not the case, and we will need to identify uncorrelated structural shocks. We approach this problem through the generalized variance decomposition (GVD) framework (Koop, Pesaran, and Potter, 1996; Pesaran and Shin, 1998), which is invariant to any ordering effects of the variables in the model. The GVD framework sets $C_{t} = \sigma_{j}^{-1}\Omega_{t}\Sigma$, where σ_{j} is the standard deviation of innovation j.

After estimating γ_{kj}^{H}, we build the variance decomposition network for an H-step forecast as follows (Diebold and Yılmaz, 2014):

$$D_{H} = \begin{pmatrix} \gamma_{11}^{H} & \gamma_{12}^{H} & \cdots & \gamma_{1N}^{H} \\ \gamma_{21}^{H} & \gamma_{22}^{H} & \cdots & \gamma_{2N}^{H} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{N1}^{H} & \gamma_{N2}^{H} & \cdots & \gamma_{NN}^{H} \end{pmatrix} \tag{8}$$

We then can define a measure of total directional connectedness to others as the sum of row elements for each column in D_{H}, and the total directional connectedness from others as the sum of column elements for each row in D_{H} (Diebold and Yılmaz, 2014). The net total directional connectedness is then the difference between the two values, formally defined as:

$$Net - Directional - Connectedness_{H}^{i} = \sum_{k=1,k\neg i}^{N} \gamma_{ki}^{H} - \sum_{j=1,i\neg j}^{N} \gamma_{ij}^{H} \tag{9}$$

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4. Network results

We compute three network measures: degree centrality from VAR estimation, Katz centrality from LASSO estimation, and net total directional connectedness from variance decomposition estimation. The lead-lag VAR and LASSO networks are estimated using minute-by-minute returns in each day. The time series of degree centrality for all 12 countries in our sample is depicted in Figure 1:A, while the time series of the Katz centrality is depicted in Figure 1:B, and the time series of the net total directional connectedness is shown in Figure 1:C. Centrality and net total connectedness values are averaged over 15-day rolling windows. Section 6.4 provides robustness checks using other windows for moving averages and our main results are consistent.[2]

All three methods depict a pattern of declining centrality for the U.S. and an increase in the centrality of China at the start of the trade war between the two countries, beginning with the U.S. implementation of global safeguard tariffs on February 7, 2018, and a memorandum to impose tariffs on Chinese products on March 22, 2018 (the initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018). We also capture a similar pattern leading up to the World Health Organization's announcement of the global Covid-19 pandemic was on March 11, 2020. Our high-frequency financial data shows that China became central well *before* the announcement of tariffs or the pandemic.

To emphasize this pattern, Figure 2 depicts the maximum values of our three network measures over time. When applied to our high-frequency data, all three methods again show the same pattern of Chinese centrality before major events. We observe that at the beginning of our sample, the U.S. was the center of the network in terms of information spillovers. Only in the last part of our sample did China become the central country (Figure 2:D). The three color-coded directed networks depict the one-day snapshot of the lead-lag network from the sparse LASSO estimation. The nodes in the networks represent

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[2]In Appendix, we calculate degree centrality from LASSO estimation of the lead-lag relationships between country-specific ETFs and Katz centrality from VAR estimation of the lead-lag relationships between country-specific ETFs. The results are consistent with our main results.

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each country ETF and the edges depict the lead-lag relationship between the countries. The larger are the nodes, the higher is their degree centrality.

We then further zoom in on the time slightly before and after the WHO Announcement of the Covid-19 pandemic: October 2019 through the end of our sample, May 2020. We calculate and depict the performance of country index returns during this period for non-European countries (Figure 3:A) and European countries (Figure 3:B). The markets have not reacted to initial lockdown in Hubei, China (January 23, 2020) or first Covid-19 cases in Europe (January 17, 2020), however, right after first lockdown measures in Italy (February 21, 2020) all international stock markets in our sample started to drop. The drop was especially pronounced around the first lockdown measures in the U.S (March 15, 2020) (Figure 3:A and 3:B). During this period we find that all international stock markets in our sample dropped at the same time with no identifiable leader or follower. Figure 3:C depicts Katz centrality measure from LASSO estimation procedure using minute-by-minute country ETF returns data from October 2019 to May 2020 for all countries in our sample. During this time period we observe an increase in centrality of China, peaking at the time of the WHO Announcement of Covid-19 pandemic (March 11, 2020). The network centrality highlights the relevance of China in providing information to the rest of the financial system (Figure 3:C). China is becoming the originating point for the spread of information to the rest of the world. It is important to emphasize that we show that return analysis is not adequate to capture this effect, and network analysis is essential.
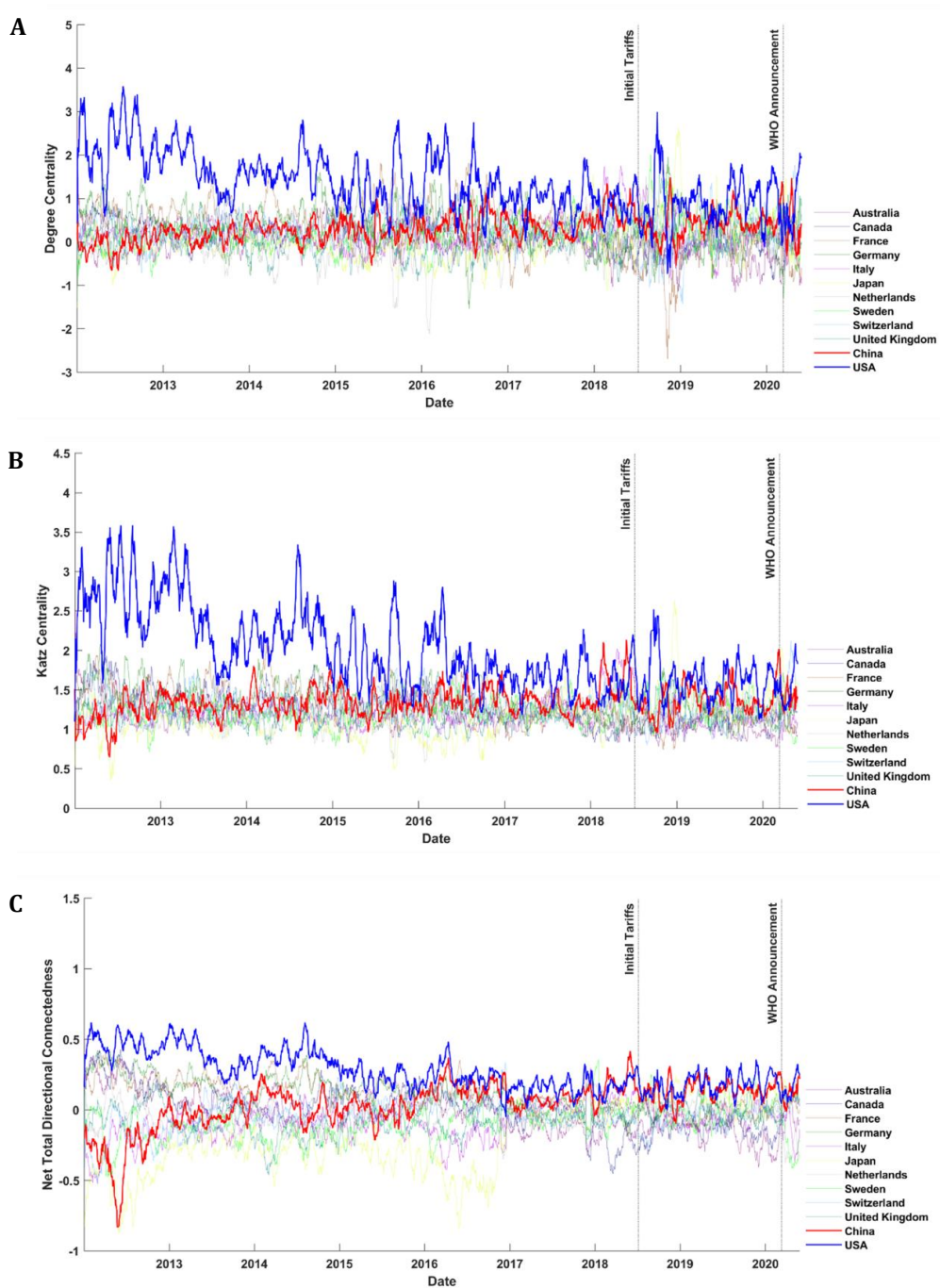
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Figure. 1. Time series of network measures through time

This figure presents the (A) degree centrality from VAR estimation; (B) Katz centrality from LASSO estimation; and (C) net total directional connectedness from variance decomposition estimation. The LASSO and VAR networks are estimated using minute-by-minute returns each day and the corresponding centrality and net directional connectedness values are averaged over 15-day intervals. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of the Covid-19 pandemic occurred on March 11, 2020.

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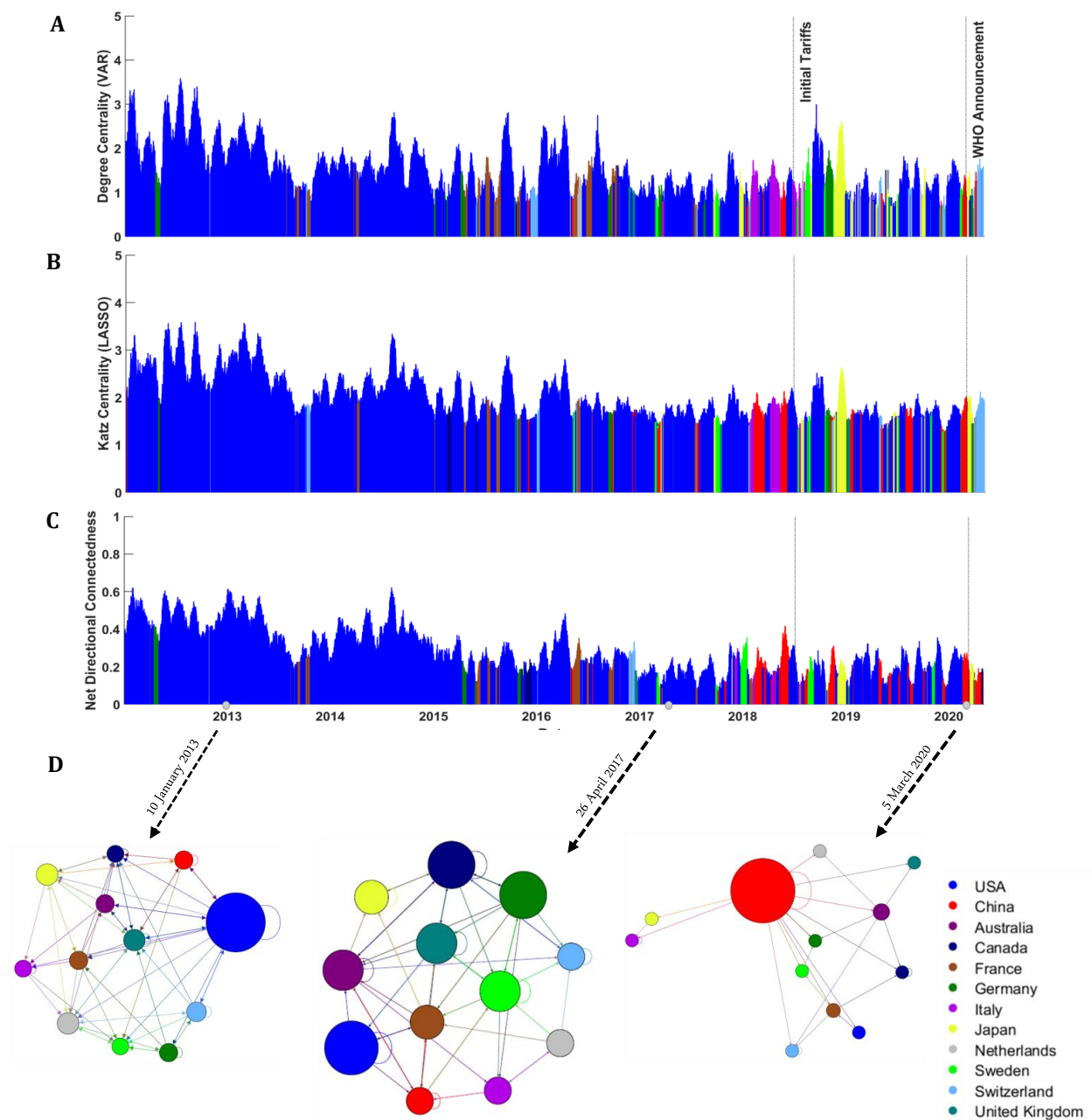
Figure. 2. Maximum country centralities and net total directional connectedness through time

Time series of maximum values of network measures through time: (A) Degree centrality using VAR estimation; (B) Katz centrality using LASSO estimation; and (C) Net total directional connectedness using variance decomposition. For each point in time, only the maximum value and corresponding country colour are depicted. The LASSO and VAR networks are estimated using minute-by-minute returns each day and the corresponding centrality and net directional connectedness values are averaged over 15-day intervals. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 as a pandemic happened on March 11, 2020. (D) The three color-coded directed networks depict the one-day snapshot of the lead-lag network from the sparse LASSO estimation. The nodes in the networks represent each country ETF and the edges depict the lead-lag relationship between the countries. The larger are the nodes, the higher is their degree centrality.
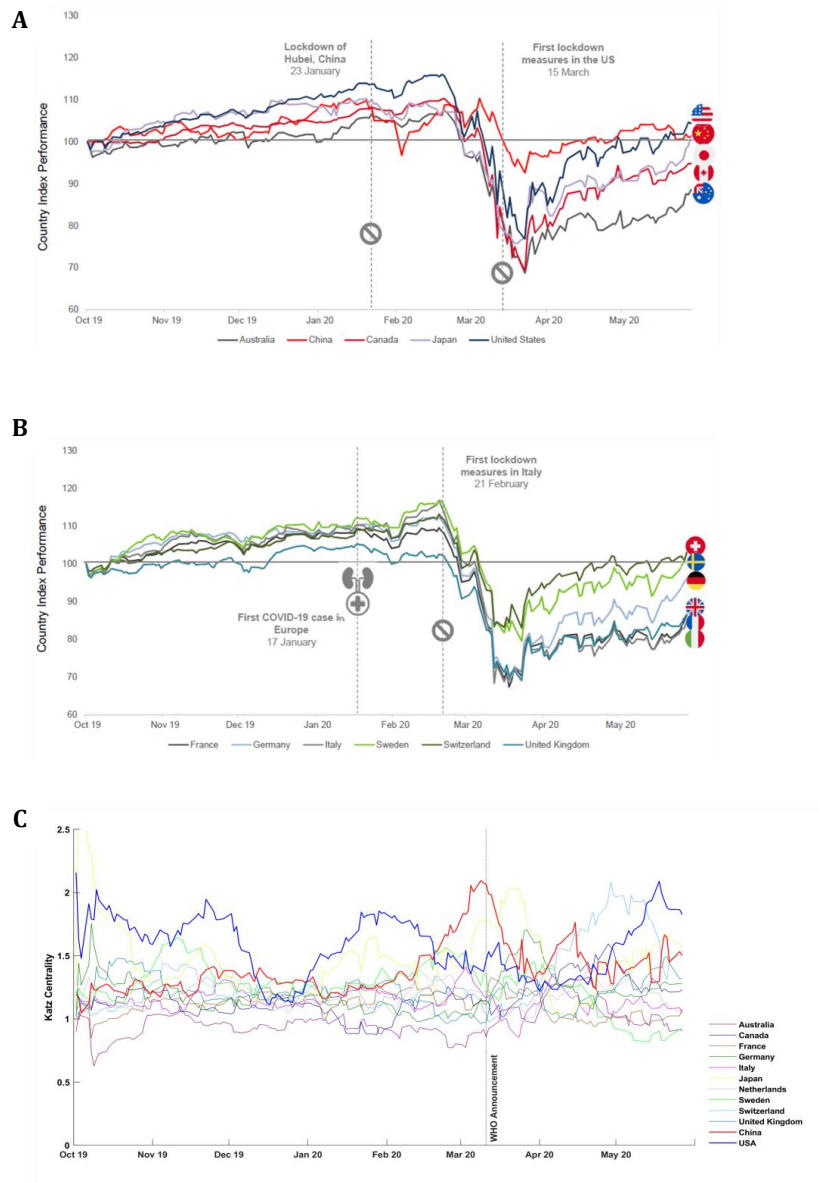
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Figure. 3. Performance of country indexes and Katz centrality measure
(A) Performance of non-European indexes from October 2019 to May 2020 using daily country index returns, (B) Performance of European indexes from October 2019 to May 2020 using daily country index returns, and (C) Katz centrality measure from LASSO estimation procedure using minute-by-minute country ETF data from October 2019 to May 2020.

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5. Covid-19 Analysis

The transmission dynamics of Covid-19 and their implications for hospital capacity, economic shutdowns, and global food security have been studied in several papers. This literature has grown impressively during the last six months (see Brodeur, Gray, Islam, and Bhuiyan (2020) for a broad overview). Here we posit a different question and ask whether the spread of Covid-19 is driving network measures. Specifically, we analyze whether there is any correlation between our calculated measures of centrality and connectedness and the past daily increase in the number of Covid-19 cases in each individual country. Each country enters the sample at the time of the first day of reported cases, e.g., for China, the data starts on January 13, and for Canada the data starts on January 27, 2020.

We run the following pooled regression to capture the predictive relationship between degree centrality; Katz centrality; and net total directional connectedness ($Y_{i,t+1}$) to daily increase in Covid-19 cases ($New\_Cases_{i,t}$).

$$Y_{i,t+1} = \beta_0 + \beta_{New\_Cases} New\_Cases_{i,t} + \beta_Y Y_{i,t} + \epsilon_{i,t} \qquad (10)$$

Table 3 provides summary statistics for variables used in the regression analysis, specifically different types of centrality and connectedness measures: degree_centrality, katz_centrality, degree_centrality_lasso, katz_centrality_lasso, and net total directional connectedness. Summary statistics for New_Cases, defined as daily change in Covid-19 cases are tabulated in Table 3. Covid-19 data comes from the World Health Organization. On average, there are 1,879 new cases each day with the maximum reaching 33,510 new daily cases.

Table 4 reports the results of the predictive relationship between degree centrality; Katz centrality; and net total directional connectedness ($Y_{i,t+1}$) and daily increase in Covid-19 cases ($New\_Cases_{i,t}$). Centrality measures are estimated using VAR, LASSO and variance decomposition estimation procedures. Table 4 shows that for all three network

Table 3: Descriptive statistics

Summary statistics for variables used in the regression analysis Equation 10. The centrality values are computed using the VAR and LASSO estimation procedures. The net total directional connectedness is computed using variance decomposition method. The Covid-19 data comes from the World Health Organization. New_Cases is daily increase in Covid-19 cases.

	Mean	Std	Skewness	Kurtosis	Min	Max
New_Cases	1,879	5,236	4	21	-525	33,510
Degree_Centrality	0.248	1.825	-0.039	4.840	-7.627	7.915
Katz_Centrality	1.284	2.615	-0.163	6.589	-16.343	11.591
Degree_Centrality_lasso	0.218	0.625	0.683	11.609	-3.531	4.156
Katz_Centrality_lasso	1.277	0.795	1.328	11.482	-3.210	7.047
Net Total Directional Connectedness	0.003	0.269	-0.237	4.320	-0.972	1.032

measures using three different estimation procedures, there is a significant relationship between increase in new Covid-19 cases and our measures of centrality and net total directional connectedness. We therefore conclude that financial markets incorporate information from the epidemiological data.

Table 4: Centrality, connectedness, and the spread of Covid-19: a pooled regression

Results of the predictive relationship between centrality and connectedness and the increase in Covid-19 cases. The values for centrality and net total directional connectedness are computed using the VAR, LASSO and variance decomposition estimation procedures. Covid-19 data comes from the World Health Organization. $New - Cases_{i,t}$ is the daily increase in Covid-19 cases reported for country i on day t. Regression estimates are represented in basis points. The numbers in parentheses are t-statistics based on White (1980) standard errors. * signifies 10%, ** 5% and *** 1%.

	VAR		LASSO		Variance Decomposition
	$degree\_centrality_{i,t+1}$	$Katz\_centrality_{i,t+1}$	$degree\_centrality_{i,t+1}$	$Katz\_centrality_{i,t+1}$	$Net\_total\_directional$ $connectedness_{i,t+1}$
$New\_cases_{i,t}$	0.324***	0.535***	0.095***	0.129***	0.062***
	(2.98)	(2.99)	(2.82)	(2.70)	(4.52)
$degree\_centrality_{i,t}$	0.067*		0.039		
	(1.85)		(1.37)		
$Katz\_centrality_{i,t}$		0.014		0.037	
		(0.39)		(1.20)	
$Net\_total\_directional$ $connectedness_{i,t}$					0.331***
					(10.78)
$intercept$	1778.933***	11739.567***	1949.215***	12071.128***	-96.84
	(2.82)	(11.45)	(8.46)	(23.92)	(-1.13)
N	953	953	953	953	953
R^2	0.014	0.012	0.008	0.009	0.135

6. Additional Results and Robustness Analysis

In this section we conduct similar analysis as in the main text, but instead of using high-frequency ETF returns, we use daily returns data for stock indices and ETFs. We also conduct robustness analysis after accounting for timing synchronization and different lengths of moving averages.

6.1. Daily Data Results – Indexes

This section presents the results of our contagion analysis applied to daily index returns. Table 5 tabulates the names of the indexes and their corresponding tickers. Table 6 provides descriptive statistics for the indexes, and Figure 4 depicts the time series of the maximum value for country centralities and the net total directional connectedness using daily index data. As the figure shows, there is not a clear pattern in the network measures, and we cannot give a clear interpretation of the ranking of countries through time. One might argue that the pattern in lead-lags emerges because we do not consider the differences between opening and closing times of different countries' stock markets. In order to ensure this is not the case, and that it is the frequency of the data that influence our results, in the Section 6.3 we examine the open-close of daily ETFs and a modified version of the daily indexes using a lead-lag timing correction.

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Table 5: Index list

The list of 12 country indexes. This list comes from 11 industrial countries in Rapach et al. (2013) plus the Chinese market index (SSE).

	Name	**Ticker**	**Country**
1	S&P/ASX 200	AXJO	Australia
2	S&P/TSX Composite index	GSPTSE	Canada
3	CAC 40	FCHI	France
4	DAX Index	GDAXI	Germany
5	FTSE MIB Index	FTSEMIB.MI	Italy
6	Nikkei 225	N225	Japan
7	AEX-INDEX	AEX	Netherlands
8	OMX Stockholm 30 Index	OMX	Sweden
9	SMI PR	SSMI	Switzerland
10	FTSE 100	FTSE	United Kingdom
11	Shanghai Stock Exchange	SSE	China
12	S&P 500	GSPC	USA

Table 6: Descriptive statistics

Summary statistics for daily returns of the 12 country indexes in Table 5. The returns are in percentages.

| **Num.**	**Country**	**Mean**	**Std**	**Skewness**	**kurtosis**	**Min**	**Max**
1	Australia	0.023	0.949	-0.826	12.658	-7.329	5.541
2	Canada	0.018	0.888	-2.268	30.234	-9.886	5.063
3	France	0.029	1.193	-0.546	7.935	-8.043	5.014
4	Germany	0.045	1.180	-0.37	6.481	-6.823	5.676
5	Italy	0.026	1.488	-0.606	8.752	-11.173	6.594
6	Japan	0.049	1.274	-0.118	7.392	-6.351	7.156
7	Netherlands	0.034	1.040	-0.447	6.284	-5.704	4.051
8	Sweden	0.037	1.082	-0.297	5.612	-5.210	4.531
9	Switzerland	0.028	0.928	-0.725	7.783	-5.964	3.423
10	United Kingdom	0.012	0.946	-0.429	6.715	-5.251	4.29
11	China	0.025	1.341	-0.702	9.126	-7.703	5.712
12	USA	0.051	1.006	-0.343	14.837	-7.597	7.036

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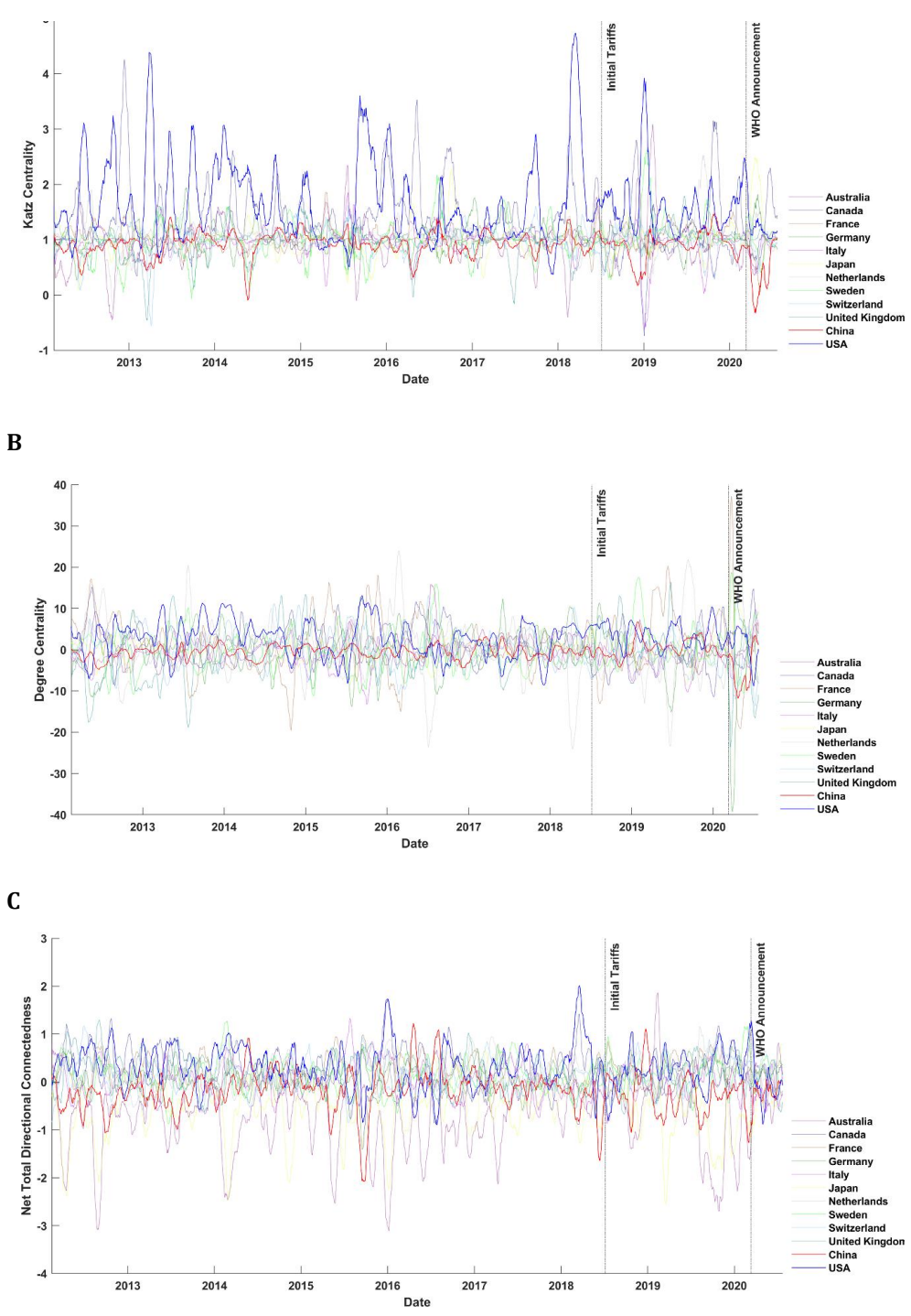
Figure. 4. Country centralities and net total directional connectedness through time (Daily Indexes)

Time series of network measures through time: (A) Katz Centrality from LASSO estimation; (B) Degree centrality from VAR estimation; and (C) Net total directional connectedness from variance decomposition estimation. The values are averaged over rolling 15-day intervals. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 pandemic was on March 11, 2020. The VAR and LASSO networks are estimated in rolling 30-day intervals using daily index returns.

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6.2. Daily Data Results – ETF

We repeat the contagion analysis in the main text using the daily ETF returns. We compute the daily ETF returns using the mid-quote prices at the end of the day, at 15:59. Table 7 reports the summary statistics for daily ETF returns. Figure 5 depicts time series of maximum country centralities and net total directional connectedness through time using daily ETF returns.

Figure 5 depicts the leading country degree centrality, Katz centrality and net total directional connectedness from 2012 to the end of May 2020. Since all ETFs used in the analysis are traded inside the United States, there is no need for timing synchronization. There are no inherent patterns among countries using these network measures from the daily data. On the other hand, using ETF minute-by-minute returns, as described in the main results, the leading role of the United States is clear in the early years of our data.

Table 7: Descriptive statistics

Summary statistics for daily returns of the 12 country-specific ETFs. The returns are in percentages. The daily ETF returns are computed using the mid-quote prices at the end of the day.

| Num.	Country	Mean	Std	Skewness	kurtosis	Min	Max
1	Australia	-0.001	1.412	-0.891	17.081	-11.927	8.564
2	Canada	0.000	1.115	-1.534	19.604	-10.945	5.723
3	France	0.020	1.296	-1.044	14.864	-11.339	6.32
4	Germany	0.022	1.276	-0.833	11.077	-9.864	6.012
5	Italy	0.013	1.628	-0.862	12.514	-13.366	8.263
6	Japan	0.029	1.053	-0.181	6.811	-4.882	5.702
7	Netherlands	0.034	1.164	-1.051	12.539	-9.560	5.196
8	Sweden	0.016	1.370	-1.040	11.648	-11.143	6.013
9	Switzerland	0.030	0.957	-0.679	10.491	-6.973	4.833
10	United Kingdom	0.001	1.164	-1.247	16.126	-9.931	6.395
11	China	0.036	1.431	-0.177	4.954	-6.636	5.956
12	USA	0.044	0.978	-0.337	14.64	-7.467	6.969

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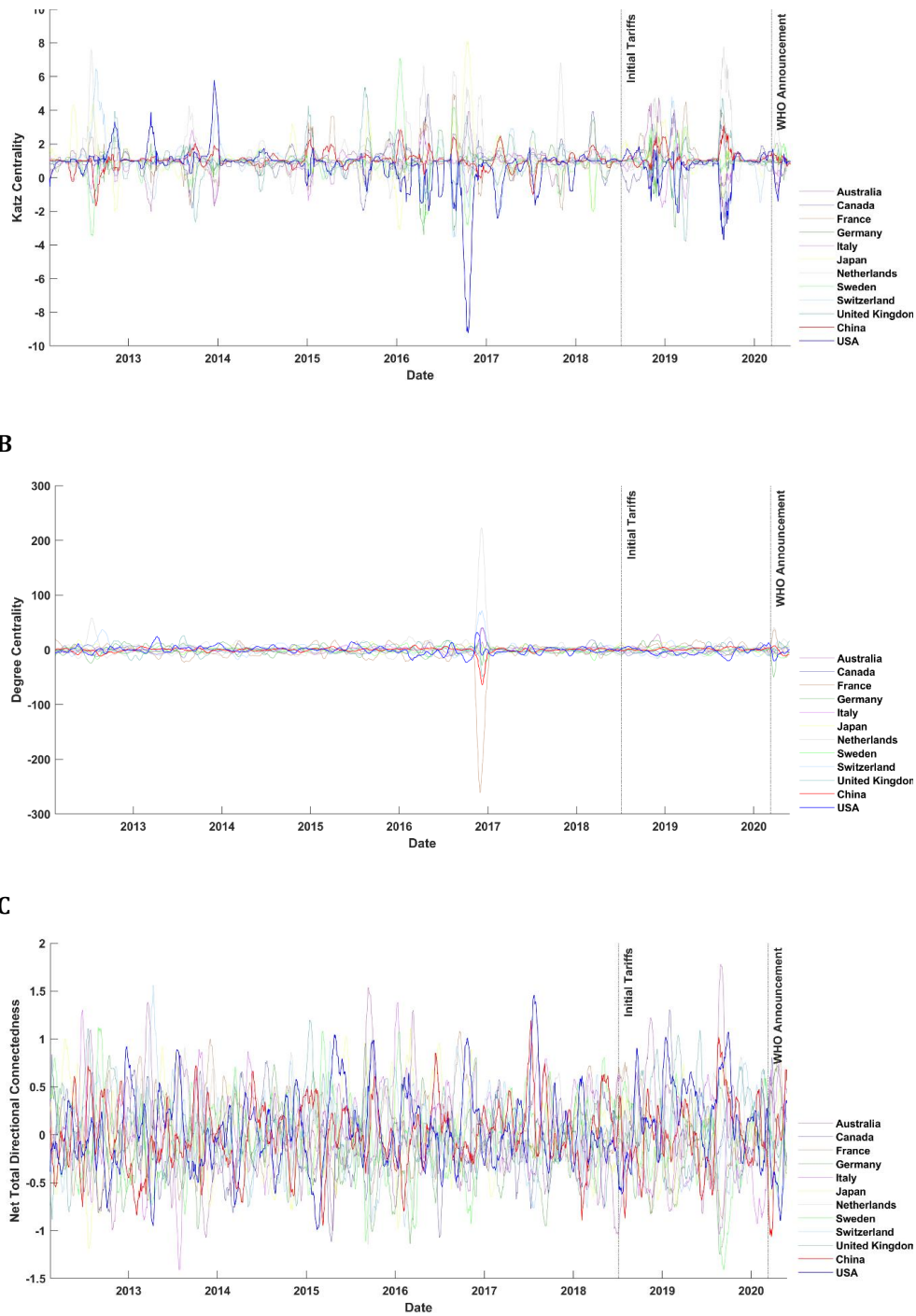
Figure. 5. Country centralities and net total directional connectedness through time (Daily ETF)

Time series of network measures through time: (A) Katz centrality from LASSO estimation; (B) Degree centrality from VAR estimation; and (C) Net total directional connectedness from variance decomposition estimation. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 pandemic was on March 11, 2020. The VAR and LASSO networks are estimated using rolling 30-day intervals on daily ETF returns.

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6.3. Daily Index Results with Timing Correction

One could claim that the daily index results are not informative because the index returns are not synchronized correctly with respect to the opening of different international markets. Here, we propose a timing synchronization approach.

Table 8:A tabulates the opening and closing times of international stock exchanges. The stock markets open and close at different hours, and due to this timing disagreement, estimating a VAR model using daily returns to identify lead-lags between markets can be misleading. In Table 8:B, we propose a timing adjustment approach in the VAR estimation process. Depending on the country that is the dependent variable in the VAR estimation, we use a lagged or simultaneous form of the open-close returns of independent country indexes. For example, if the United States is the dependent variable, we use the same-day open-close returns of European and Asian countries and the lagged value of North American countries in the VAR estimation. This is because in one day (a day defined in the UTC system), the markets in Asia and Europe open before the market in the North America opens. We compute the daily open-close ETF returns using the mid-quote prices in the beginning of the day, at 9:31 and the mid-quote price at the end of the day, at 15:59. Table 9 reports the summary statistics of open-close index returns.

Figure 6 shows that no clear patterns emerge among country indexes using daily data even after accounting for timing synchronization. This confirms the advantage of high-frequency returns to extract lead-lags between countries' stock markets and to capture centrality in terms of information spillover. We note that another approach in dealing with timing synchronization is to use monthly returns and follow the procedure in (Rapach et al., 2013). However, in our setting, there are too few observations using monthly returns to compute a time-series picture of dynamic centralities.

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Table 8: Time Synchronization of Indexes

Panel A shows the UTC timing of market opening and closing in different countries. Europe* stands for Sweden, Italy, Germany, the Netherlands, and Switzerland. Panel B shows the lead-lag timing treatment of country indexes. Each day, t, is defined in UTC time format. We have three sets of countries: **North America**: US, Canada; **Asia**: Japan, China, Australia; **Europe**: France, United Kingdom, Sweden, Italy, Germany, the Netherlands, Switzerland.

Panel A. Market open and close time

UTC TIME	USA	Canada	Europe*	UK	China	Japan	Australia
0						Tokyo	Australian
1					Shanghai	Stock	Securities
2					Stock	Exchange	Exchange
3					Exchange		
4					01:30		
5					07:00	00:00	00:00
6						08:00	06:00
7							
8							
9			Euronext				
10			Paris	London			
11				Stock			
12				Exchange			
13	New York	Toronto	08:00	08:00			
14	Stock	Stock	16:30	16:30			
15	Exchange	Exchange					
16							
17	13:30	13:30					
18	20:00	21:00					
19							
20							
21							
22							
23							

Panel B. Open to close return synchronization

Today		Lag	
$NorthAmerica_t$	$Asia_t$	$Europe_t$	$NorthAmerica_{t-1}$
$Asia_t$	$NorthAmerica_{t-1}$	$Europe_{t-1}$	$Asia_{t-1}$
$Europe_t$	$Asia_t$	$NorthAmerica_{t-1}$	$Europe_{t-1}$

Table 9: Descriptive statistics (open-close index returns)

Summary statistics for daily open-close returns of the 12 country indexes described in Table 1. The returns are in percentages.

| Num.	Country	Mean	Std	Skewness	kurtosis	Min	Max
1	Australia	0.022	0.935	-0.799	12.825	-7.329	5.541
2	Canada	-0.002	0.662	-0.388	11.407	-4.651	4.377
3	France	-0.005	0.911	-0.189	4.956	-3.687	3.994
4	Germany	-0.006	0.923	-0.174	4.842	-3.757	3.948
5	Italy	-0.041	1.294	-0.891	11.346	-11.092	5.57
6	Japan	0	0.925	-0.31	9.196	-5.96	5.143
7	Netherlands	-0.002	0.812	-0.143	5.842	-3.66	4.308
8	Sweden	0.005	0.915	-0.384	5.194	-4.737	3.354
9	Switzerland	0.01	0.766	-0.903	9.83	-5.548	3.472
10	United Kingdom	0.013	0.943	-0.429	6.765	-5.251	4.29
11	China	0.123	1.179	-0.306	7.857	-6.523	5.147
12	USA	0.028	0.815	-0.426	8.63	-4.883	4.389

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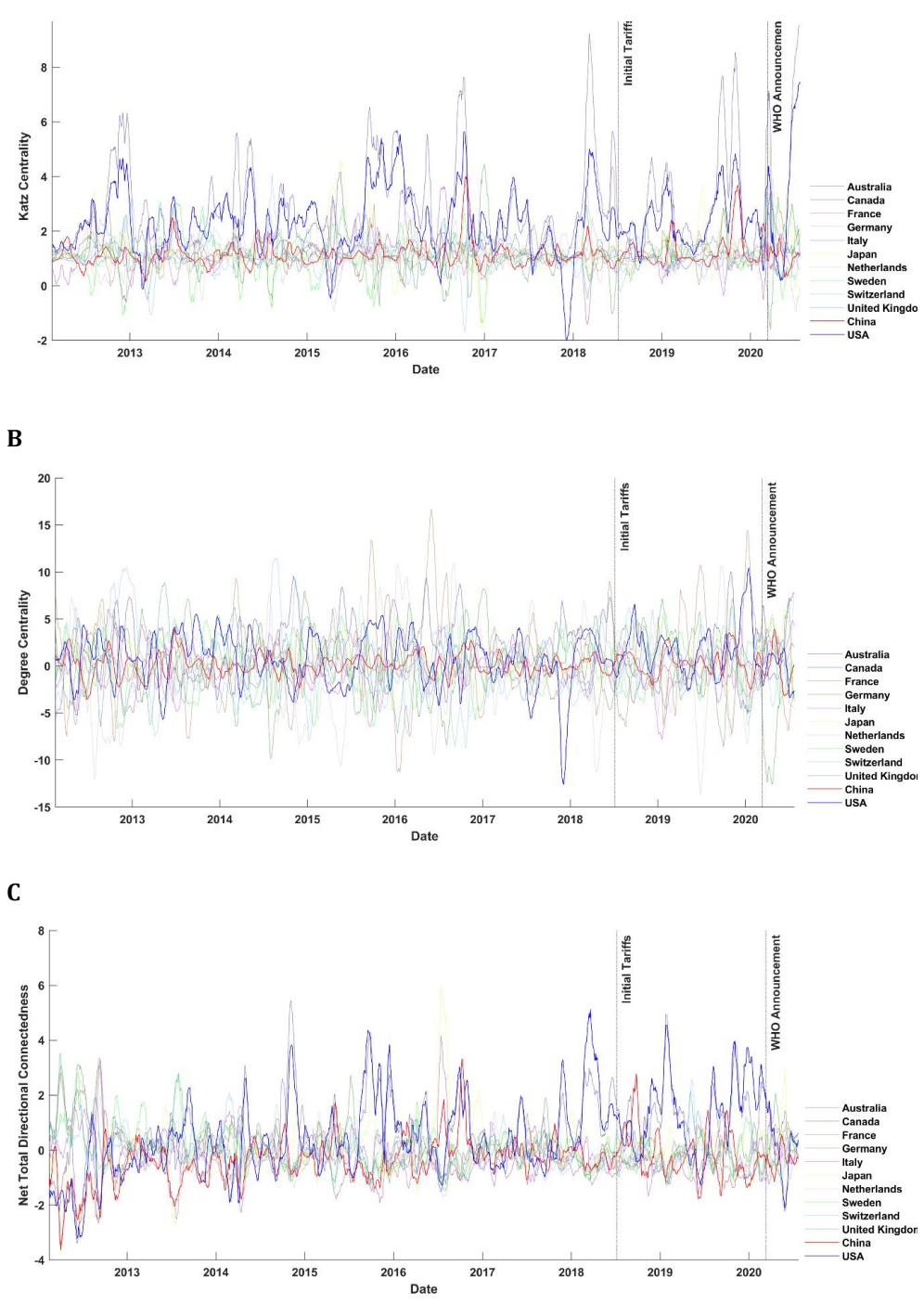
Figure. 6. Country centralities and net total directional connectedness through time (Daily Indexes with Timing Adjustment)
Time series of network measures through time: (A) Katz centrality from LASSO estimation; (B) Degree centrality from VAR estimation; and (C) Net total directional connectedness from variance decomposition estimation. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 pandemic was on March 11, 2020. The VAR and LASSO networks are estimated in rolling 30-day intervals using daily open-close index returns adjusted for timing synchronization in Table 8.

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6.4. Different Length of Moving Averages

In the main analysis we depict network analysis results averaged over rolling 15-day intervals. In this section, we conduct robustness analysis on the length of our rolling average, and allow for rolling 30-day intervals (Figure 7) and rolling 60-day intervals (Figure 8). We find that our main results are unchanged. Using high-frequency data on ETFs, we show that China became central well before the announcement of tariffs or the pandemic while the centrality of the U.S. has decreased during these times.
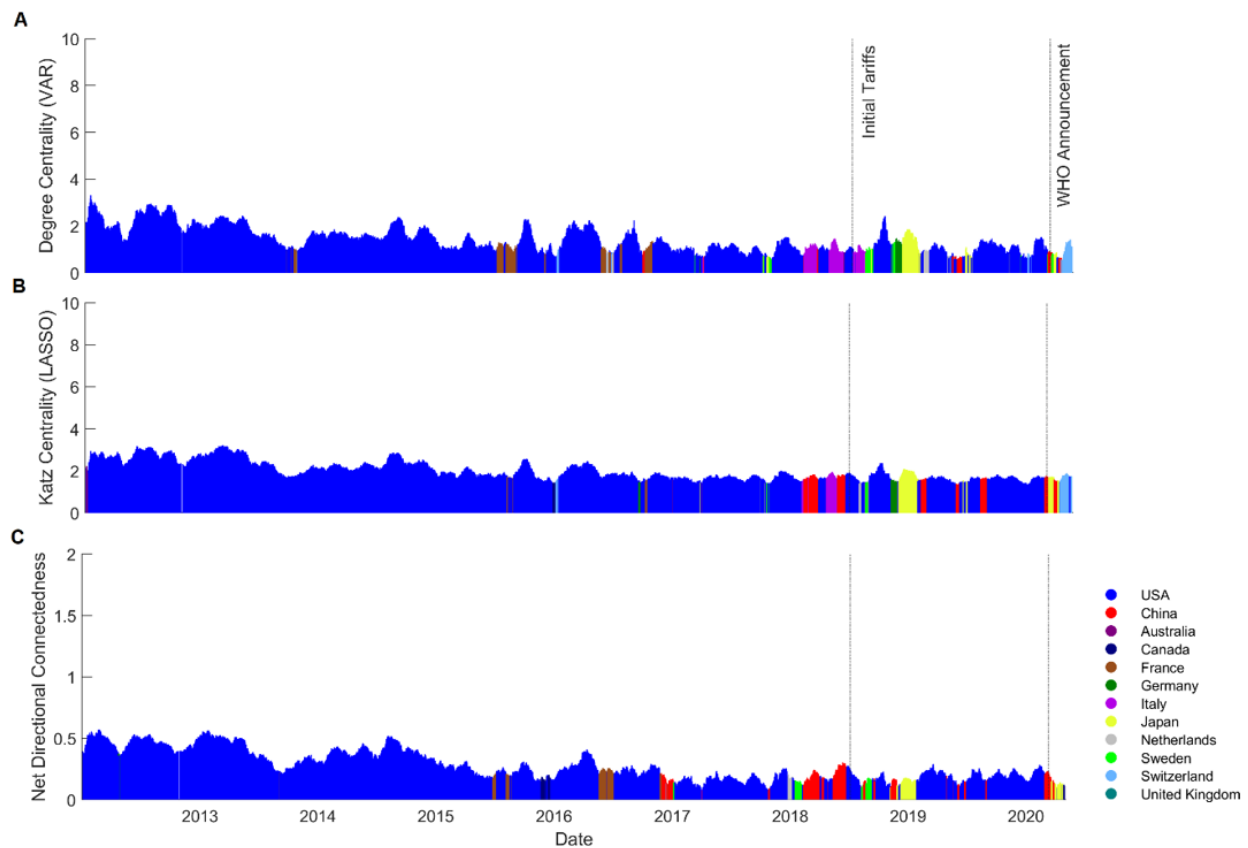
Figure. 7. Maximum country centralities and net total directional connectedness through time (30-day average)

Time series of maximum values of network measures through time: (A) Degree centrality from VAR estimation; (B) Katz centrality from LASSO estimation; and (C) Net total directional connectedness from variance decomposition estimation. For each point in time, only the maximum value and corresponding country colour are depicted. The values are averaged over rolling 30-day intervals. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 pandemic was on March 11, 2020.

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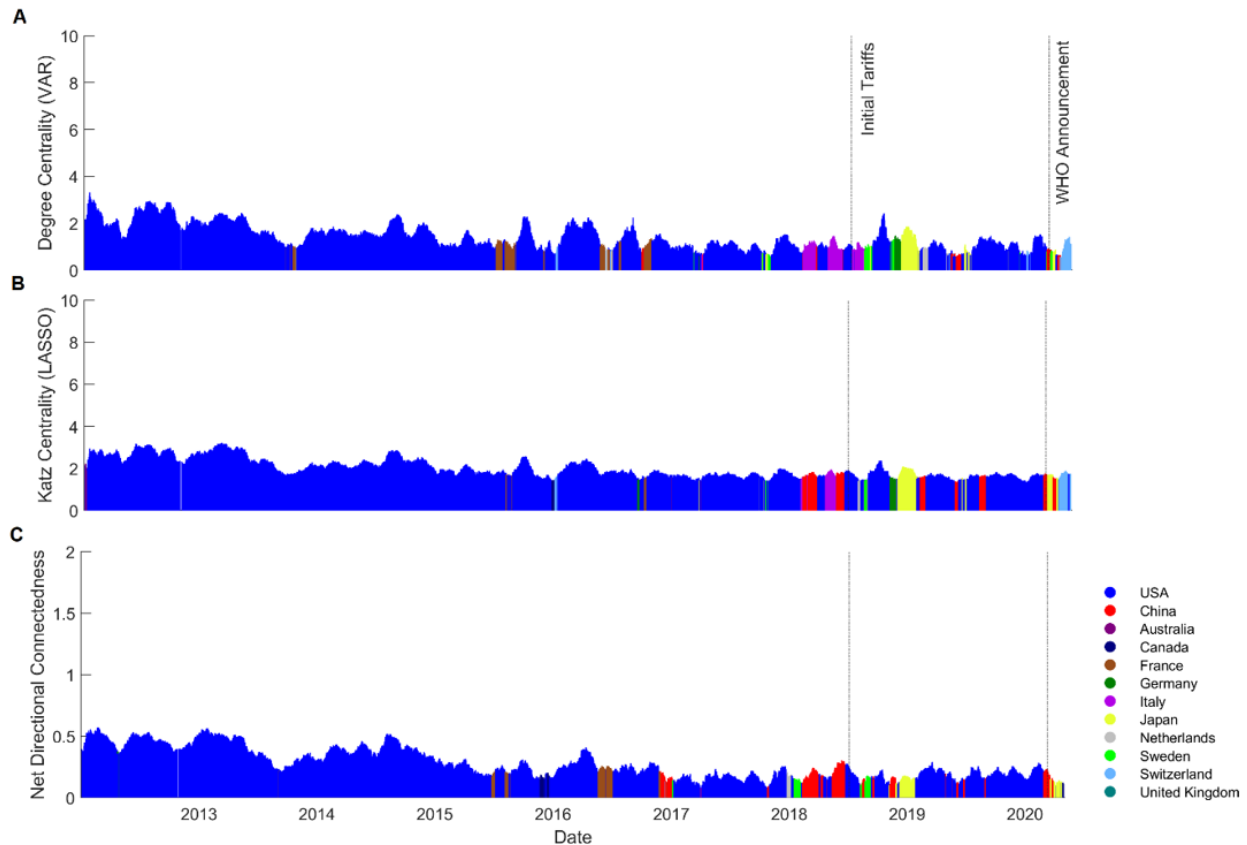
Figure. 8. Maximum country centralities and net total directional connectedness through time (60-day average)

Time series of maximum values of network measures through time: (A) Degree centrality from VAR estimation; (B) Katz centrality from LASSO estimation; and (C) Net total directional connectedness from variance decomposition estimation. For each point in time, only the maximum value and corresponding country colour are depicted. The values are averaged over rolling 60-day intervals. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 pandemic was on March 11, 2020.

7. Conclusion

Network theory and high-frequency financial data show that the world has started to move from a unipolar system to a bipolar one. Is this phenomenon captured by country-specific index returns or low-frequency data? The answer is no, based on the analysis of the daily returns data. We show that the high-frequency financial data is forward-looking in capturing the rise of centrality of China. Simultaneously, the data show that

some European countries also became more financially central during the pandemic, but none quite as central as either the U.S. or China. We posit that Europe is fragmented enough that it does not offer a counterweight to the newly formed bipolar relationship between the U.S. and China. It is clear that both political and epidemiological forces can significantly affect the structure of global networks. The high centrality of the U.S. and its political hegemony in the unipolar system once gave it unchallenged influence over global power, economics, culture, and moral leadership. Our data shows that the U.S. has recently lost its edge, the world map becoming more bipolar as the U.S. has lost its central authority and power.

It must be underscored that the centrality of China is a very recent phenomenon, and may be transient. It is ironic, however, that one of the first indications of a newly bipolar financial system was caused by the strained relationship between the U.S. and China, at a time when scientific collaboration between the nations is especially needed to fight the pandemic and develop a vaccine against the coronavirus (Silver, 2020). It remains to be seen if the "Thucydides trap" of conflict during hegemonic decline can be prevented. As we move from a unipolar world to a bipolar one, we must prevent further escalation and instead pursue scientific collaboration and cultural exchange.

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Appendices

A.   Network Measures Through Time

This appendix reports the dynamics of the degree centrality and Katz centrality for the estimated network measures from our minute-by-minute ETF returns. In Figure 9, the Katz centrality from VAR estimation is presented and in Figure 10, the degree centrality is presented from LASSO estimation of the lead-lag relationships between country-specific ETFs. The results are consistent with main results in the paper.
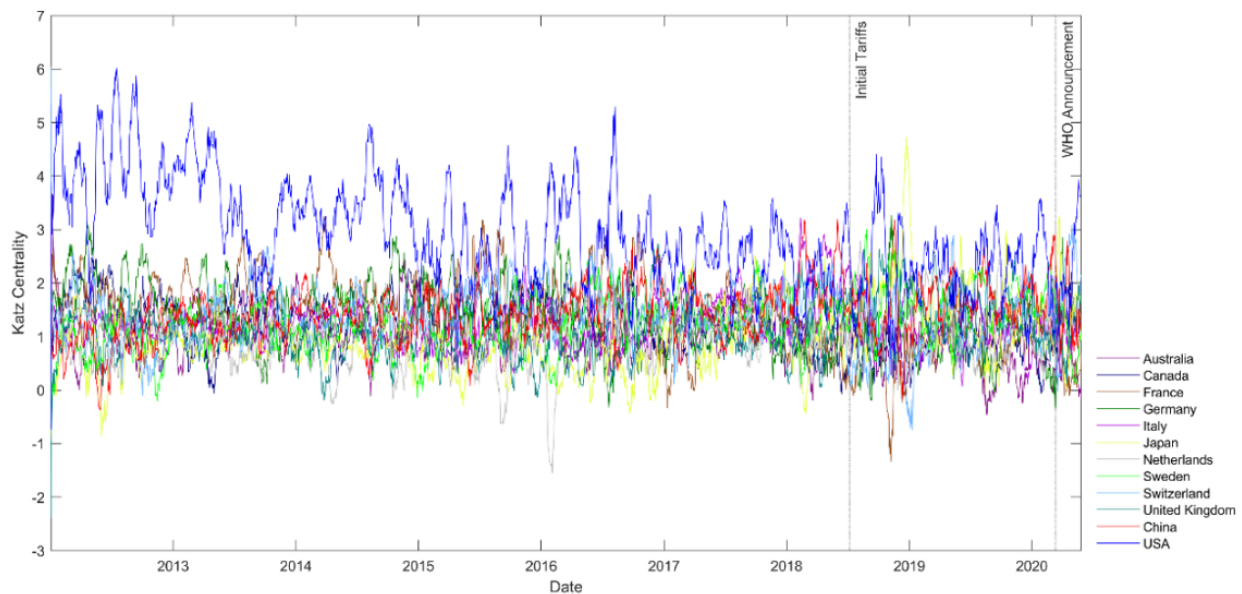
Figure. 9. Katz centrality through time (VAR estimation)
Time series of degree centralities (VAR estimation) for each country-specific ETF through time. We estimate the lead-lag relationships between country-specific ETFs via VAR using minute-by-minute returns in each day. The Katz centralities are computed each day and averaged over rolling 15-day intervals. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 as a pandemic happened on March 11, 2020.
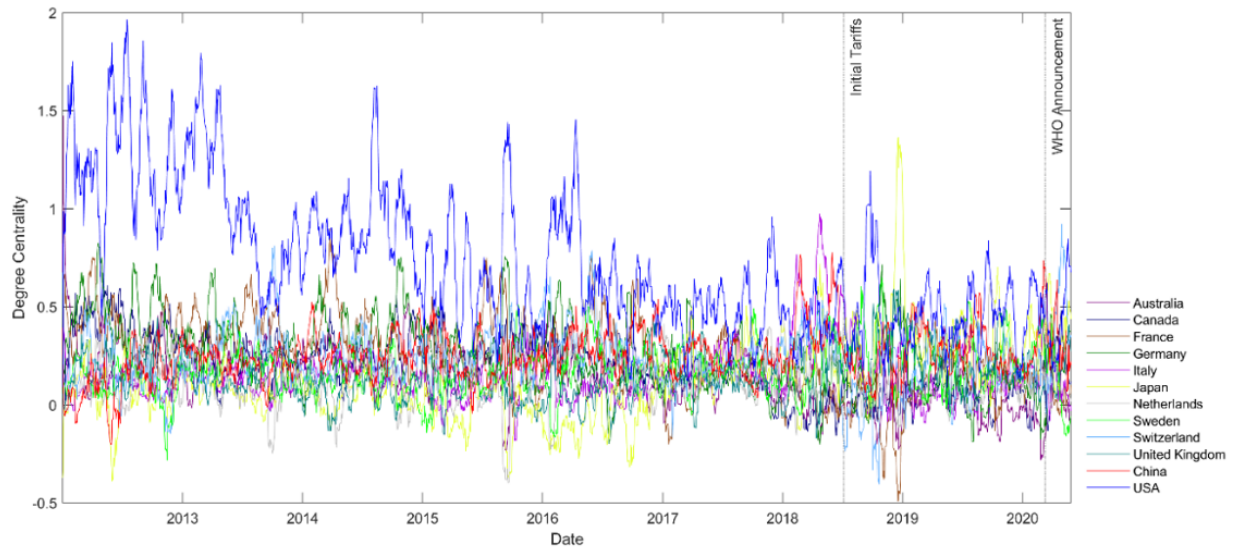
Figure. 10. Degree centrality through time (LASSO estimation)

Time series of degree centralities of each country-specific ETF through time. We estimate the lead-lag relationships between country-specific ETFs via LASSO using minute-by-minute returns in each day. The degree centralities are computed each day and averaged over rolling 15-day intervals. The initial U.S. imposition of Chinese-specific tariffs took place on July 6, 2018 and the WHO's initial announcement of Covid-19 as a pandemic happened on March 11, 2020.

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