AN EMPIRICAL INVESTIGATION
OF BORSA ISTANBUL SINGLE STOCK FUTURES:
A TVP-VAR APPROACH

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DECLARATION OF ORIGINALITY

I, Burak Kalkan, certify that

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- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
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ABSTRACT

An Empirical Investigation of Borsa Istanbul Single Stock Futures: A TVP-VAR Approach

In this thesis, the dynamic connectedness between 20 single stock futures (SSFs) of Borsa Istanbul is analyzed based on the time-varying parameter vector autoregression (TVP-VAR) methodology to evaluate the change in the degree of interconnectedness and identify which stocks are net shock transmitters or net shock receivers during turbulent times. The dynamic connectedness between spot prices, 1-month futures prices and the combination of spot and 1-month futures prices are analyzed for the period between 02.03.2016 and 07.12.2020. Results indicate that stock prices are highly interconnected during the whole period. Shock transmissions reach their highest levels during periods of increased uncertainty, currency crisis, and the outbreak of the COVID-19. Furthermore, it is found out that GARAN, AKBNK, VAKBN, ISCTR, YKBNK, and HALKB are the main net shock transmitters to the network. Also, the majority of spot prices of stocks dominate their 1-month futures prices based on the net pairwise directional connectedness. The results of this thesis can be valuable for investors, managers, and policymakers.

ÖZET

Borsa İstanbul Pay Vadeli İşlem Sözleşmelerinin Ampirik İncelenmesi:

TVP-VAR Yaklaşımı

Bu tezde, kriz dönemlerinde Borsa İstanbul'da bulunan pay vadeli işlem sözleşmelerinin aralarındaki bağlılık derecelerinde gözlemlenen değişimi incelemek ve hangi hisse senedinin net şok yollayıcı veya net şok alıcı olduğunu belirlemek amaçlanmıştır. 20 adet pay vadeli işlem sözleşmesi arasındaki dinamik bağlantılılık zamanla değişen parametreli vektör otoregresif (TVP-VAR) metodolojisi ile incelenmiştir. Çalışmada spot fiyatlar, 1 aylık vadeli fiyatlar ile spot ve 1 aylık vadeli fiyatların kombinasyonu arasındaki dinamik bağlantılılık, 02.03.2016 ve 07.12.2020 arasındaki dönem kapsamında analiz edilmiştir. Sonuçlar, hisse senedi fiyatlarının tüm dönem boyunca yüksek oranda birbirleriyle bağlantılı olduğunu göstermektedir. Şokların iletiminin artan belirsizlik, kur krizi ve COVID-19'un çıktığı dönemlerde en yüksek seviyelere ulaştığı gözlemlenmiştir. Ayrıca GARAN, AKBNK, VAKBN, ISCTR, YKBNK ve HALKB hisselerinin, sisteme net şok yollayan hisseler olduğu belirtilmiştir. Net ikili bağlantılılıklar değerlendirildiğinde ise spot fiyatların 1 aylık vadeli fiyatlara hakim olduğu gözlemlenmiştir. Spot fiyatların, 1 aylık vadeli fiyatlardan aldığı şoktan daha fazlasını karşı tarafa şok olarak yolladığı bulunmuştur. Bu tezin sonuçları, yatırımcılar, yöneticiler ve politika yapıcılar için değerli sonuçlar barındırmaktadır.

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Last but not least, I would like to thank my friends and family for their unconditional support and for always being by my side.

DEDICATION

I dedicate this thesis to my father, Atila Kalkan, to my mother, Serap Kalkan, to my brother, Oğuz Kalkan, and to my uncle, Abdullah Kalkan.

TABLE OF CONTENTS

LIST OF FIGURES

ABBREVIATIONS

AKBNK	Akbank T.A.Ş.
ARCLK	Arçelik A.Ş.
EKGYO	Emlak Konut Gayrimenkul Yatırım Ortaklığı A.Ş.
EREGL	Ereğli Demir ve Çelik Fabrikaları T.A.Ş.
GARAN	Türkiye Garanti Bankası A.Ş.
HALKB	Türkiye Halk Bankası A.Ş.
ISCTR	Türkiye İş Bankası A.Ş.
KCHOL	Koç Holding A.Ş.
KRDMD	Kardemir Karabük Demir Çelik San. ve Tic. A.Ş.
PETKM	Petkim Petrokimya Holding A.Ş.
PGSUS	Pegasus Hava Taşımacılığı A.Ş.
SAHOL	Hacı Ömer Sabancı Holding A.Ş.
SISE	Türkiye Şişe ve Cam Fabrikaları A.Ş.
TCELL	Turkcell İletişim Hizmetleri A.Ş.
THYAO	Türk Hava Yolları A.O.
TOASO	Tofaş Türk Otomobil Fabrikası A.Ş.
TTKOM	Türk Telekomünikasyon A.Ş.
TUPRS	Tüpraş-Türkiye Petrol Rafinerileri A.Ş.
VAKBN	Türkiye Vakıflar Bankası T.A.O.
YKBNK	Yapı ve Kredi Bankası A.Ş.

CHAPTER 1

INTRODUCTION

The increasing extent of linkages in the financial assets and markets have intensified the spillover transmissions and exposure to both internal and external shocks which limits the possible hedging and diversification strategies of investors and financial managers. During crisis periods and times of uncertainty, these linkages and spillovers become more evident. Particularly, the domino effect of the Global Financial Crisis has stimulated the need for understanding the connectedness between assets, institutions and markets to observe the size and direction of spillovers so that necessary trading strategies can be applied. Although it is a challenging task to forecast the period when a new crisis may strike, relevant precautions can be taken since transmission patterns exhibit clear similarities (Reinhart & Rogoff, 2008).

Following the crisis periods, investors search for safer investment alternatives. One way of achieving the goal of minimizing exposure to unwanted changes is taking an opposite position. Here, future derivatives can be a suitable option since you can offset your exposure in the spot market by entering into the futures market. Therefore, understanding the relationship between spot and futures become crucial for investors. In efficient markets, simultaneous response to new information is expected in both spot and futures markets (Fama, 1970). However, restrictions and costs that are available create a lead-lag relationship between the spot and futures market which makes it important to analyze the spillover transmissions between two markets. SSFs, contract agreements that buyers and sellers agree to buy and sell a specific stock at an agreed price on an agreed date, are frequently studied in the literature to analyze the price discovery process between spot and futures markets. Although there are studies that explore which market leads the other (Fung & Tse, 2008; Shrinivasan & Bhat, 2009; Aggarwal & Thomas, 2019), the connectedness of the SSFs and how it reacts during crisis periods requires attention in the literature.

Connectedness is a term that explains the relationship between variables and how they affect each other. The degree of connectedness determines the impact that one variable has on others. These impacts are transferred between variables with spillovers. Thus, spillovers display how the impact of a shock in one variable spills over to different variables within the network. So, it can be inferred that a higher degree of connectedness results in a higher degree of spillovers. According to Diebold and Yilmaz (2014), connectedness is a vital component in measuring and managing the risk as they associate return and portfolio connectedness with market risk, default connectedness with credit risk, contractual connectedness with counterparty risk and systemwide connectedness with systemic risk.

The connectedness approach of Diebold and Yilmaz (2009, 2012, 2014) to determine the interdependence of a network has created substantial interest in the literature (Antonakakis & Kizys, 2015; Wang et al., 2016; Kang & Yoon, 2019). Their proposed framework which is based on forecast error variance decompositions from vector autoregressions (VARs) provides a beneficial method to observe and measure the impact of both idiosyncratic shocks and shocks coming from the network. So that connectedness can be classified as total connectedness, directional connectedness and net connectedness. In their study in 2009, they introduced a connectedness table that explains the connectedness between variables in the network. However, the way that variables are ordered within the network makes the results sensitive to the ordering. This deficiency was improved in their study in 2012, which explains both total and directional spillovers. Furthermore, Diebold and Yilmaz introduced the use of network graphs to visually illustrate the pairwise and network-wise connectedness in their study in 2014.

In this thesis, the time-varying parameter vector autoregressive model which is described in Antonakakis and Gabauer (2017) and Antonakakis, Chatziantoniou and Gabuer (2020) is employed. The suggested TVP-VAR model with a time-varying covariance structure improves the model of Diebold and Yilmaz (2009, 2012, 2014) which is based on the constant-parameter rolling-window method. Dynamic connectedness based on the TVP-VAR model is superior comparing to the earlier model since there is no need to arbitrarily determine the size of the rolling windows, there is no loss of information due to setting the rolling windows either too big which may smoothen the effect of events or too small which may lead an overreaction towards the effect of events, and there is less sensitivity against outliers. Several studies study the dynamic connectedness of the network and spillover transmissions between financial assets and markets based on the TVP-VAR model and it is emphasized that dynamic connectedness is indeed time-variant. In other words, it is adjusted accordingly to the events and the level of connectedness increases during turbulent times (Gabauer & Gupta, 2018; Adekoya & Oliyide, 2021).

Dynamic connectedness based on the TVP-VAR model has been studied in the literature to analyze the shock transmissions between financial assets and markets. To my best knowledge, this thesis is the first study that analyzes the dynamic connectedness between SSFs which may represent stimulating results with employing TVP-VAR. In this thesis, dynamic connectedness between returns of 20 SSFs that are traded in Borsa Istanbul is investigated for the period between

02.03.2016 and 07.12.2020. The dynamic connectedness of spot prices, 1-month futures prices and the combination of spot and 1-month futures prices are analyzed separately. SSFs traded in Borsa Istanbul provides a notable research area since Borsa Istanbul leads other exchanges with more than one billion contracts traded in terms of the number of SSFs traded in 2020 and Borsa Istanbul constitutes almost 80% of total volumes traded together with Brasil Bolsa Balsao and Korea Exchange markets (World Federation of Exchanges, 2021a). In this thesis, it is aimed to find answers to the following questions: “Does the dynamic connectedness between SSFs vary during the sample period and respond to crisis periods?” and “Which SSFs are net transmitters or net receivers of shocks?”.

This thesis is organized as follows. Chapter 2 presents studies in the literature regarding SSFs and studies which employ the TVP-VAR model to analyze the dynamic connectedness between assets and markets. Chapter 3 explains the data and methodology of dynamic connectedness based on TVP-VAR. Chapter 4 discusses the empirical results following the analysis. Finally, the conclusion of the thesis is provided in the last chapter together with suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

In this literature review, an introduction to SSFs is provided. The background, the criteria to form SSFs, their advantages and differences comparing to trading regular stocks and the price discovery roles of SSFs are given based on the examined literature. Next, studies that utilize the dynamic connectedness methodology of Diebold and Yilmaz (2009, 2012, 2014) together with the extended version of dynamic connectedness with the TVP-VAR model of Antonakakis and Gabauer (2017) and Antonakakis et al. (2020) are presented. The review of the literature indicates that there is an undiscovered area to study the dynamic connectedness of SSFs by applying the TVP-VAR methodology.

2.1 Single stock futures

Futures, as an example of derivatives, are financial contracts that take place between two counterparties that obligate them to transact an asset at a certain future date with a certain price. These transactions are realized in exchanges. Investors can benefit from the usage of futures in terms of hedging, speculating and price discovery purposes (Ederington, 1979; Adam & Fernando, 2006; Garbade & Silber, 1983). Concerns towards adverse movements in prices lead investors to hedge their risks by taking an opposite position in the futures market against the related asset in the cash market so that they can minimize their market exposure (Ekincioğlu, 2010). On the other hand, investors who wish to benefit from the price fluctuations also enter the futures market intending to make a profit by accepting the higher risk. Furthermore, investors use the futures market as a price discovery tool since trades in the futures market occurred at a predetermined price at a certain date. As Black (1975) argues, the derivatives market facilitates cheaper trading options with the benefits of financial leverage.

SSFs have been started to attract the interest of investors as a relatively new innovation in stock derivatives. Contrary to conventional futures contracts like the ones based on currencies, commodities or indexes, SSFs are based on individual stocks. World Federation of Exchanges (2021b) defines SSFs as standardized tradable futures contracts which obligate its buyer (seller) to buy (sell) individual stocks at an agreed price and on a specified date. Telser and Higinbotham (1977) argue that standardization in the future market is an important factor to ensure a smooth transaction between two parties in terms of the underlying number of shares, underlying component and delivery month. In general, the contract size consists of 100 shares of the underlying stock. Trading of SSFs has started to emerge since 2000 mainly because of two developments. The first one is the introduction of 95 SSFs in the London International Financial Futures and Options Exchange (LIFFE) at the beginning of 2001. The second one is the lifting of the ban on SSFs in the United States in November 2002 with the Commodity Futures Modernization Act. The ban of 20 years was due to the conflict on whether to evaluate SSFs as stocks or as futures which created a disagreement between the Securities and Exchange Commission and Commodities Futures Trading Commission. This disagreement resulted in the ban of trades of futures that were written on individual stocks and narrowly established stock indices with the Shad-Johnson Accord signed between two parties in 1982. Following the repeal of the ban, trading of SSFs started to be realized in two exchanges which were OneChicago, a joint venture between the

Chicago Mercantile Exchange, the Chicago Board of Options Exchange and the Chicago Board of Trade, and NQLX, a joint venture between NASDAQ and LIFFE.

Ang and Cheng (2005a) discuss how these exchanges decide to select which stocks to list. They argue that the success of exchange is determined accordingly with its competence in choosing stocks that can create high trading volume and the quality in carrying out a trade. Underlying stocks' trading volume gives a good estimate of the trading volume of SSFs since what attracts investors by the underlying stocks may influence trading in futures as well. Furthermore, greater volatility of stocks is a good indicator of the higher trading volume of trades in SSFs. So, it can be argued that SSFs that have underlying securities with high capitalization, volume and volatility draw more attention from traders (Ang & Cheng, 2005a). Along with high volume and volatility, Bialkowski and Jakubowski (2012) also refer to a low level of institutional ownership which is tied with higher SSFs trading activity. Since institutional owners are more rational, they will discard overpriced stocks. On the other hand, stocks will be kept by investors when stocks have low institutional ownership and cause a lower supply of stocks to exercise a short-sale which directs investors towards SSFs.

It is also required to point out that trading regular stocks and trading SSFs are two dissimilar incidents since holding SSFs has different rights and opportunities comparing to holding their underlying stocks. Ekincioglu (2010) lists these differences. Firstly, holding SSFs does not give owners a voting right. To put it differently, an investor does not become an owner of the company as in holding a stock for the reason that holding SSFs provides just an agreement to buy a stock at a specified date with a specified price. Due to the same reason, SSFs do no provide investors with dividend payments and the ownership period cannot last until the company runs out of business (Lascalles, 2002). Another difference is that stocks do not have an expiry date while SSFs expire on the maturity date of the contract. Furthermore, SSFs have the advantage of utilizing leverage and investors can pay only a certain amount to purchase a stock. On the contrary, investors must pay the full amount to purchase an underlying stock. Also, investors cannot conduct short-selling as easily as in SSFs due to certain constraints.

SSFs provide two main benefits over trading their underlying assets. Firstly, usage of leverage in trading SSFs allows investors not to pay the full amount for the purchased shares. Instead, investors can take a position by paying a certain margin amount. Therefore, it is less costly to trade SSFs with the advantage of leverage than trading stocks due to lower margin requirement which is usually around 20% for SSFs (Ang & Cheng, 2005b; Fung & Tse, 2008). Secondly, investors who are facing constraints in short-selling of underlying stocks may move towards trading SSFs as a low-cost substitute. Short-selling is the process in which investors can take a position against a stock that they believe the price of that stock is going to decrease. In order to exercise short-selling, investors should borrow stock from a broker and sell it in the market. When the price decreases, investors can buy the stock back to close the position at a cheaper price and return the borrowed stock to the broker. Mitchell (2003) expresses that the uptick rule, which forces investors to execute short-selling at a price higher than the previous executions, limits investors in the underlying market to conduct short-selling multiple times at a cheaper price. However, the uptick rule does not apply to create a short sale position in SSFs and attracts investors to trade in SSFs. According to Danielsen, Van Ness and Warr (2009), the introduction of SSFs decreases the level of short-selling and the cost of short-selling in the underlying stock market based on their study of 111 SSFs listings in the United

States between November 2002 and December 2003. Furthermore, it is also stated that during the ban period of short-selling in the 2008 Global Financial Crisis, a considerable level of increase in the number of new listing of SSFs and trading volume was observed in the United States and the United Kingdom (Benzennou, Gwilym & Williams, 2017; Jiang, Shimizu, & Strong, 2019). Hence, SSFs provide a low-cost alternative with lesser constraints that may enhance a better price discovery process.

2.2 Price discovery role of single stock futures

The majority of studies regarding SSFs evolved around the price discovery mechanism. Price discovery stands for the process of how new information is reflected in prices. In other words, whether the spot or derivatives market process a piece of new information more swiftly and influence the price discovery. In efficient markets, as Fama (1970) states prices fully reflect all available information. Thus, a simultaneous response is expected to new information from both the spot and futures market and not a lead-lag relationship. Cox (1976) analyzes the influence of futures trading on price behaviour by assessing the introduction of futures trading on six commodities on the New York and Chicago exchanges. He argues in line with Fama (1970) that trading in the futures market increases the existing information level which will be simultaneously transferred to the spot market and increases the market efficiency. However, Mutlu and Arık (2015) discuss that constraints such as transaction costs and short-sale restrictions can be effective in weak and semi-strong markets and attract the interest of investors towards SSFs. So, trades in both derivatives and their underlying markets can deliver information (Back, 1993). This situation will create a lead-lag relationship between the spot and futures market.

Shrinivasan and Bhat (2009) analyze the lead-lag relationship between spot and futures prices of 21 commercial bank stocks in the Indian exchange and they present that futures are responsible for 43% of the price discovery while spot prices are responsible for 28.5%. The remaining 28.5% shows that there is also a bilateral relationship between spot and futures trading. A different study conducted in the Indian market by Aggarwal and Thomas (2011) represents a 49% lead in price discovery by the SSFs which also increases up to 56% with the arrival of new information. Plus, Aggarwal and Thomas (2011) add that the roles of the spot and futures market are dynamic as traders move between two options accordingly with the changes in leverage and cost of trading. For instance, negative news increases the price discovery of futures to 61% due to short-sale restrictions that are applied in the spot market (Aggarwal & Thomas, 2019). Songyoo (2012) states in the analysis of Taiwanese exchange, futures market leads their underlying stocks in the short-run. On the other hand, a bilateral relationship is observed in the long run. The cross-country analysis of Mutlu and Arık (2015) highlights that SSFs have a positive role in price discovery with 47% when the daily data is depicted from exchanges of India, Korea, Poland and Russia, but they showed the contribution of SSFs' price discovery decreases to 36% when intraday data is exercised. A study conducted for the stocks in the energy sector reports futures market contributes to price discovery with 75% comparing to the spot market with 25% (Anjana Raju & Shirodkar, 2020).

Ang and Cheng (2005b) argue that SSFs create a greater market efficiency as the unexplained changes in stock returns decrease for stocks listed on the SSFs market. In their study of 137 SSFs traded on OneChicago, Shastri, Thirumalai and Zutter (2008) express that the level of the informativeness of the underlying stocks increases with the introduction of SSFs and the quality of the market for underlying stocks is higher on the day of futures trading comparing to days with no futures trading and their result reports that SSFs are accounted for the only 24% of the price discovery in their underlying stocks. Furthermore, price discovery of SSFs increases with a narrower spread in futures comparing to the spread in their underlying stocks. In another study, Fung and Tse (2008) analyze the intraday bid-ask quotes of SSFs traded on the Hong Kong Exchange and they state more than 80% of underlying quotes are superior to their SSFs' quotes. Furthermore, Boney, Giannikos and Guirguis (2018) argue that the relationship of the price discovery process between spot and futures markets may shift due to changes in market conditions and during financial distress periods. Their study of 30 SSFs from the Dow Jones Industrial Average shows that the spot market leads SSFs on price discovery with 70%. While this level remains the same during market turbulences, a deterioration in the price discovery level was observed with a change in regulation regarding the short sales in 2010. Kumar and Tse (2009) discuss that the underlying stock market performs better with 72% than the SSFs market with 28% in price discovery contrary to previous studies. On the contrary, quotes of SSFs lead quotes of their underlying stocks by 61% to 39%. Therefore, it is argued that both underlying stocks and SSFs have predictive ability for each other and they are mutually dependent.

2.3 Dynamic connectedness

During turbulent times and crisis periods, risk factors in the financial market become more evident and the negative effects which rise in these periods create more vulnerability. Furthermore, the increasing number of crises together with globalization deepens the interconnectedness between financial assets and markets. According to Guidolin and Tam (2013), Global Financial Crisis that occurred in 2008 is one of the most damaging crises since the Great Depression. The crisis aroused with the price bubble burst occurred in the real estate market in the United States and the effects of the crisis heightened with the bankruptcy of Lehman Brothers in 2008. Effects of the spillover transmissions of the Global Financial Crisis have been studied in the literature extensively and studies express that the level of spillover transmissions increases following the crisis period which strengthens the theory of connectedness. (Dooley & Hutchison, 2009; Coudert, Couharde & Mignon, 2011; Yin & Han, 2014).

Diebold and Yilmaz (2009), put forward a framework that shows the return spillovers and volatility spillovers of 19 stock market indexes between 1992 and 2007. Their study explains what percentage of the forecast error variances of an asset can be explained with shock spillovers coming from the network. Furthermore, it is reported that the level of spillovers is time-varying and responding to events like the Global Financial Crisis with the help of spillover plots which are constructed with the varying spillover index throughout the sample period. Their paper presents different dynamic behaviour for return spillovers and volatility spillovers. While return spillovers have a gradually increasing trend with no bursts, volatility spillovers do not reflect a trend but have apparent bursts. Thus, their study was helpful to show the increasing connectedness during crisis periods.

In their next study, Diebold and Yilmaz (2012) investigate the daily volatility spillovers between United States stock, bond, foreign exchange and commodities markets with a generalized vector autoregressive framework for the period between 1999 and 2010. This study improves Diebold and Yilmaz (2009) and provides results that are robust to the variable ordering. They also extend their study by measuring directional volatility spillovers and connectedness in terms of identifying spillovers that are transmitted to a variable from the network, spillovers that are transmitted to the network from a variable and the net connectedness as the difference between transmitted and received spillovers from the network. They restate that spillovers between markets were heightened during turbulent times as Global Financial Crisis with clear spillover transmissions from the stock market to other studied markets.

In addition to the previous two studies, Diebold and Yilmaz (2014) study the time-varying connectedness of large financial institutions' stock return volatilities in the United States over the period between 1999 and 2010 and they display both the pairwise and system-wide spillover transmissions with focusing on the crisis periods of the 9/11 attacks, Enron scandal and Global Financial Crisis. The total connectedness is found to be 78.3% which states a high level of connectedness. Moreover, the connectedness of the network is visualized with a network graph which helps to identify the direction of the spillovers between selected pairs.

Pivotal studies of Diebold and Yilmaz (2009, 2012, 2014) contribute a growing body of literature that emphasizes the importance of exploring the connectedness of a network by identifying the transmission of shock spillovers with a rolling-window vector autoregression approach. The current studies in the literature examine the connectedness in the financial markets such as stock markets (Mensi, Boubaker, Al-Yahyaee & Kang, 2018; Jiang, Zhu, Tian & Nie, 2019), bond markets (Antonakakis & Vergos, 2013; Ahmad, Mishra & Daly, 2018), currency markets (Antonakakis & Kizys, 2015) and commodity markets (Chevallier & Ielpo, 2013; Zhang & Broadstock, 2018).

Baruník, Kočenda, and Vácha (2016) study the connectedness between seven sectors in the United States which are consisted of stocks for the sample period between 2004 and 2011. It is found that the connectedness between stocks reached a peak level at close to 90% during the Global Financial Crisis. Furthermore, they find that the consumers, telecommunications, and health care sectors display spillover asymmetries comparing to financial, information technology and energy sectors. Although they do not identify stocks as net spillover transmitters or net spillover receivers, they show that the direction of the spillovers varies during the period. The connectedness between different sectors is also examined by Umar, Jareño, and Escribano (2020). They analyze the connectedness between sector equity indices of Spain and oil price shocks for the duration between 2000 and 2019. It is stated that financials, industrials, utilities and telecommunications act as net spillover transmitters while consumer goods, technology, and retails act as net spillover receivers. The total connectedness index signals a medium interconnectedness level between sectoral indices at 57%. They also indicate that connectedness between stock and commodity futures increases during the Global Financial Crisis and sovereign debt crisis periods as reflected in the spillover index.

Yarovaya, Brzeszczyński, and Lau (2016) explore the return and volatility spillovers across 10 developed and 11 emerging markets between 2005 and 2014. It is discussed that markets are more sensitive towards volatility shocks coming from domestic and regional markets comparing to interregional shock spillovers. Moreover, stock index futures markets exhibit a larger magnitude of spillovers in terms of return and volatility compared to stock indices. Since the spillovers between emerging markets are lower than developed markets, investors can apply a diversification strategy in their international portfolio by investing in emerging markets.

Antonakakis, Floros and Kizys (2016) analyze the dynamic spillover transmissions of spot and futures market volatilities between the United Kingdom and the United States for the period between 2008 and 2013. A bidirectional relationship is found among the spillover transmissions between spot and futures markets. Also, an increase in the level of spillover transmissions is observed when the Global Financial Crisis and debt crisis were effective in Europe.

In a different study, Mensi et al. (2018) also argue that connectedness and volatility spillovers intensify during crisis periods as they show in their study that analyzes the spillover transmissions between stock markets of Greece, Ireland, Portugal, Spain and Italy together with S&P 500, Stoxx 600 and Dow Jones Asia index for the period between 2002 and 2016. They find that spillover transmissions are affected by economic and political events such as Global Financial Crisis and Eurozone Sovereign Debt Crisis. It is also argued that Greece and Spain act as net shock receivers.

A certain amount of literature examines the connectedness across different financial markets. Magkonis and Tsouknidis (2017) investigate the dynamic volatility spillover transmissions for the spot and futures market of oil commodities. It is found that the futures volatility of crude oil transmits significant spillovers to futures volatilities of both gasoline and heating oil. Also, it is stated that the futures volatility of crude oil, gasoline and heating oil transmit spillovers to their spot volatilities. Wang et al. (2016) investigate the volatility spillovers among Chinese stock, bond, commodity futures and foreign exchange markets between 2005 and 2015. It is stated that stock and bond markets are net transmitters while commodity futures and foreign exchange markets are net receivers. According to Xiao, Yu, Fang and Ding (2020), 70% of the uncertainty for commodity futures can be attributed to the shocks coming from the commodity futures market as the total connectedness of 19 commodities indicates. They find that metal futures are net transmitters while energy futures and agricultural futures are net receivers. So, it is argued that authorities need to take relevant hedging actions to minimize possible risks.

Kang and Yoon (2019) assess the return and volatility spillovers between the Chinese stock market and commodity futures market between 2005 and 2009. For return spillovers, copper is the strongest net spillover transmitter while Chinese Securities Exchange 300 (CSI 300) is the net receiver. For the volatility spillovers, the copper and index display opposite net volatility spillover dynamics. In another study, Kang and Lee (2019) analyze the volatility spillover transmissions between 12 international index futures together with two commodity futures between 2002 and 2018. The Financial Times Stock Exchange 100 (FTSE 100) index from London is found to be the highest net transmitter, while the Korea Composite Stock Price 200 (KOSPI 200) index from Korea acts as a net receiver. In both studies, the transmissions of spillovers increase during stress periods of the Global Financial Crisis and European Debt Crisis between 2008 and 2012.

2.4 Dynamic connectedness based on TVP-VAR

The dynamic connectedness approach based on TVP-VAR (Antokakanis & Gabauer, 2017; Antonakakanis et al., 2020) provides advantages over the rolling windows-based methodology of Diebold and Yilmaz (2009, 2012, 2014). This approach overcomes the necessity of arbitrarily choosing the size of the rolling window which also prevents the loss of observations. Additionally, sensitivity towards outliers also decreases. Following these studies, there is a growing literature that studies the dynamic connectedness based on the TVP-VAR methodology. These studies mostly concentrate on the dynamic connectedness between uncertainties, commodity markets, bond markets and stock markets.

Antonakakis, Gabauer, Gupta, & Plakandaras (2018) examine the dynamic connectedness of uncertainty based on the TVP-VAR model between the United States, European Union, United Kingdom, Canada and Japan with the time-varying framework using daily macroeconomic uncertainty indices for the period between 2003 and 2017. The total connectedness display spikes around 2004, 2008 and 2011 which shows that connectedness between countries varies in time. Furthermore, Japan and European Union act as net transmitters of uncertainty. It is also argued that total connectedness increases at longer horizons. This shows that uncertainty in longer horizons is mostly arisen by exogenous effects since domestic uncertainties are reflected in the economy in the long term.

Gabauer and Gupta (2018) investigate the transmission of economic policy uncertainty spillovers that occurred between the United States and Japan between 1987 and 2017. It is stated that monetary policy uncertainty is the main force between the connectedness and it is followed by the policy uncertainties of fiscal, currency market and trade. The most substantial peak in the total connectedness index is observed in 2010 which coincides with the nuclear accident that occurred in Japan. This is represented in the total connectedness index of Japan based on internal spillovers, but the total connectedness index of the United States based on internal spillovers did not increase. Still, a greater increase is detected in the overall total connectedness index than the increase in the Japanese total connectedness index which means that economies in the globalized world are interlinked. This interconnectedness is also discussed in Jiang et al. (2019) that analyze the trade, monetary and fiscal uncertainties for the period of 2000 to 2019 and it is argued that bilateral trades and key episodes like trade conflict between the United States and China impact the direction of spillover transmissions between two countries.

Gabauer and Gupta (2020) examine the spillovers between financial, macroeconomic and real estate uncertainties by using the TVP-VAR model between 1970 and 2017. The level of spillovers varies during the period and dynamic connectedness is higher in turbulent periods like the recession in 1980 and Global Financial Crisis in 2008. Furthermore, it is found that financial uncertainty transmits shocks to the macroeconomic and real asset uncertainties which makes it important to give emphasis on systemic risks available in the financial system.

Assaf, Charif and Mokni (2021) study the dynamic connectedness between uncertainty indices and energy markets for the period between 2001 and 2020. It is expressed that economic policy uncertainty transmits the highest spillovers to energy markets while the oil market transmits the highest spillovers to the uncertainty. Furthermore, it is argued that the total connectedness index shows high connectedness during the Global Financial Crisis and COVID-19 outbreak.

Demirer, Gabauer, Gupta and Ji (2021) examine how monetary policy drives the connectedness of speculative activities between stocks, treasury bonds, gold and crude oil in the United States. It is argued that speculative activities can be transmitted, and the stock market is the net speculative shock transmitter. Moreover, they state that the level of speculative spillover transmissions increases when unconventional monetary policies are applied.

Among the studies which analyze the dynamic connectedness between commodities, Dahir et al. (2020) study the dynamic connectedness between Bitcoin and equity markets of Brazil, Russia, India, China and South Africa. The total volatility connectedness is around 45% which states that shocks that are transmitted between Bitcoin and equity markets can explain almost half of the total forecast error variance of variables. However, shock transmissions from Bitcoin to equity markets display a low transmission level. In another study, Jiang, Tian and Mo (2020) examine the dynamic connectedness between oil price and stock returns of Group of Seven (G7) countries and they express that oil supply shock acts as a net spillover transmitter to all countries.

Liu, Tang, and Chang (2020) study the spillover transmissions among carbon spot and futures prices in the European Union Allowance carbon trading market by separating them into two phases and utilizing the TVP-VAR model. In the first phase (2008-2012), spot prices acted as a net transmitter while future prices were net transmitters in the second phase (2013-2020). This shows a bidirectional relationship. Furthermore, the fluctuations in the spillover intensify during the crisis periods of the Global Financial Crisis and European Debt Crisis which also show an increasing degree of connectedness.

Mandacı, Cagli, and Taşkın (2020) analyze the dynamic connectedness between global commodity futures, global stock markets, the bond market in the United States and the US dollar index between 1992 and 2019. The total connectedness index is found as 39.1% which reflects a rather medium connectedness that reaches its peak point during the Global Financial Crisis. It is also argued that hedging amongst the different classes is more effective than hedging amongst the same asset classes.

Studies that analyze the dynamic connectedness with TVP-VAR also focus on the COVID-19 pandemic and its effect on the spillover transmissions. According to Gunay (2021), total spillovers due to COVID-19 reflect eight times greater spillover transmissions comparing to total spillovers due to Global Financial Crisis. Adekoya and Oliyide (2021) study the effect of COVID-19 in the United States between January 2020 and July 2020 for the connectedness between commodities and financial assets. It is stated that gold and dollar-euro exchange rates are net receivers of volatility spillovers while gold, stock and bitcoin are net volatility transmitters. It is also expressed that the dynamic connectedness is higher for the initial part of the pandemic since the panic was at the highest level during that time.

Corbet, Hou, Hu, Oxley & Xu (2021) study the effects of COVID-19 on the futures prices of CSI 300 index, gold, oil, soybean US dollar/ RMB spot exchange rate and bitcoin price with incorporating coronavirus index and influenza index. They argue that the coronavirus index reflects a more significant effect on financial markets compared to the regular influenza index which shows that COVID-19 created bigger problems for the economy which is the case in the CSI 300 index. Furthermore, volatility spillovers are transmitted to gold and oil futures markets from coronavirus and influenza indices which supports the idea of flight to safety approach. The volatility transmissions towards Bitcoin are witnessed from the coronavirus index which explains the highly volatile character of Bitcoin during the pandemic.

Bouri, Cepni, Gabauer & Gupta (2021) review the return connectedness of gold, currencies, crude oil, bonds, and world equities to observe the effect of the COVID-19 outbreak. They argue that connectedness of the overall network of assets increases during the outbreak as well as in the connectedness of the cross-assets. The relationship of connectedness also alters. While the equity and US dollar indices acted as a net shock transmitter before the outbreak, the bond index becomes the main shock transmitter with the COVID-19 pandemic and the US dollar index also become a net receiver.

Youssef, Mokni and Ajmi (2021) investigate the dynamic connectedness between stock indices of eight countries together with the effect of economic policy uncertainty. It is expressed that an increase in the dynamic connectedness between stock markets is spotted during the COVID-19 pandemic. This supports the idea that connections between stock markets become more visible during stress periods. They find that European stock markets act as net transmitters. Furthermore, it is stated that high uncertainty in the economic policy has significant effects on the dynamic connectedness.

Fassas (2020) study the dynamic connectedness of the risk aversion connectedness across the United States, developed markets and emerging markets. The connectedness increases with the COVID-19 outbreak and the main transmitter of the shocks become the sentiment of investors of emerging markets which was the sentiment of investors from the United States before the pandemic. This study is helpful to show that dynamic transmission of spillovers varies during the studied period.

Chatziantoniou, Gabauer, and Marfatia (2020) analyze the dynamic connectedness of stock market sectors of India by using sectoral indices. It is stated that the connectedness of the sectors varies and an increase in the connectedness level is observed during turbulent times like Global Financial Crisis, the crash of the stock market and high inflation in 2011, national elections of 2014 and the demonization of two high-value notes in 2016. The total connectedness index is almost 75% which indicates a strong relationship between sectors. Furthermore, it is argued that finance, industry, consumer spending and the basic material sector act as net shock transmitters while telecommunications, healthcare, information technology and fast-moving consumer goods act as net shock receivers.

Applying the TVP-VAR model of Primiceri (2005), Zhou, Dong and Wang (2014) investigate the volatility spillovers between CSI 300 index futures and spot markets and they find a bidirectional relationship that states that new information in the market is simultaneously reflected in both spot and futures markets. In addition, Polat (2020) applied the same model to analyze the shocks that Borsa Istanbul receives from the global oil market and real economic activity. He argues that positive oil shocks have a negative impact on Borsa Istanbul which diminishes in the long run. On the contrary, positive global economic activity shocks have a positive impact on the return of Borsa Istanbul. In another study, Toparlı, Çatık and Balcılar (2019) study how oil prices and economic activities impact the Borsa Istanbul over the period between 1988 and 2017. They state that stock returns are mainly affected by the exchange rate and interest rate and shocks are significant during the crisis period of the Gulf War, 1994 local financial crisis and 2008 Global Financial Crisis. Although the TVP-VAR model is used in these studies, it does not measure the degree of interconnectedness among the variables in the context of connectedness.

As shown in the literature reviewed above, dynamic connectedness based on the TVP-VAR model to examine the relationship between spot and futures prices has been understudied. Studies that analyze the spot and futures prices are mainly focused on the relationship between index futures and commodity futures. Also, studies that applied only the TVP-VAR model did not approach the relationship between variables from the connectedness perspective. In this thesis, the aim is to fill the gap by analyzing the dynamic connectedness between SSFs that are traded in Borsa Istanbul by employing the TVP-VAR model.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Descriptive statistics

The dataset contains the daily return prices of 20 SSFs stocks that are traded in Borsa Istanbul. These stocks are selected due to their liquidity. Both spot prices and 1-month futures prices are included in the analysis which are extracted from the Bloomberg database. The sample period is selected between 02.03.2016 and 07.12.2020 in order to obtain the most comprehensive dataset that is available in terms of traded SSFs. In Table 1, SSFs that are included in the thesis are given.

Table 1. List of Stocks and Sectors

Stock Ticker	Company Name	Sector
AKBNK	Akbank T.A.Ş.	Banking
ARCLK	Arçelik A.Ş.	Manufacturing
EKGYO	Emlak Konut Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Invesment Trusts
EREGL	Ereğli Demir ve Çelik Fabrikaları T.A.Ş.	Manufacturing
GARAN	Türkiye Garanti Bankası A.Ş.	Banking
HALKB	Türkiye Halk Bankası A.Ş.	Banking
ISCTR	Türkiye İş Bankası A.Ş.	Banking
KCHOL	Koç Holding A.Ş.	Holding
KRDMD	Kardemir Karabük Demir Çelik San. ve Tic. A.Ş.	Manufacturing
PETKM	Petkim Petrokimya Holding A.Ş.	Manufacturing
PGSUS	Pegasus Hava Taşımacılığı A.Ş.	Transportation
SAHOL	Hacı Ömer Sabancı Holding A.Ş.	Holding
SISE	Türkiye Şişe ve Cam Fabrikaları A.Ş.	Manufacturing
TCELL	Turkcell İletişim Hizmetleri A.Ş.	Telecommunication
THYAO	Türk Hava Yolları A.O.	Transportation
TOASO	Tofaş Türk Otomobil Fabrikası A.Ş.	Manufacturing
TTKOM	Türk Telekomünikasyon A.Ş.	Telecommunication
TUPRS	Tüpraş-Türkiye Petrol Rafinerileri A.Ş.	Manufacturing
VAKBN	Türkiye Vakıflar Bankası T.A.O.	Banking
YKBNK	Yapı ve Kredi Bankası A.Ş.	Banking

According to (Borsa Istanbul, 2018), the contract sizes of SSFs consist of 100 shares for each contract. Tick sizes are one Turkish Lira for each contract. All months in the calendar are counted as contract months. Settlement occurs with physical delivery with the settlement date being two days after the date of expiration. Settlement prices are set daily following the end of the session and the daily price limit is calculated as ±20% of each contract's base price. Moreover, SSFs' final settlement price is determined as the closing price of the underlying spot market on the last date of trading which is the contract month's last business day.

The returns of both prices are calculated by taking the logarithmic return of spot and 1-month futures prices which are taken into consideration in the calculations. Furthermore, stationarity of the returns of spot and 1-month futures prices are tested by applying Augmented Dickey and Fuller test (Dickey and Fuller, 1979). The result of the test states that both of the return prices are stationary at the 5% level of significance. The descriptive statistics of log-return series for both spot and 1-month prices are given in Table A1-A2 (Appendix A). There is a total of 1244 daily observations for each stock. The majority of the return prices are negatively skewed and display an excess kurtosis that expresses a leptokurtic distribution with fat tails. Spot prices of AKBNK, EKGYO, HALKB and 1-month future prices of EGKYO, HALKB display the lowest average returns. On the other hand, spot and 1-month futures prices of KRDMD, PGSUS and EREGL exhibit the highest average returns. According to the measurement of variance, spot prices and 1-month futures prices of PGSUS, KRDMD and THYAO present the riskiest stocks while KCHOL, SAHOL and TCELL depict the less risky stocks in terms of spot and 1-month futures prices.

3.2 TVP-VAR approach

In this thesis, the dynamic connectedness based on TVP-VAR methodology is applied which is proposed by Antonakakis et al. (2020) in order to analyze the time-varying connectedness between SSFs. Their study improves the connectedness framework of Diebold and Yilmaz (2009, 2012, 2014) since the size of the rolling window does not affect the results. There are several advantages that TVP-VAR based dynamic connectedness methodology presents:

- An insensitivity towards outliers occurs due to the employment of Kalman filter estimation and instantaneously adapts to events
- It helps to overcome the arbitrarily choosing the size of the rolling windows
- It eliminates the problem of loss of valuable observations and makes it possible to employ the methodology for datasets with short samples

The methodology that is applied in Antonakakis et al. (2018) and Gabauer and Gupta (2018) is also applied in this thesis. Furthermore, the optimal lag length of one according to the Bayesian information criterion (BIC) is chosen. TVP-VAR can be outlined as:

$$z_t = B_t z_{t-1} + u_t \qquad u_t \sim N(0, S_t) \qquad (1)$$

$$vec(B_t) = vec(B_{t-1}) + v_t \qquad v_t \sim N(0, R_t) \qquad (2)$$

Here, z_t, z_{t-1} and u_t represent $k \times 1$ dimensional vectors and A_t, B_t and S_t represent $k \times k$ dimensional matrices. Also, $vec(B_{t-1})$ and v_t stand for $k^2 \times 1$ dimensional vectors while R_t describes a $k^2 \times k^2$ dimensional matrix.

Moreover, H-step ahead scaled generalized forecast error variance decomposition (GFEVD) proposed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) is calculated. The reason why the GFEVD is used because it is not affected by the order of variables compared to the orthogonalized forecast error variance decomposition (Diebold & Yılmaz, 2009). Furthermore, the TVP-VAR model is transformed to its vector moving average (VMA) form according to the Wold representation theorem by utilizing the following equation:

$$z = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j}. \tag{3}$$

In order to reach unity when each row sums up, the scaled version of GFEVD normalizes the unscaled version of GFEVD which is described with the following notation, $\phi_{ij,t}^{g}(H)$. Thus, $\tilde{\phi}_{ij,t}^{g}(H)$ indicates the influence that variable *j* has on variable *i* with regards to its forecast error variance share. In other words, it is described as the pairwise directional connectedness from *j* to *i*. This indicator can be illustrated as the following:

$$\phi_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(\iota_i' A_t S_t \iota_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\iota_i A_t S_t A_t' \iota_i)^2} \qquad \tilde{\phi}_{ij,t}^{g}(H) = \frac{\phi_{ij,t}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij,t}^{g}(H)} \tag{4}$$

Here, $\sum_{j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H) = k$, and ι_i signifies a selection vector with unity on the *i*th position and zero otherwise. Thereafter, the calculation of the total connectedness index (TCI) is depicted in the following equations.

As stated earlier, $\tilde{\phi}_{ij,t}^{g}(H)$ portrays the impact of a shock in variable *j* that has on variable *i*. Thus, Equation (5) states the total directional connectedness to others which is the aggregated impact a shock in variable *j* has on all other variables in the network.

$$TO_{jt} = \sum_{i=1,\ i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) \tag{5}$$

Equation (6) expresses the total directional connectedness from others which demonstrate the aggregated impact all other variables in the network have on variable *j*.

$$FROM_{jt} = \sum_{i=1,\ i \neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) \tag{6}$$

In Equation (7), the computation of the net total directional connectedness is provided which subtracts the impact variable *j* has on others in the network by the impact of others in the network have on variable j. This subtraction explains whether a variable in the network is a net transmitter of shocks or a net receiver of shocks. If the impact that variable *j* has on others in the network is larger compared to the impact that variables in the network have on variable *j*, it can be argued that variable *j* drives the network. On the contrary, if the impact that variable *j* has on others in the network is smaller compared to the impact that variables in the network have on variable *j*, it can be claimed that variable *j* is driven by the network.

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{7}$$

The average impact that one variable has on all others in the network is described as the total connectedness index (TCI_t) which is described in Equation (8). A high TCI indicates a high level of interconnectedness among the variables in the network. It also signals a high level of market risk since the impact of a shock received by one variable will also be perceived by the network. On the other hand, a low level of TCI indicates that variables in the network are to a certain extent independent and will be affected less by an impact transmitted from other variables in the network.

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} = k^{-1} \sum_{j=1}^{k} FROM_{jt} \tag{8}$$

Lastly, Equation (9) illustrates the bilateral relationship between variables *j* and *i* which is expressed as the net pairwise directional connectedness ($NPDC_{ij,\,t}$). It exhibits whether variable *j* or variable *i* is the driving variable.

$$NPDC_{ij,\,t} = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H) \tag{9}$$

CHAPTER 4

EMPIRICAL RESULTS

4.1 Analysis of spot prices

4.1.1 Dynamic connectedness of spot prices

The dynamic connectedness table in Appendix B shows the averaged dynamic connectedness between underlying spot prices of 20 SSFs as a result of the TVP-VAR model between 02.03.2016 and 07.12.2020. Hence, the dynamic connectedness table is useful to show the exchanged *H*-step forecast variance between variables *j* and *i*, as well as aggregated impact a shock in variable *j* has on other variables which are labelled as “To” and aggregated impact all other variables have on variable *j* which are labelled as “From”. While diagonal elements show the own-stock shock transmissions, off-diagonal elements show interaction across all stocks. The row labelled as “Net”, highlights the difference between “To” and “From” that gives the measure for the net total directional connectedness. Lastly, the bottom right corner gives the total connectedness index which is the average impact one variable has on all other variables and a high TCI expresses a strong co-movement between studied stock prices.

According to the dynamic connectedness table for the spot prices of SSFs, the TCI of 78.20% states that there is a high interconnectedness between spot prices of SSFs. The highest forecast error variances are observed throughout the diagonal values which express that the own connectedness of stocks is highest as it is expected. The highest pairwise directional connectedness is detected from THYAO to PGSUS (10.84%) which can be explained by the fact that both companies operate in the airline industry. On the other hand, the lowest pairwise directional connectedness is observed from TUPRS to GARAN (1.33%). Moreover, the highest forecast error variances among stock prices are transmitted by companies that operate in the banking sector. GARAN (5.89%) sends the highest shock to the network and followed by AKBNK (5.87%), VAKBNK (5.81%), ISCTR (5.43%), YKBNK (5.38%) and HALKB (4.76%). It is also the case when banks receive the highest shocks from the network. AKBNK and GARAN receive the highest shocks from the network with 4.32% and they are followed by VAKBNK (4.31%), ISCTR (4.27%), YKBNK (4.27%) and HALKB (4.18%). Also, it can be noted that GARAN (1.56%) is the highest net transmitter while TUPRS (-1.33%) has the lead as a net receiver.

Figure 1 presents the dynamic total connectedness index between 02.03.2016 and 07.12.2020 which is effective to identify the specific turbulent periods which affect the connectedness over time. Overall, TCI is high during the whole period and TCI varies between 70% and 90%. In the beginning, the index starts with an over 80% level and stays above this level between July 2016 and March 2017. Between June 2017 and February 2018, TCI fluctuates around 75% with two peaks which are observed in November 2017 and August 2018. Moreover, TCI reaches its lowest point during March 2019. However, it is followed by a sharp increase and the index reaches its peak point at close to 90% level around March 2020 which coincides with the announcement of the first Covid-19 case in Turkey. Although TCI starts to fall after the initial shock of the pandemic, it still stays above the 80% level for the remainder of the sample period.

Figure 1. Dynamic total connectedness of spot prices

4.1.2 Total directional connectedness to others of spot prices

Figure C1-C2 (Appendix C) depict the aggregated impact a shock in one variable has on all other variables. In other words, these two time series figures show the level of shocks that are transmitted by each stock to the network. For companies operating in the banking sector, (AKBNK, GARAN, HALKB, ISCTR, VAKBN and YKBNK) the patterns of total directional connectedness to others reflect nearly constant spillover levels and these spillovers do not vary during the sample period. Furthermore, shock transmissions are higher among these stocks and the average level ranges between 4.76% and 5.89%. Two industrial conglomerate companies, KCHOL and SAHOL, reflect relatively more dynamic spillover transmissions than banks with average transmission levels of 4.57% and 4.73%. Apart from the above mentioned eight stocks, the remaining 12 stocks signal more dynamic and time-varying transmission patterns. However, the average level of shock transmissions to the network is lower and it ranges between 1.79% and 4.26%. Among these stocks, TUPRS is the least impactful company with 1.79% in terms of sending shocks to the network. Furthermore, peaks in the spillovers that are transmitted to the network from EREGL, KRDM, PETKM, and THYAO are identified in March 2020. ARCLK, EKGYO, TTKOM, and TUPRS transmit their highest spillover transmissions in the summer of 2020. On the other hand, PGSUS, SISE and TCELL reach their highest level of transmissions in the summer of 2018. One common observation that can be made about these 12 stocks is that an increase in the spillover transmissions is observed around March 2020.

4.1.3 Total directional connectedness from others of spot prices

Figure C3-C4 (Appendix C) illustrate the aggregated impact that all other variables have on one single variable. Hence, these two time series figures show the levels of shocks that are received from the network by each stock. The observed transmission patterns of shocks from the network to the banking companies (AKBNK, GARAN, HALKB, ISCTR, VAKBN and YKBNK) are static and maintains an average level of shock transmissions which ranges between 4.18% and 4.32%. Although similar time-varying transmission patterns can be observed for the remaining 14 stocks as occurred in total directional connectedness to others, these stocks reflect more homogeneous patterns since they show fewer variations over time. Among these 14 stocks, SAHOL (4.17%) receives the highest level of shocks while TUPRS (3.12%) receives the least level of shocks. Furthermore, apart from EREGL and TOASA which receive the highest levels of shocks in March 2016, shocks that are received from the network by these stocks reach their highest levels in March 2020.

4.1.4 Net total directional connectedness of spot prices

Figure C5-C6 (Appendix C) portray the difference between the total directional connectedness of shock transmitters and receivers for each stock within the network of stocks. If the difference is positive, that stock is a net transmitter of shocks. In other words, it is driving the network. If the difference is negative, it means that the stock is a net receiver of shocks and it is driven by the network.

All banking companies act as net transmitters of shocks and they are the main driver of the network. GARAN (1.56%) leads the way and it is followed by AKBNK (1.55%), VAKBN (1.50%), ISCTR (1.16%), YKBNK (1.11%) and HALKB (0.58%). While AKBNK, VAKBN, and ISCTR act as persistent net shock transmitters, HALKB and YKBNK act as net receivers for a brief time interval. Although the period in which YKBNK act as a net receiver lasts for a couple of days, HALKB play the role of a net transmitter from November 2017 to August 2018. In addition to banking companies, SAHOL (0.56%), KCHOL (0.49%) and THYAO (0.21%) operate as net transmitters with momentary exceptions. When we look at from the other side, TUPRS (-1.33%), TCELL (-1.20%), TOASA (-1.15), EREGL (-1.13%), PETKM (-0.80%), ARCLK (-0.75%), SISE (-0.69%), PGSUS (-0.62%), TTKOM (-0.61%), KRDMD (-0.32%) and EKGYO (-0.12%) are net receivers of shocks from the network. Moreover, TUPRS, TCELL, TOASA, EREGL have been net receivers during the sample period with time-varying shock transmission patterns. However, PETKM, ARCLK, SISE, PGSUS, TTKOM, KRDMD and EKYGO have heterogonous patterns and perform as net transmitters from time to time. As we observe that transmission levels intensify after March 2020 from the total directional connectedness to others and from others, we can detect which stocks act as a net transmitter or net receiver after March 2020. Banking companies play the role of net shock transmitters after March 2020 together with KCHOL, SAHOL, THYAO and TTKOM. On the contrary, ARCLK, EREGL, PGSUS, SISE, TCELL, TOASA and TUPRS appear as net shock receivers following the period after March 2020. Lastly, EKGYO, KRDMD, PETKM are net transmitters but they receive spillovers more than they transmit for most of the duration after March 2020.

4.1.5 Net pairwise directional connectedness of spot prices

Figure 2 presents the network connectedness based on the dynamic connectedness table in terms of net pairwise directional connectedness. Nodes are representatives for each stock. A red node indicates the net pairwise transmitters while a green node denotes a net pairwise receiver. The size of a node shows the intensity of shock transmissions. Nodes are connected with arrow lines. The direction of the connectedness is shown with the arrow and the width of the line is an indicator of the degree of the connectedness.

In order to observe the most significant pairwise directional connectedness, an 80% threshold is applied and stocks above that threshold are represented in the figure. GARAN, AKBNK, VAKBN, ISCTR, YKBNK, HALKB, SAHOL, KCHOL and THYAO are net pairwise transmitters based on the red colour. It can be also inferred that GARAN, AKBNK, and VAKBN are the strongest net pairwise transmitters of shocks based on their node sizes. When we look at the green nodes, it is observed that TUPRS, TCELL, TOASA, EREGL, PETKM, ARCLK, SISE, PGSUS, TTKOM, KRDMD and EKGYO are net pairwise receivers of shocks. Additionally, node sizes of TUPRS, TCELL and TOASA implies that these single stock futures receive the highest spillovers from their pairs.

The figure with an 80% threshold is a good indicator of showing the high connectedness among the underlying spot prices of SSFs since it still gives a complex structure with the applied threshold. Also, it gives the most important net pairwise connectedness based on the width of the line between nodes. The strongest relationships are observed between nodes with bigger and smaller sizes which is the case when transmissions occur from banking companies to remaining companies in the network. Still, there are some other observed transmissions of shocks between nodes. For instance, there is a net pairwise connectedness that is observed from THYAO to PGSUS and from KRDMD to EREGL and these two connectedness can be related to operating in the same sectors. Furthermore, the highest net pairwise connectedness is observed from KCHOL to TUPRS. Together with KCHOL and TUPRS connectedness, the high net pairwise directional connectedness between KCHOL and TOASA may be explained by KCHOL being a parent company.

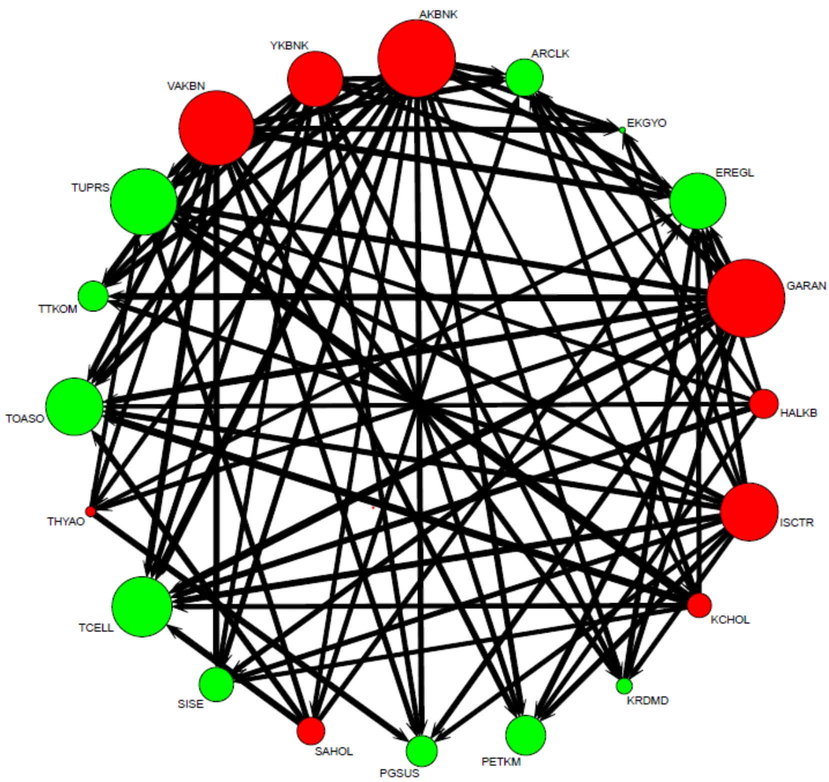

Figure 2. Net pairwise directional connectedness of spot prices

4.2 Analysis of 1-month futures prices

4.2.1 Dynamic connectedness of 1-month futures prices

The averaged dynamic connectedness between the 1-month futures prices of 20 SSFs between 02.03.2016 and 07.12.2020 is depicted in Appendix D. In this table, it is helpful to see how the impact of shock in one variable is transmitted to the network and how one variable receives the shock spillovers from the network. TCI which shows the degree of connectedness among the stocks in the network reflects a connectedness level at 71.92% as a sign that 1-month futures prices are highly connected with each other. In other words, a shock in one stock has a great effect on other stocks. Diagonal values which carry the own-stock spillovers exhibit the highest forecast error variances. From the pairwise directional connectedness perspective, the highest connectedness is from GARAN to AKBNK (10.83%). On the contrary, spillover transmission from TUPRS to HALKB (1.18%) is the lowest pairwise directional connectedness. The highest shock transmitters to the network are banking companies. GARAN (5.87%) leads the banking companies as the highest shock transmitter to the network and it is followed by VAKBN (5.57%), AKBNK (5.53%), ISCTR (5.52%), YKBNK (5.38%) and HALKB (4.67%). When we look at the highest receivers of shocks from the network, banks are in lead again as similar to spot prices. GARAN (4.21%) receives the highest shock from the network and it is followed by AKBNK (4.18%), VAKBN (4.17%), ISCTR (4.17%), YKBNK (4.14%) and HALKB (4.04%). Furthermore, GARAN (1.66%) is the highest net transmitter of shocks to the network while TUPRS (-1.13%) receives the largest net level of shocks from the network.

Figure 3 illustrates the dynamic total connectedness index between 02.03.2016 and 07.12.2020. TCI gives valuable insight in order to observe fluctuations during the period. Although fluctuations are perceived from the figure, TCI is still considerably high during the whole period and it varies between 55% and 90% levels. At the beginning of the period, the index starts around at 75% level and a sudden 10% decline in the TCI can be noticed. Furthermore, the lowest point that connectedness reaches occur at 55% level during the summer of 2017. Following this point, TCI adjusts itself between 70% and 75% until March 2020, with few exceptions as fluctuations continue to appear. One of the exceptions is the peak at 79% in August 2018. Also, two slight drops are observed around March 2019 and October 2019. The connectedness index reaches its highest point in March 2020 with a significant increase and maintains a certain level above 80% until the end of the period.

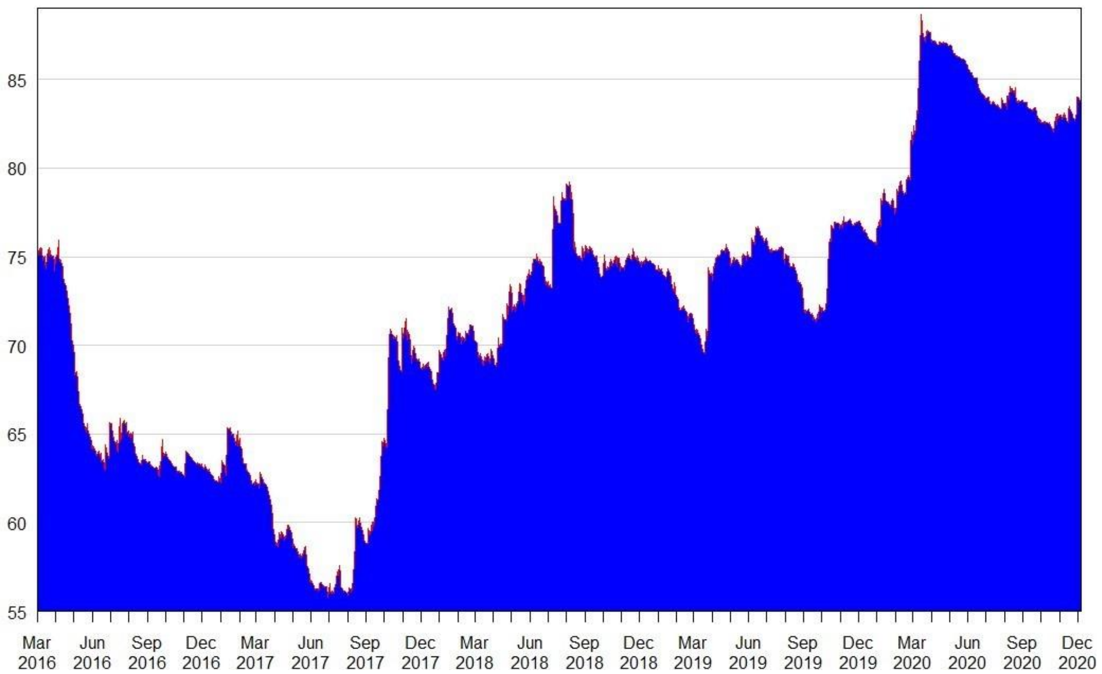

Figure 3. Dynamic total connectedness of 1-month futures prices

4.2.2 Total directional connectedness to others of 1-month futures prices

Figure E1-E2 (Appendix E) describe the aggregated impact a shock in one variable has on all other variables and that impact shows the levels of shocks that are transmitted by each stock's 1-month futures prices to the network. It can be inferred that the levels of shocks that are transmitted to the network from banking companies reflect high and steady transmission patterns. The levels of shock transmissions from AKBNK, GARAN, HALKB, ISCTR, VAKBN and YKBNK range between 4.67% and 5.87%. From the remaining stocks, THYAO (4.19%) and SAHOL (4.44%) demonstrate reasonably high dynamic spillover transmission patterns. Comparing to THYAO and SAHOL, significant time-varying transmission forms can be identified for the remaining stocks in the network. Especially, PETKM (2.55%), TTKOM (2.88%) and KRDMD (3.05%) display considerably strong dynamic transmission patterns while TUPRS has the least amount of impact on the network with 1.67%. The spillovers that are transmitted by KRDM, PETKM and SISE reach a peak in March 2020. Moreover, transmitted spillovers from ARCLK, EKGYO, TOASA and TUPRS reach their highest level in the summer of 2020. Also, KCHOL and TTKOM transmit their highest levels of spillovers towards the end of the period. Although transmitted spillovers from EREGL, TCELL and PGSUS peak in 2018, there is an overall increase in the levels of shock transmissions after March 2020.

4.2.3 Total directional connectedness from others of 1-month futures prices

The aggregated impact that all other variables have on a single variable is represented in Figure E3-E4 (Appendix E). The levels of shocks that are received from the network by each stock are represented through these time series figures. The highest levels of dynamic transmissions are received by AKBNK, GARAN, HALKB, ISCTR, VAKBN and YKBNK with static and high levels of spillovers which are between 4.04% and 4.21%. Comparing to banking companies, remaining stocks display slightly more heterogonous spillover transmissions. Additionally, SAHOL (4.01%), THYAO (3.91%) and EKGYO (3.82%) are the most impacted ones by the network among the non-banking stocks.Whereas, SISE (3.01%), TOASA (2.89%), TUPRS (2.80%) receive the least amount of spillovers from the network. As occurred in the spot prices, shocks that are transmitted to 1-month futures by the network reach their highest levels during March 2020 and high levels of spillovers can be observed following the peak points.

4.2.4 Net total directional connectedness of 1-month futures prices

Figure E5-E6 (Appendix E) display the net total directional connectedness which is derived from the difference between total directional connectedness to others and from others. Companies operating in the banking sector, AKBNK, GARAN, HALKB, ISCTR, VAKBN and YKBNK, are net transmitters of spillovers to the network throughout the majority of the period. In other words, they transmit spillovers to the network more than they receive from the network. Only, AKBNK, HALKB and YKBNK act as net receivers for a short period of time. In addition to banking companies, SAHOL and THYAO are also net transmitters, however, they are not as homogenous as banking companies as they perform as net receivers for multiple periods. The highest net transmitter is GARAN (1.56%) and it is followed by AKBNK (1.55%), VAKBN (1.50%), ISCTR (1.16%), YKBNK (1.11%) and HALKB (0.58%). Stocks that receive more shocks than they transmit to the network are TUPRS (-1.13%), TOASA (-1.10), TCELL (-1.07%), EREGL (-0.93%), ARCLK (-0.74%), SISE (-0.73%), PGSUS (-0.69%), PETKM (-0.67%), TTKOM (-0.46%), KRDMD (-0.42%), EKGYO (-0.21%) and KCHOL (-0.18%). While TUPRS and TCELL are net receivers throughout the whole period, remaining net receiver stocks occasionally appear as net transmitters. As examined in total directional connectedness to and from parts, the levels of spillovers transmitted are increased after March 2020. Net total directional connectedness illustrates which stocks are net shock transmitters or net shock receivers during this period. It can be seen that banking companies are net shock transmitters after March 2020 together with SAHOL, THYAO and TTKOM. On the other hand, ARCLK, EREGL, PGSUS, SISE, TCELL, TOASA and TUPRS appear as net shock receivers. Furthermore, EKGYO, KRDMR and PETKM are net transmitters initially but they play the role of a net receiver for the remaining period.

4.2.5 Net pairwise directional connectedness of 1-month futures prices

The net pairwise directional connectedness represents spillovers that are transmitted between pairs of the 1-month futures prices. Based on Figure 4, it can be argued that the network of 1-month futures of Borsa Istanbul SSFs displays a strong net pairwise connectedness. As it is observed from Figure 4 which is drawn with an 80% threshold, a certain level of connectedness is apparent.

GARAN, VAKBN, AKBNK, ISCTR, YKBNK, HALKB, SAHOL, and THYAO are net pairwise transmitters based on the red colour. According to the size of the red nodes, GARAN, VAKBN and AKBNK are the strongest net pairwise transmitters of shocks. When we look at the green nodes, it is observed that TUPRS, TOASA, TCELL, EREGL, ARCLK, SISE, PGSUS, PETKM, TTKOM, KRDMD, EKGYO and KCHOL are net pairwise receivers of shocks. Furthermore, node sizes of TUPRS, TOASA and TCELL state that these SSFs receive the highest net pairwise spillovers from their counterparts. The most important net pairwise connectedness is easier to observe based on the width of the line that connects nodes with the applied threshold. Among the examined net pairwise spillovers, we can count spillovers from ISCTR to EREGL, from GARAN to TCELL, from VAKBN to TCELL, from KCHOL to TUPRS and from THYAO to PGSUS as the highest levels of spillovers.

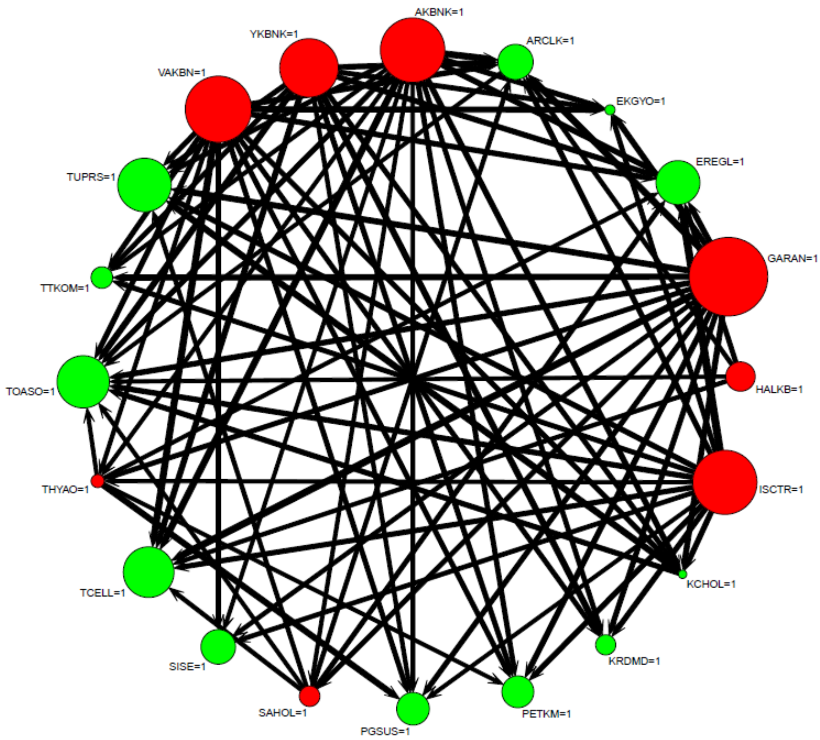

Figure 4. Net pairwise directional connectedness of 1-month futures prices

4.3 Analysis of spot and 1-month futures prices

4.3.1 Dynamic connectedness of spot and 1-month futures prices

The connectedness table in Appendix F illustrates the averaged dynamic connectedness of the network of combined spot and 1-month futures prices of 40 SSFs between 02.03.2016 and 07.12.2020. The TCI for the combined sample which is depicted in the bottom right corner of the table is 86.12% and it is higher than the TCI of both spot and 1-month futures when they are analyzed separately. This suggests that the interconnectedness of spot and futures prices are higher since we expect that futures prices and spot prices are influenced by each other. As occurred in spot and 1-month prices, diagonal values reflect the highest own-stock spillovers of forecast error variances. In terms of own-stock spillovers, spillovers that are transmitted between spot prices and between 1-month futures prices reflect higher spillover transmissions. Following the diagonal values, pairwise directional connectedness between a spot price and the 1-month futures price of each stock presents the second-highest spillovers. When we look at the pairwise directional connectedness between different companies, spillover transmission between spot prices of GARAN and AKBNK and spillover transmission between spot prices of THYAO and PGSUS have higher spillover transmissions compared to the other pairwise connectedness in the network.

Banking companies are in lead for both spillover transmissions to the network and from the network as observed when we analyze spot and 1-month futures prices separately. GARAN's 1-month futures (3.28%) and spot prices (3.26%) transmit the highest shocks to the network and they are followed by the spot and 1-month futures prices of AKBNK (3.19%, 2.14%), VAKBN (3.18%, 3.06%), ISCTR (3.00%, 3.06%), YKBNK (2.95%, 297%) and HALKB (2.69%, 2.58%). 1-month futures (2.31%) and spot prices (2.31%) of GARAN also receives the highest shocks from the network which are followed by spot and futures prices of AKBNK (2.31%, 2.29%), VAKBN (2.31%, 2.30%), ISCTR (2.30%, 2.30%), YKBNK (2.29%, 2.29%) and HALKB (2.27%, 2.27%). Furthermore, GARAN is the highest net transmitter of shocks in terms of both spot (0.94%) and 1-month futures (0.97%) prices, while 1-month futures price of TOASA (-0.81%) receives the highest shock from the network of SSFs.

Figure 5 shows the dynamic total connectedness index between 02.03.2016 and 07.12.2020. It is important to analyze the dynamic connectedness through this figure as it reflects how TCI of the network react to turbulent and crisis periods. Although the average TCI is higher compared to the average TCI of 1-month futures, dynamic TCI of the combination of spot and 1-month futures prices have similar fluctuations as in the dynamic TCI of 1-month futures. TCI index ranges between 77% and 94% during the whole period. TCI level starts with close to 90% in March 2016. Furthermore, the connectedness level reaches the lowest point at 77% level around July 2017 which still indicates a high connectedness among the stocks in the network of spot and 1-month futures prices. It climbs back to over 85% level and reaches its first peak in August 2018. After few fluctuations, the TCI level reaches its second and highest peak at 94% in March 2020 and preserved the level above 90% for the remainder of the period.

4.3.2 Total directional connectedness to others of spot and 1-month futures prices

Figure G1-G2-G3-G4 (Appendix G) represent the aggregated impact a shock in one variable has on all other variables. These time series figures are helpful to show the amount of shock transmitted by each SSFs to the network as well as the transmission patterns. The transmission patterns of spillovers of spot prices of the network of spot and 1-month futures prices follow similar trends as to when the network only consists of spot prices. This case is also true for the spillovers of the 1-month futures prices of the network of spot and 1-month futures prices which shows a similar transmission pattern when the network consists of only 1-month futures prices. However, the levels of shock transmissions are lower in both cases.

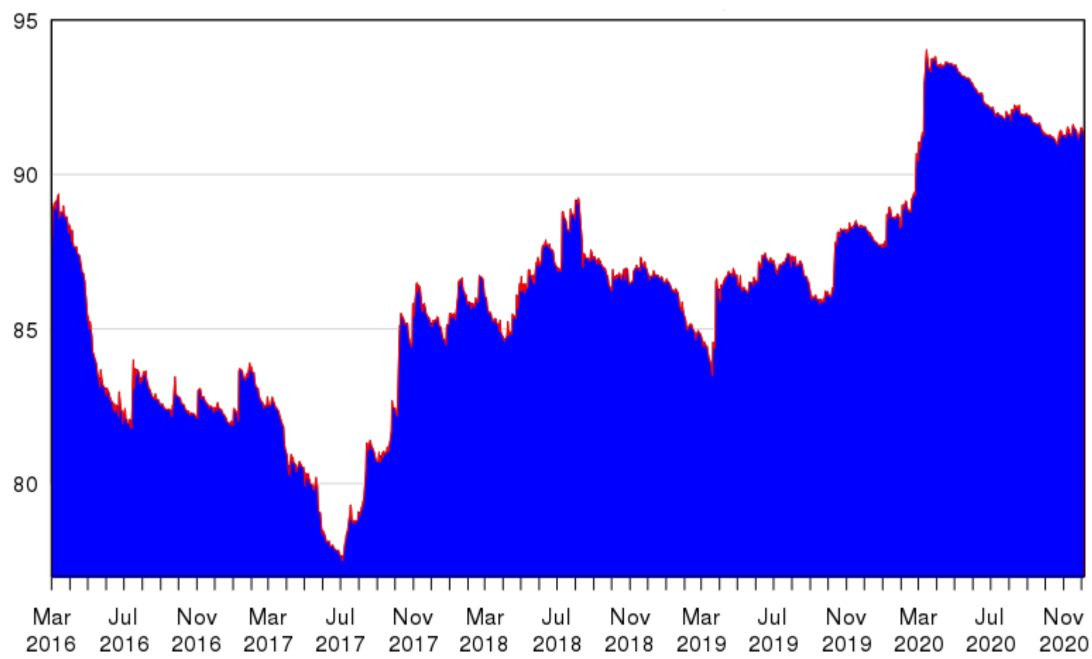

Figure 5. Dynamic total connectedness of spot and 1-month futures prices

When we look at the transmissions of shocks to the network from spot and 1-month futures prices, banking companies have more static and higher levels of shocks that are transmitted to the network comparing to shocks that are transmitted by remaining companies. The average level of shocks that are transmitted by banking companies ranges between 2.58% and 3.28%. Moreover, the shocks that are transmitted by spot prices of SAHOL (2.59%), KCHOL (2.54%) and THYAO (2.44%) illustrate higher shock transmission patterns comparing to non-banking companies. On the contrary, remaining stocks have more dynamic and time-varying transmission patterns with lower spillovers. The 1-month futures prices of TOASA (1.05%), TUPRS (1.13%), TCELL (1.25%) and SISE (1.31%) transmit the lowest shocks to the network. When we compare the shocks transmitted to the network from spot prices and 1-month future prices of each company, it can be observed that only 1-month future prices of GARAN (3.28%), ISCTR (3.06%) and YKBNK (2.97%) transmit higher shocks than shocks transmitted by their spot prices.

When we look at the spot prices, shock transmissions from EKGYO, KCHOL, and TOASA reach a peak during the summer of 2016 while THYAO and PGSUS transmit the highest levels of shocks in May 2016. Moreover, the transmission of shocks from EREGL, PGSUS, SISE, and TCELL peak in the summer of 2018. Lastly, ARCLK, KRDMD, PETKM, TTKOM, and TUPRS transmit their highest level of shocks following March 2020. For the 1-month futures prices, KRDMD and SAHOL send the highest levels of shocks to the network in 2016 while EREGL and THYAO send in 2017. PGSUS and TCELL transmit the highest level of shocks during 2018. For the majority of 1-month futures prices which are ARCLK, EKGYO, KCHOL, PETKM, SISE, TOASA, TTKOM and TUPRS, the levels of shocks that are transmitted to the network reach the highest level in March 2020. Also, an increase in spillover transmissions for the stocks can be observed following March 2020.

4.3.3 Total directional connectedness from others of spot and 1-month futures prices

The aggregated impact which is received from all other variables by one variable is represented in Figure G5-G6-G7-G8 (Appendix G). These time series figures visualize the levels of shocks that are received from the network by each stock. The transmission patterns of shocks that are received from the network of spot and 1-month futures prices are as similar as when these stocks receive shocks separately from their respective network. However, received shocks are relatively lower.

Among the shock receiving stocks, AKBNK, GARAN, HALKB, ISCTR, VAKBN and YKBNK represent homogeneous transmission patterns during the whole period with high spillovers. Furthermore, the levels of shocks that are received from the network range between 2.27% and 2.31% with the lead of GARAN. In addition to banking companies, spot and 1-month futures of SAHOL (2.27%,

2.25%), KCHOL (2.24%, 2.19%), THYAO (2.24%, 2.24%) and EKGYO (2.22%, 2.21%) also receive high spillovers from the network. The remaining stocks show more heterogonous transmission patterns throughout the period with lower spillovers. Among these stocks, 1-month futures of TUPRS (1.87%), TOASA (1.87%), SISE (1.89%) and PGSUS (1.93%) receive the least spillovers from the network. Overall, 1-month future prices of GARAN, ISCTR and YKBNK receive higher shocks than shocks that are received by their spot prices. Also, the levels of shocks that are received from the network reach a peak in March 2020 apart from spot and 1-month futures prices of EREGL, the spot price of TOASA and the 1-month futures price of KCHOL which receive the highest levels of shocks in March 2016.

4.3.4 Net total directional connectedness of spot and 1-month futures prices

Figure G9-G10-G11-G12 (Appendix G) illustrate the net total directional connectedness which is derived from the difference between total directional connectedness to and from others. Spot and 1-month futures prices of banking companies, GARAN (0.94%, 0.97%), AKBNK (0.88%, 0.65%), VAKBN (0.88%, 0.76%), ISCTR (0.71%, 0.76%), YKBNK (0.65%, 0.68%), HALKB (0.42%, 0.31%), are consistent net transmitters of spillovers during the sample period. The spot prices of HALKB, YKBNK and the 1-month futures price of AKBNK act as net receivers for a short amount of time. Along with banking companies, spot and 1-month prices of SAHOL (0.33%, 0.15%) and THYAO (0.21%, 0.19%) and spot prices of KCHOL (0.31%) and EKGYO (0.01%) are also net transmitters of shocks to the network. However, these stocks behave more heterogeneously comparing to banking companies since they perform the role of net receivers for multiple periods.

The average net transmissions of spillovers to the network range between 0.15% and 0.97%. Moreover, spot and 1-month futures prices of GARAN are the highest net transmitters. On the other hand, spot and 1-month futures prices of KRDMD (-0.08%, -0.39%), PGSUS (-0.18%, -0.56%), TTKOM (-0.23%, -0.45%), SISE (-0.29%, -0.58%), ARCLK (-0.29%, -0.55%), PETKM (-0.36%, -0.57%), EREGL (-0.49%, -0.52%), TOASA (-0.53%, -0.81%), TCELL (-0.54%, -0.70%) and TUPRS (-0.64%, -0.73%) are net shock receivers together with 1-month futures prices of EKGYO (-0.12%) and KCHOL (-0.18%). Among the net receiver stocks, spot and 1-month futures prices of EREGL, TCELL, TUPRS and the 1-month futures price of TOASA are homogeneous net receivers while remaining net receiver stocks seldomly transmit more shocks than they receive. Among the net receiver stocks, the 1-month future price of TOASA receives the highest level of shocks from the network. As the dynamic total connectedness increases in March 2020, we can observe which stocks act as net transmitters or net receivers following this period. For spot prices, banking companies together with KCHOL and THYAO are net shock transmitters. Also, SAHOL and TTKOM are net shock transmitters, however, they show periods of a role of a net receiver. Furthermore, ARCLK, EREGL, PGSUS, SISE, TCELL, TOASA and TUPRS are net receivers after March 2020. EKGYO, KRDMD and PETKM start as net transmitters but they complete the period as net receivers. Apart from SAHOL being a net transmitter, the roles of net transmitters and net receivers are also valid for 1-month futures prices.

4.3.5 Net pairwise directional connectedness of spot and 1-month futures prices

Spillovers transmitted between pairs of spot and 1-month futures prices of SSFs are described with the net pairwise directional connectedness. Figure 6 illustrates a highly significant net pairwise connectedness between spot and 1-month prices of Borsa Istanbul SSFs. The complexity of the shape in Figure 6 is because of both the high number of SSFs represented and the high level of TCI. To be able to show the leading net pairwise connectedness, a 90% threshold is applied and represented in Figure 6.

According to the net pairwise directional connectedness figure, spot prices of GARAN, AKBNK, VAKBN, ISCTR, YKBNK, HALKB, SAHOL, KCHOL, THYAO and EKGYO are net pairwise transmitters which are indicated with red nodes. In addition to spot prices, 1-month futures of GARAN, VAKBN, YKBNK, AKBNK, HALKB, THYAO and SAHOL are also net pairwise transmitters of shocks. Based on the size of the red nodes, 1-month futures and spot prices of GARAN are the strongest net pairwise transmitters. To observe the net pairwise receivers, we should look at the green nodes. Spot and 1-month futures prices of KRDMD, PGSUS, TTKOM, SISE, ARCLK, PETKM, EREGL, TOASA, TCELL, TUPRS together with the 1-month futures of KCHOL and EKGYO are net pairwise receivers. When we check the size of the nodes in order to see which stocks receive the highest net pairwise spillovers from their corresponding pairs, we detect 1-month futures prices of TOASA, TUPRS, and TCELL. To investigate the most significant net pairwise connectedness, the width of the lines which connects paired nodes should be checked. The highest net pairwise directional connectedness is observed from the spot price of TOASA to the 1-month future price of TOASA. The second highest net pairwise directional connectedness also occurred from the spot price of PGSUS to the 1-month future price of PGSUS. On the other hand, the biggest net pairwise directional connectedness between different stocks can be detected from the spot price of KCHOL to the 1-month future price of TUPRS. When the net pairwise directional connectedness between spot and 1-month futures prices of each stock is examined, it can be identified that underlying spot prices of stocks dominate their counterparts of 1-month futures prices except for GARAN and ISCTR. For GARAN and ISCTR, 1-month futures prices dominate their underlying spot prices.

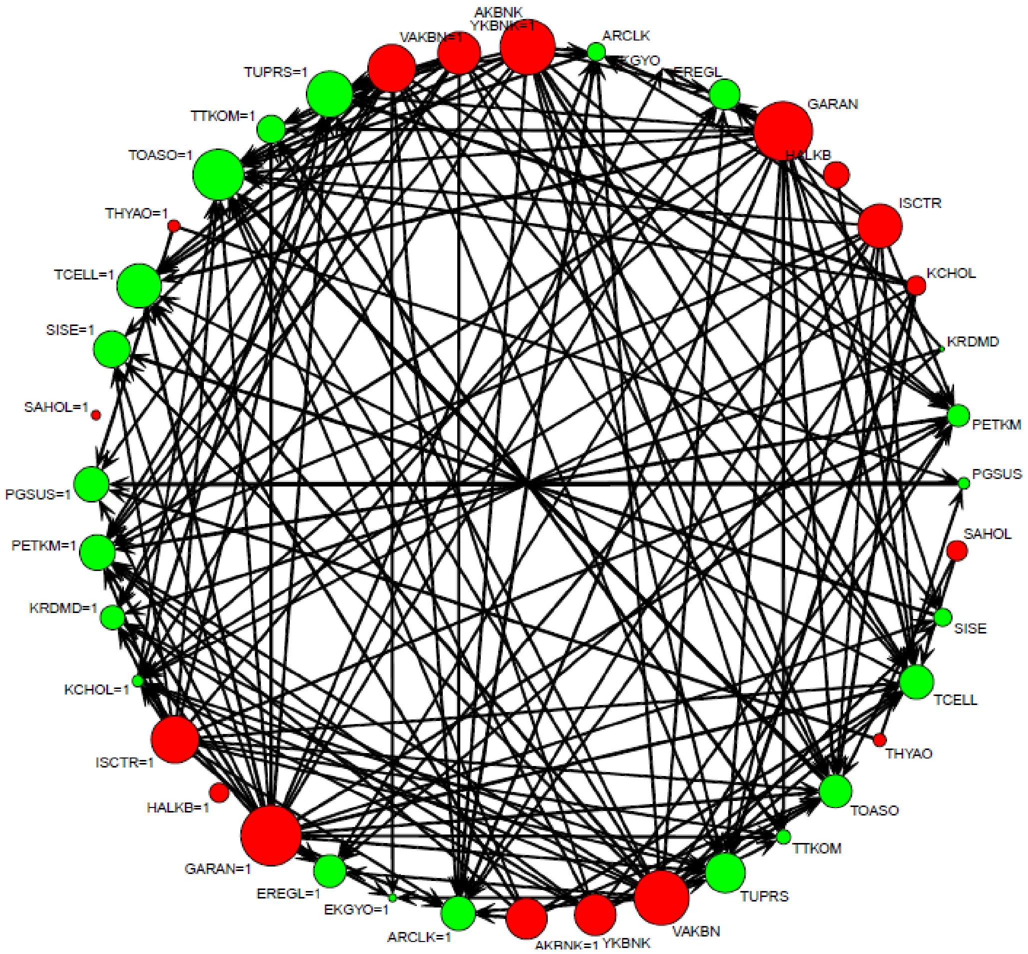

Figure 6. Net pairwise directional connectedness of spot and 1-month futures prices

4.4 Discussion

Linkages between stocks become more evident during the heightened stress periods since it damages the financial stability and increases the level of uncertainty. Additionally, the impact of shocks that occur during these crisis periods is more apparent due to the high interconnectedness of the financial market. Hence, dynamic connectedness figures are effective to understand the relationship as the applied methodology of TVP-VAR adjusts to events immediately. From the beginning of the period, TCI of the network of SSFs stays above 70% for spot prices, 55% for 1-month futures prices and 75% for the network of combined spot and 1-month futures prices. The averaged connectedness levels are 78.20%, 71.92% and 86.12% respectively. These high connectedness indexes indicate that SSFs are highly interconnected which can be explained by the economic and political upheavals that Turkey has been facing between 2016 and 2020.

The high connectedness at the beginning of the period coincides with the failed coup d'état against the state institutions that occurred in July 2016. A state of emergency started right after the failed attempt and had lasted until July 2018 which increased the uncertainty in the market. During 2016, the Turkish lira was the most depreciated currency (-20.8%) among the Fragile Five countries which are Brazil, Indonesia, South Africa, India, Turkey (Polat and Ozkan, 2019). Also, during this period, Turkey's five-year CDS premiums jumped to 267 points from 218 points while Standard & Poor (S&P) downgraded its rating from BB+ to BB with a negative look (World Government Bonds, 2021a; World Government Bonds, 2021b). The decrease in TCI in the summer of 2017 can be explained by the recovery in the Turkish economy. In the first quarter of 2017, the Turkish economy grew by 5% which exceeded the expectations. The annual consumer price index (CPI) inflation which was peaked in April 2017 at 11.87% fell to 9.79% in July 2017 (Türkiye Cumhuriyet Merkez Bankası, 2021). Furthermore, the US dollar/ Turkish lira exchange rate fell to 3.40 level in July 2017 which was at 3.70 level at the beginning of 2017 (Investing.com, 2021).

An increase in the TCI can be observed in the summer of 2018. This increase coincides with the crash in the Turkish lira. Trade war concerns between the United

States and China, the political dispute between Turkey and United States, and corporate indebtedness are some of the reasons which led to the crash. The corporate debt to GDP ratio rose to 77% in the third quarter of 2018 from 56% in 2014 and almost 90% of this increase caused by the rise in the foreign exchange debt (World Bank Group, 2018). The highest single-day fell in the Turkish lira since the devaluation of the currency in 2001 was observed on August 10, 2018, and a depreciation of 58% in the Turkish lira against the US dollar was observed in August 2018 (Arbaa and Varon, 2019; Polat, 2020). The US dollar/ Turkish lira exchange rate peaked at close to the 7.00 level. Moreover, the annual CPI inflation reached its highest level at 17.9% in August 2018 since the base year of 2003 while five-year CDS premiums increased to 575 points (Türkiye Cumhuriyet Merkez Bankası, 2021; World Government Bonds, 2021a). Also, credit rating agencies downgraded the credit rating of Turkey. S&P downgraded to B+ and Moody's downgraded to Ba3 due to depreciation in the Turkish lira and a high level of inflation (World Government Bonds, 2021b).

The last catastrophic event that took the whole world under its effect is the COVID-19 outbreak which started as a health crisis, however, it was followed by the financial and economic crisis. COVID-19 brought social isolation, travel restrictions and lockdowns which damaged economic activities and created financial instability which intensified uncertainties. The sharp increase in the TCI around March 2020 coincides with the first observed case in Turkey which was recorded on March 11, 2020. Due to deteriorations in supply and demand sides, purchasing managers' index declined to 33.4 in April 2020 due to decline in exports (Türkiye İş Bankası, 2020a). Although the current account balance reflected a surplus of 1.1 billion US dollars in May 2019, 3.8 billion US dollars of deficit was recorded in May 2020 because of the increasing foreign trade deficit (Türkiye İş Bankası, 2020b). In addition to the depreciation of the Turkish lira by 20% between March and May, usage of foreign exchange reserves to combat the current account deficit led to the largest monthly change in foreign exchange reserves with a decrease of 16.6 billion US dollars in March 2020 (World Bank Group, 2020). Also, the unpredictability of the impact of the virus in Turkey and the rapid spread of the virus in Europe where Turkey have high trade volumes increases the uncertainty. Thus, the CDS premium of Turkey rose to 660 points in April 2020 (World Government Bonds, 2021a).

Thus, companies need to analyze the risk factors that they may face in order to evaluate and implement the necessary risk management strategies. These risk factors can be categorized as credit risk, liquidity risk, market risk and operational risk (Bank for International Settlements, 2003).

Credit risk arises due to the inability of a counterparty to meet their obligations and default on their parts of agreements which will cause a financial loss. Companies can mitigate their exposure to credit risk in several ways. They can make deals with companies that are creditworthy according to their credit rating information, financial statements and their credit default history. Furthermore, the credit limits and creditworthiness of counterparties should be followed frequently. If necessary, extra collateral can be required in order to provide a guarantee against default.

Liquidity risk stands for the risk that companies cannot meet their obligations of payments on the agreed time because of the failure to access cash resources. In order to mitigate the liquidity risk, companies should monitor cash flows and the maturity of assets and liabilities should be followed and mismatches should be avoided.

Market risk expresses the financial losses that are resulted from movements in market prices and it can be separated into foreign exchange risk, interest rate risk and commodity price risk. Foreign exchange risk occurs due to transactions that are exercised in foreign currency. Assets and liabilities that are denominated in a foreign currency form the risk’s basis. Companies should have an adequate level of cash in the foreign currency that they are exposed to. Also, derivatives can be preferred to mitigate the risk. Interest rate risk affects the asset and liabilities that are sensitive to changes in the interest rate. Companies can manage their exposure by having the necessary combination of fixed and floating interest rates with derivate instruments of swaps and options. Commodity price risk is another important factor that companies need to manage which stands for the fluctuations in commodity prices that are held by companies as an inventory for production and operations. Oil prices, fuel prices, iron ore prices can be given as an example for commodities that constitute a risk exposure. Hedging transactions should be conducted with relevant swap and option instruments

Lastly, operational risk can be defined as the risk which caused by insufficient or unsuccessful domestic failures, people and system. Also, it can be caused by external events such as frauds, violent attacks, climate change and pandemics. It is not straightforward as earlier mentioned crisis types to generate risk management tools for operational risk, but companies can develop and sustain a fitting company culture against operational risks by effectively defining and controlling operational processes.

CHAPTER 5

CONCLUSION

Connectedness has become a crucial term to reflect the degree of relationship between financial instruments. Understanding the nuances of the connectedness based on the transmissions of spillovers has gained vital importance especially during turbulent periods and uncertain times since the level of spillover transmission become more evident during these unstable phases. Thus, it is essential to examine these dynamic connectednesses in order to take actions to minimize the risks that can be faced in the market by applying relevant hedging and diversification strategies.

In this thesis, dynamic connectedness between returns of 20 SSFs that are traded in Borsa Istanbul is studied for the period between 02.03.2016 and 07.12.2020. For the analysis, dynamic connectedness based on the TVP-VAR model explained in Antonakakis and Gabauer (2017) and Antonakakis et al. (2020) is applied which can be considered as the extension of Diebold and Yilmaz (2009, 2012, 2014). It provides a more refined measurement as there is no need to choose the size of the rolling window arbitrarily which prevents the loss of observations. Also, this model is insensitive to outliers in the model. Lastly, it reflects and adjusts to the events since the model is time-variant. For the purpose of finding answers for whether dynamic connectedness between SSFs varies and responds to crisis periods or not and to identify which SSFs are net transmitters or net receivers of shocks, the dynamic connectedness of spot prices, 1-month futures prices and the combination of spot and 1-month futures prices are examined. Dynamic connectedness is analyzed to reflect total connectedness, directional connectedness and net connectedness as well net pairwise connectedness. This thesis contributes to the literature as being the first study that analyzes the TVP-VAR based dynamic connectedness of SSFs.

For the dynamic connectedness of spot prices, TCI of 78.20% expresses a high interconnectedness between the network of spot prices. Furthermore, it is stated that GARAN (1.56%), AKBNK (1.55%), VAKBN (1.50%), ISCTR (1.16%), YKBNK (1.11%) and HALKB (0.58%) are net shock transmitters together with SAHOL (0.56%), KCHOL (0.49%) and THYAO (0.21%). On the contrary, TUPRS (-1.33%), TCELL (-1.20%), TOASA (-1.15), EREGL (-1.13%), PETKM (-0.80%), ARCLK (-0.75%), SISE (-0.69%), PGSUS (-0.62%), TTKOM (-0.61%), KRDMD (-0.32%) and EKGYO (-0.12%) are net shock receivers. Also, connectedness between KCHOL and TUPRS reflects the highest net pairwise connectedness.

When the dynamic connectedness of 1-month futures prices is studied, the TCI level of 71.92% shows that 1-month futures prices are highly connected with each other. When we analyze the stocks in terms of net shock transmitter and net shock receiver, GARAN (1.56%), AKBNK (1.55%), VAKBN (1.50%), ISCTR (1.16%), YKBNK (1.11%) and HALKB (0.58%) are found to be net shock transmitters. Also, SAHOL (0.43%) and THYAO (0.28%) transmit shocks more than they receive from the network. On the other hand, stocks that receive more shocks than they transmit to the network can be listed as TUPRS (-1.13%), TOASA (-1.10), TCELL (-1.07%), EREGL (-0.93%), ARCLK (-0.74%), SISE (-0.73%), PGSUS (-0.69%), PETKM (-0.67%), TTKOM (-0.46%), KRDMD (-0.42%), EKGYO (-0.21%) and KCHOL (-0.18%). Furthermore, the highest net pairwise connectedness is illustrated between ISCTR and EREGL.

When the dynamic connectedness of spot and 1-month futures prices are analyzed together, TCI is measured at 86.12% which stands for a significant connectedness among the spot and 1-month futures prices in the network. Moreover, spot and 1-month futures prices of GARAN (0.94%, 0.97%), AKBNK (0.88%,

0.65%), VAKBN (0.88%, 0.76%), ISCTR (0.71%, 0.76%), YKBNK (0.65%, 0.68%) and HALKB (0.42%, 0.31%), are net shock transmitters. Similarly, spot and 1-month prices of SAHOL (0.33%, 0.15%), THYAO (0.21%, 0.19%) and only spot prices of KCHOL (0.31%) and EKGYO (0.01%) are also net shock transmitters. In contrast, spot and 1-month futures prices of KRDMD (-0.08%, -0.39%), PGSUS (-0.18%, -0.56%), TTKOM (-0.23%, -0.45%), SISE (-0.29%, -0.58%), ARCLK (-0.29%, -0.55%), PETKM (-0.36%, -0.57%), EREGL (-0.49%, -0.52%), TOASA (-0.53%, -0.81%), TCELL (-0.54%, -0.70%) and TUPRS (-0.64%, -0.73%) are net shock receivers along with the 1-month futures prices of EKGYO (-0.12%) and KCHOL (-0.18%). Furthermore, it can be expressed that spot prices of stocks drive their matching parts of 1-month futures prices apart from GARAN and ISCTR when they are examined based on the net pairwise directional connectedness.

In all three cases, SAHOL and THYAO act as net shock transmitters while KCHOL acts as net shock receiver when its 1-month futures price is examined. Furthermore, banking companies which are GARAN, AKBNK, VAKBN, ISCTR, YKBNK and HALKB perform a significant role of as net shock transmitters. Although dynamic connectedness is analyzed at the sectoral level, Umar et al. (2020) and Chatziantoniou et al. (2020) also argue that the financial sector act as a net shock transmitter in their analysis of sectoral indices. This result can be explained by the fact that banks are the primary fund providers for companies. Hence, a shock that is received by a bank distinctly spillovers to other companies through the borrowing channel.

It can be inferred that TCI reflects a high level of connectedness for the duration of the sample period for all three cases. TCI of the combination of spot and 1-month futures prices is in the lead and it is followed by the TCI of spot prices and

TCI of 1-month futures prices. The higher TCI of spot prices compared to the TCI of 1-month futures and spot prices are being the driving force when the net pairwise dynamic connectedness of the combination of spot and 1-month futures prices are assessed can be linked with the price discovery literature in which spot prices are in the lead in terms of reflecting the information more quickly. (Shastri et al., 2008; Fung & Tse, 2008; Boney et al., 2018). Besides, it is observed that TCI indicates time-varying transmission patterns which signify the claim that TCI reacts to turbulent events. In the analysis of SSFs traded in Borsa Istanbul, three main events are identified in which TCI is increased. The first one is observed for the period following July 2016 when political conditions created uncertain aftermath. The second event that increases the TCI is observed when a currency crisis occurred in August 2018. The last event that increases the level of TCI is the outbreak of COVID-19 which created instability in the market due to lockdowns, travel restrictions and damaged demand and supply. The increase in the TCI during turbulent times like Global Financial Crisis, 9/11 attacks and COVID-19 is also studied in the literature (Liu et al., 2021; Adekoya & Oliyide, 2021; Corbet et al., 2021).

There are several implications that can be deducted from this thesis. For investors and portfolio managers, analyzing the dynamic connectedness between SSFs may provide advantages for designing arbitrage, hedging and diversification policies. To cope with risks during turbulent times, classifying stocks as net shock transmitters or net shock receivers and monitoring the connectedness will offer effective risk management strategies. Also, policymakers should implement appropriate policies in a timely manner to prevent the adverse effect of spillovers in the network since connectedness increases during crisis periods.

Due to limitations on the sample period, the number of SSFs that are included in this study does not allow for grouping since groups will not be even so that each sector is equally covered. As a further study, the dynamic connectedness between SSFs can be analyzed with grouping according to the industry when the data is available. Also, the dynamic connectedness of SSFs between different countries can be studied to assess whether spillovers are transmitted across international markets.

APPENDIX A

DESCRIPTIVE STATISTICS

Table A1. Descriptive Statistics for Spot Return Prices

	AKBNK	ARCLK	EKGYO	EREGL	GARAN	HALKB	ISCTR	KCHOL	KRDMD	PETKM	PGSUS	SAHOL	SISE	TCELL	THYAO	TOASO	TTKOM	TUPRS	VAKBN	YKBNK
Mean	-0.00004	0.00031	-0.00019	0.00101	0.00016	-0.00052	0.00028	0.00030	0.00122	0.00072	0.00104	0.00012	0.00070	0.00026	0.00040	0.00031	0.00023	0.00019	0.00009	0.00013
Median	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Std. Dev.	0.02190	0.02008	0.02123	0.02171	0.02328	0.02376	0.02160	0.01855	0.02728	0.02175	0.03006	0.01876	0.02053	0.01890	0.02469	0.02133	0.02247	0.02030	0.02390	0.02215
Variance	0.00048	0.00040	0.00045	0.00047	0.00054	0.00056	0.00047	0.00034	0.00074	0.00047	0.00090	0.00035	0.00042	0.00036	0.00061	0.00045	0.00051	0.00041	0.00057	0.00049
Kurtosis	2.25852	3.45492	3.91581	4.48257	3.13728	3.94716	3.21949	2.18726	1.49065	5.36717	2.48603	2.04117	2.42865	2.64094	2.77350	2.74831	3.00118	4.54655	2.25142	3.28565
Skewness	0.03840	-0.36946	-0.32024	-0.45526	-0.19834	-0.35072	-0.32887	-0.25767	-0.08490	0.20961	0.12863	-0.26749	0.03239	-0.18787	-0.23807	-0.27773	-0.33287	-0.54423	-0.14260	-0.11996
Minimum	-0.08562	-0.13285	-0.13445	-0.17762	-0.12288	-0.15387	-0.14175	-0.09778	-0.13062	-0.10992	-0.11985	-0.10435	-0.09413	-0.09786	-0.13449	-0.11201	-0.11707	-0.13054	-0.10626	-0.13950
Maximum	0.09435	0.07676	0.10038	0.09280	0.09254	0.11445	0.09413	0.07513	0.10577	0.16545	0.13834	0.06736	0.11419	0.09494	0.09523	0.09498	0.08943	0.09629	0.09426	0.10952
Count	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1243	1244	1244	1244

Table A2. Descriptive Statistics for 1-Month Futures Return Prices

	AKBNK=1	ARCLK=1	EKGYO=1	EREGL=1	GARAN=1	HALKB=1	ISCTR=1	KCHOL=1	KRDMD=1	PETKM=1	PGSUS=1	SAHOL=1	SISE=1	TCELL=1	THYAO=1	TOASO=1	TTKOM=1	TUPRS=1	VAKBN=1	YKBNK=1
Mean	0.0000	0.0003	-0.0002	0.0010	0.0002	-0.0005	0.0003	0.0003	0.0012	0.0005	0.0010	0.0001	0.0007	0.0003	0.0004	0.0003	0.0002	0.0002	0.0001	0.0001
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Std. Dev.	0.0206	0.0205	0.0210	0.0212	0.0227	0.0239	0.0208	0.0177	0.0295	0.0233	0.0333	0.0186	0.0219	0.0191	0.0245	0.0222	0.0222	0.0198	0.0237	0.0216
Variance	0.0004	0.0004	0.0004	0.0005	0.0005	0.0006	0.0004	0.0003	0.0009	0.0005	0.0011	0.0003	0.0005	0.0004	0.0006	0.0005	0.0005	0.0004	0.0006	0.0005
Kurtosis	3.9027	5.3339	3.3131	3.2466	3.6619	4.2849	3.4858	2.9280	3.0934	17.6437	7.9014	2.7616	15.7030	6.4532	3.1212	7.2076	3.9456	4.9165	2.8233	2.9878
Skewness	0.0081	-0.4087	-0.1119	0.1235	-0.2298	-0.3171	-0.2429	-0.3015	0.1099	0.2734	0.0207	-0.2156	-0.0892	-0.4921	-0.2660	-0.0210	-0.4944	-0.5630	-0.1185	-0.1147
Minimum	-0.1137	-0.1255	-0.1043	-0.1107	-0.1264	-0.1546	-0.1326	-0.1042	-0.1520	-0.2179	-0.2230	-0.1040	-0.2163	-0.1435	-0.1472	-0.1211	-0.1327	-0.1111	-0.1115	-0.1171
Maximum	0.0963	0.1163	0.0998	0.1373	0.0910	0.1093	0.0950	0.0739	0.1515	0.2232	0.2053	0.0807	0.1975	0.0953	0.1064	0.1825	0.0786	0.0968	0.1063	0.0969
Count	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244

APPENDIX B

DYNAMIC CONNECTEDNESS TABLE FOR SPOT PRICES

	AKBNK	ARCLK	EKGYO	EREGL	GARAN	HALKB	ISCTR	KCHOL	KRDMD	PETKM	PGSUS	SAHOL	SISE	TCELL	THYAO	TOASO	TTKOM	TUPRS	VAKBN	YKBNK	FROM
AKBNK	13.58	2.78	4.12	1.91	10.38	6.47	8.08	4.64	3.18	2.29	2.76	6.93	2.55	2.58	4.16	2.20	3.39	1.40	8.72	7.87	4.32
ARCLK	5.09	25.30	3.61	2.31	5.29	4.28	4.63	6.92	3.15	2.81	2.81	5.06	3.52	3.21	3.33	4.42	3.39	1.64	4.93	4.32	3.73
EKGYO	5.93	2.94	19.73	2.45	6.24	6.03	5.64	4.08	3.87	3.14	3.88	4.95	3.66	1.95	4.90	2.52	3.32	1.85	6.52	6.41	4.01
EREGL	4.04	2.72	3.64	29.16	3.93	3.85	4.24	4.17	7.61	3.72	2.77	4.00	4.23	1.74	4.10	3.18	2.33	1.99	4.73	3.84	3.54
GARAN	10.32	2.90	4.32	1.88	13.58	6.37	8.36	4.51	3.24	2.41	2.90	6.14	2.46	2.36	4.22	2.15	3.67	1.33	8.74	8.14	4.32
HALKB	7.77	2.76	5.07	2.22	7.64	16.36	7.13	3.86	3.76	2.78	3.01	5.09	2.71	2.48	4.74	1.87	3.50	1.40	8.86	7.00	4.18
ISCTR	8.62	2.74	4.17	2.12	8.96	6.41	14.54	4.64	3.43	2.62	2.99	6.14	2.68	2.27	4.01	1.91	3.47	1.54	8.66	8.07	4.27
KCHOL	6.08	5.06	3.75	2.56	5.95	4.28	5.72	18.41	3.20	2.69	3.03	6.81	3.77	2.79	3.81	4.13	3.13	3.36	5.66	5.80	4.08
KRDMD	5.04	2.82	4.21	5.59	5.12	4.91	5.08	3.81	21.93	4.06	4.49	3.68	3.33	1.71	5.81	2.25	3.46	1.82	5.35	5.54	3.90
PETKM	4.37	2.90	4.03	3.21	4.57	4.35	4.69	3.83	4.80	26.66	3.41	3.72	3.80	2.74	5.00	2.31	3.69	2.86	4.66	4.39	3.67
PGSUS	4.71	2.77	4.56	2.07	4.88	4.23	4.62	4.01	4.57	3.10	25.77	3.49	3.01	1.48	10.84	1.88	2.43	1.88	4.85	4.85	3.71
SAHOL	8.51	3.38	4.23	2.32	7.56	5.23	7.00	6.38	2.78	2.39	2.53	16.57	2.83	2.97	3.69	2.69	3.70	1.82	6.75	6.67	4.17
SISE	4.52	3.52	4.62	3.67	4.35	3.96	4.49	5.30	3.82	3.66	3.12	4.22	25.87	2.20	4.64	3.43	3.03	2.44	4.91	4.22	3.71
TCELL	5.57	3.56	3.14	1.83	5.13	4.66	4.56	4.50	2.47	2.98	1.98	5.27	2.75	29.76	3.19	1.87	6.30	1.82	4.72	3.94	3.51
THYAO	5.74	2.67	4.53	2.64	5.94	5.40	5.30	3.85	5.04	3.68	8.63	4.13	3.41	1.90	18.96	1.57	3.03	2.04	6.06	5.49	4.05
TOASO	4.79	5.21	3.81	3.15	4.54	3.37	3.88	6.87	3.12	2.59	2.20	4.81	3.98	2.02	2.51	30.13	2.56	1.94	4.10	4.43	3.49
TTKOM	5.55	3.14	3.77	1.81	6.05	4.86	5.32	4.04	3.66	3.34	2.75	4.94	2.87	5.18	4.00	2.01	23.84	1.78	5.75	5.33	3.81
TUPRS	3.52	2.42	2.99	2.38	3.54	2.92	3.58	6.78	2.84	4.08	2.48	3.73	3.36	2.46	3.51	2.39	2.59	37.52	3.69	3.23	3.12
VAKBN	8.79	2.78	4.58	2.26	8.83	7.46	8.20	4.40	3.41	2.50	2.95	5.58	2.82	2.19	4.42	1.89	3.58	1.46	13.78	8.13	4.31
YKBNK	8.49	2.59	4.76	1.91	8.81	6.24	8.17	4.76	3.72	2.53	3.08	5.85	2.58	1.92	4.25	2.19	3.50	1.43	8.60	14.59	4.27
TO	5.87	2.98	3.89	2.41	5.89	4.76	5.43	4.57	3.58	2.87	3.09	4.73	3.02	2.31	4.26	2.34	3.20	1.79	5.81	5.38	**78.20**
NET	1.55	-0.75	-0.12	-1.13	1.56	0.58	1.16	0.49	-0.32	-0.80	-0.62	0.56	-0.69	-1.20	0.21	-1.15	-0.61	-1.33	1.50	1.11	

Notes: The results of this table are built on a TVP-VAR framework which has a lag length of order one with a 10-step-ahead generalized forecast error variance decomposition (BIC).

APPENDIX C

DIRECTIONAL AND NET CONNECTEDNESS FOR SPOT PRICES

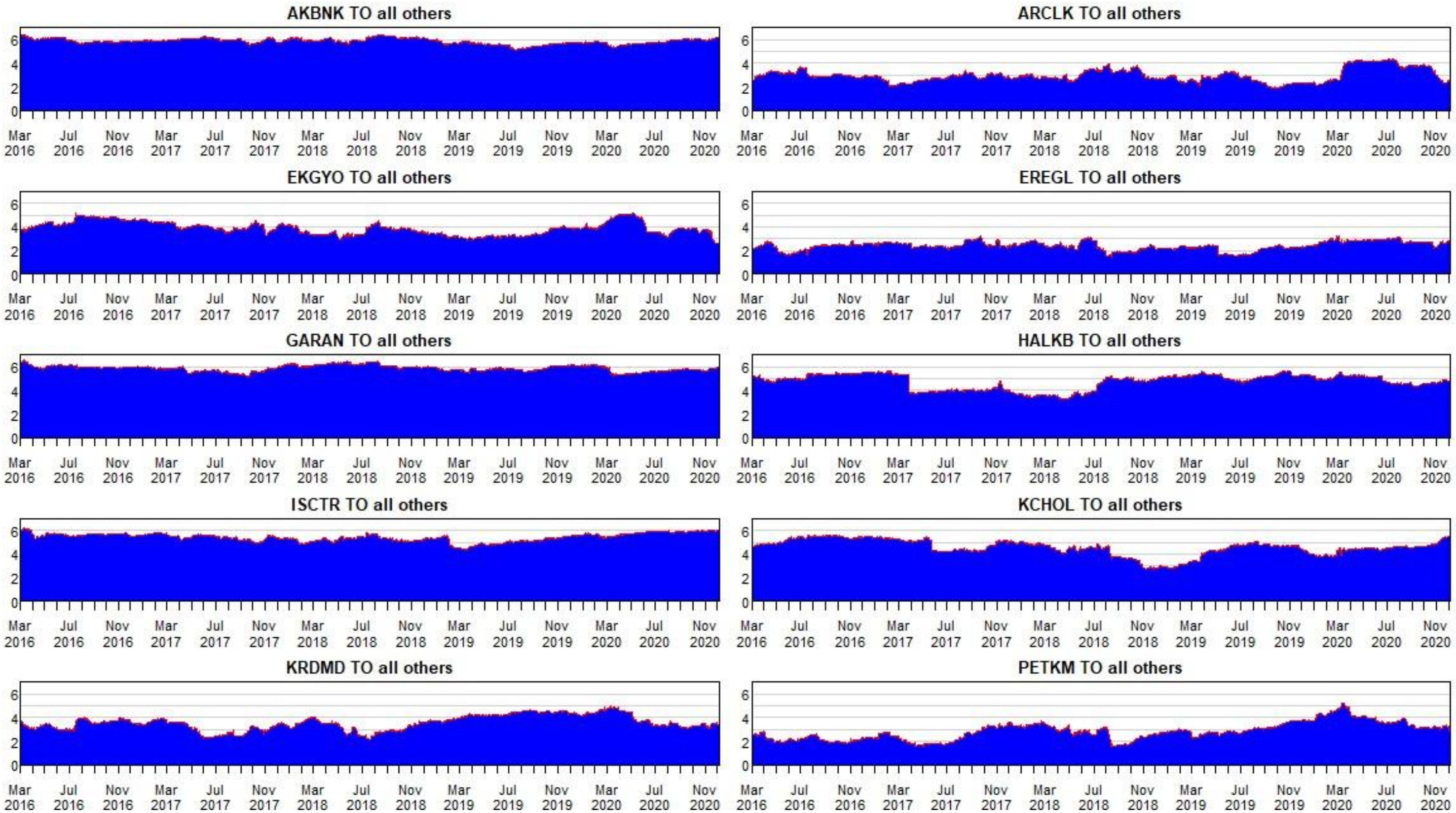

Figure C1. Total directional connectedness to others (Part 1)

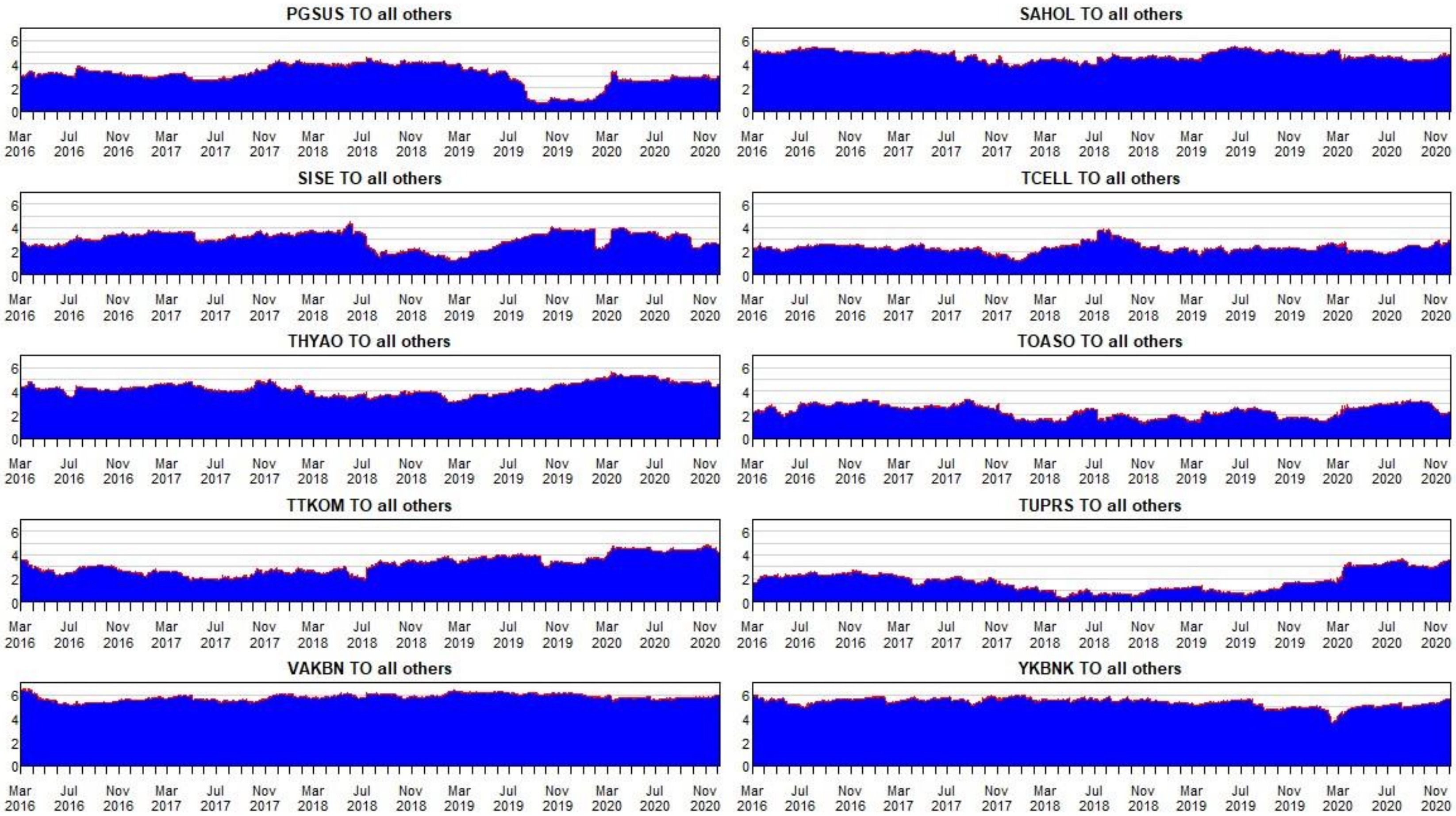

Figure C2. Total directional connectedness to others (Part 2)

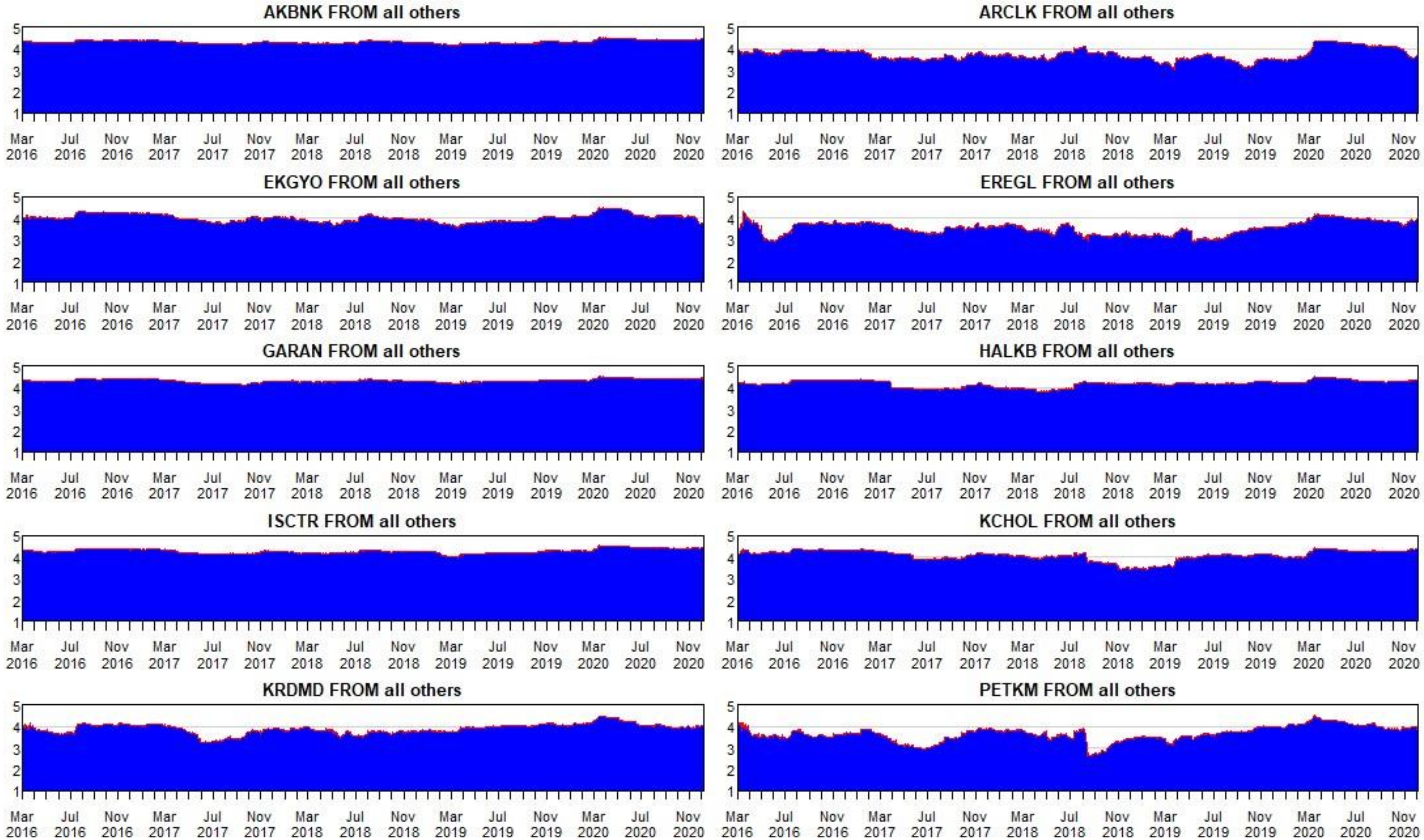

Figure C3. Total directional connectedness from others (Part 1)

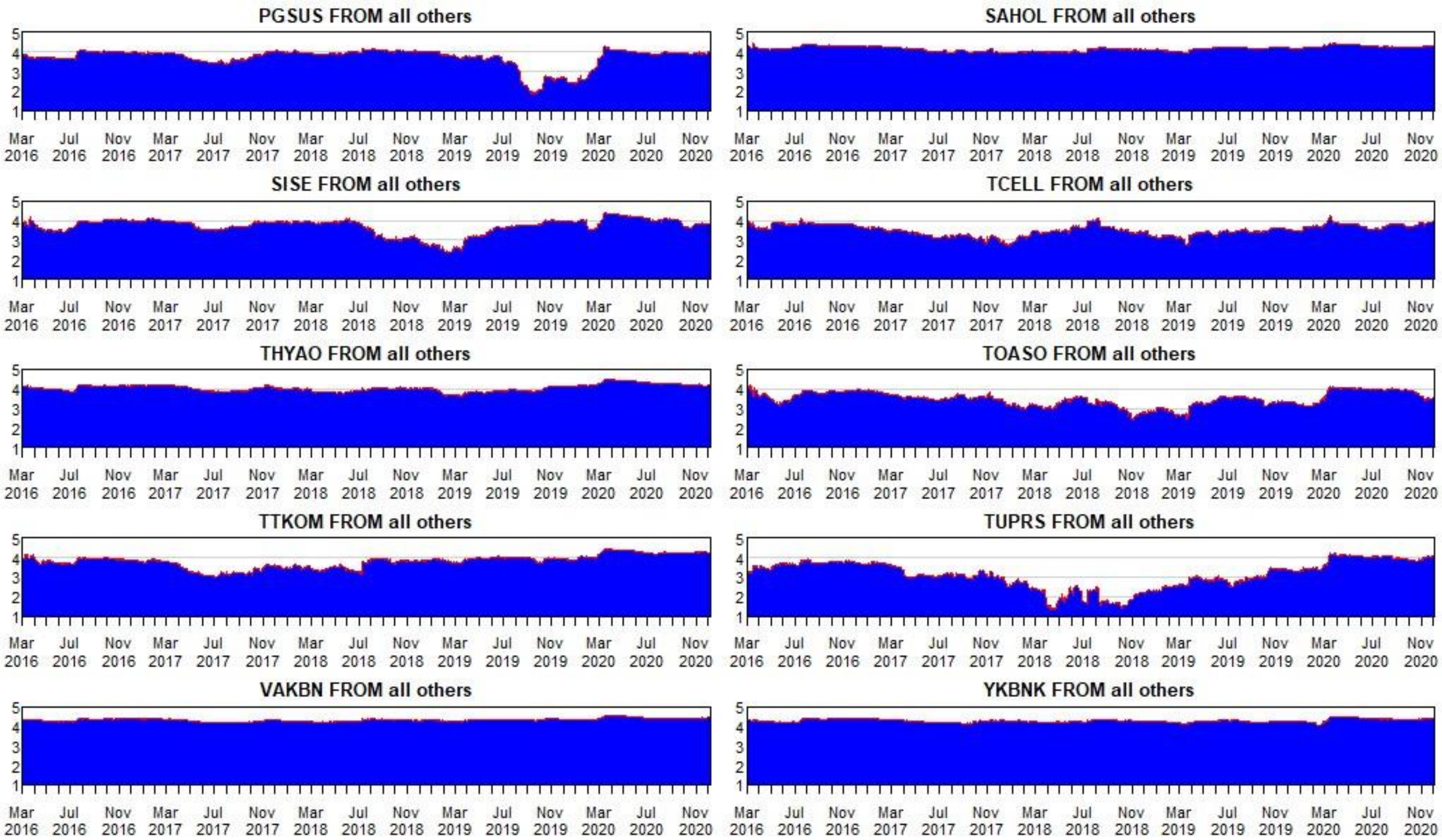

Figure C4. Total directional connectedness from others (Part 2)

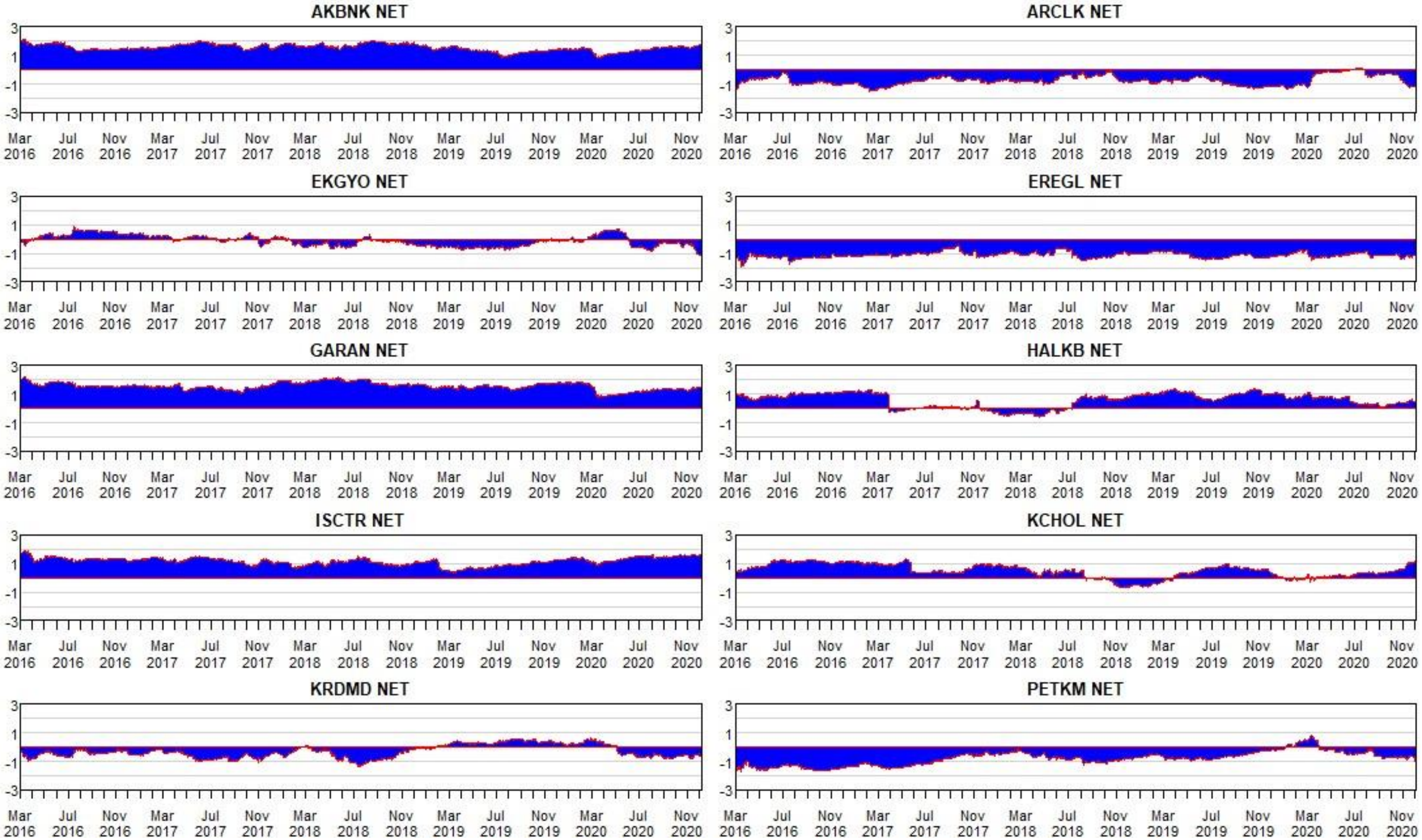

Figure C5. Net total directional connectedness (Part 1)

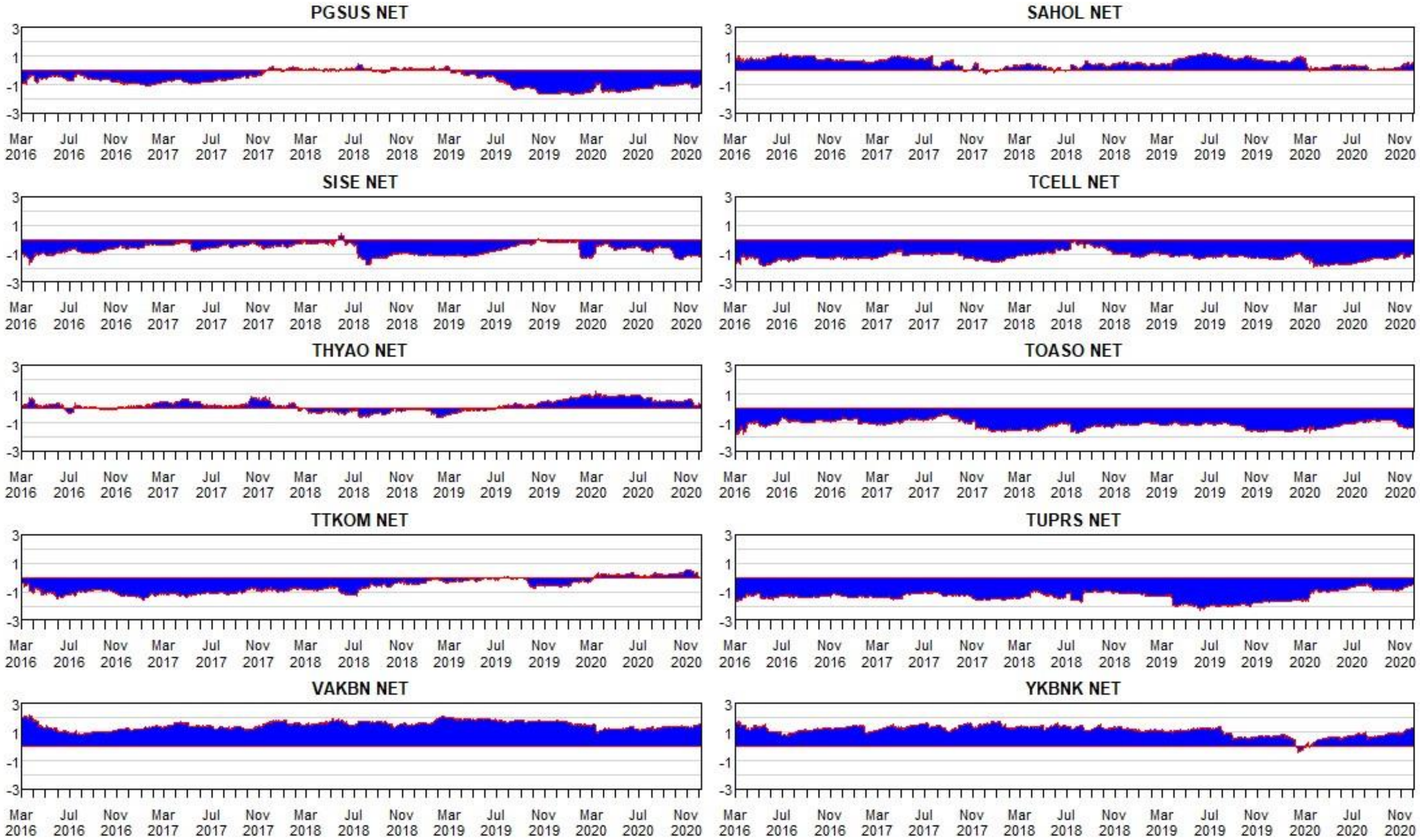

Figure C6. Net total directional connectedness (Part 2)

APPENDIX D

DYNAMIC CONNECTEDNESS TABLE FOR 1-MONTH FUTURES PRICES

	AKBNK=1	ARCLK=1	EKGYO=1	EREGL=1	GARAN=1	HALKB=1	ISCTR=1	KCHOL=1	KRDMD=1	PETKM=1	PGSUS=1	SAHOL=1	SISE=1	TCELL=1	THYAO=1	TOASO=1	TTKOM=1	TUPRS=1	VAKBN=1	YKBNK=1	FROM
AKBNK=1	16.50	2.55	4.38	2.20	10.83	6.60	8.80	4.17	2.75	1.91	1.82	6.91	1.56	2.12	4.90	1.32	2.85	1.27	8.51	8.07	4.18
ARCLK=1	5.06	33.70	3.39	2.23	4.86	4.08	4.18	4.99	2.80	2.72	2.51	4.43	2.02	3.01	2.90	3.16	3.61	1.69	4.32	4.33	3.32
EKGYO=1	6.38	2.54	23.67	2.73	6.46	6.45	6.08	3.24	2.95	2.32	2.18	5.64	2.42	1.66	5.12	1.60	3.47	1.55	7.03	6.50	3.82
EREGL=1	4.30	2.17	3.70	33.39	4.19	4.52	6.02	2.87	6.06	3.21	2.05	4.67	2.66	1.99	4.22	1.61	1.93	2.00	4.20	4.24	3.33
GARAN=1	10.32	2.32	4.30	2.04	15.83	7.02	9.57	3.66	2.57	1.78	1.91	6.24	1.61	2.15	4.94	1.32	3.36	1.49	9.05	8.54	4.21
HALKB=1	7.55	2.41	5.08	2.67	8.42	19.11	7.81	3.36	3.24	1.69	1.97	5.65	1.75	1.97	5.12	1.40	3.00	1.18	9.23	7.38	4.04
ISCTR=1	8.84	2.19	4.26	3.10	10.07	6.87	16.64	3.77	2.88	1.87	1.82	6.04	1.89	1.79	4.53	1.24	3.20	1.37	8.80	8.83	4.17
KCHOL=1	6.29	4.00	3.45	2.57	5.79	4.77	5.81	24.54	2.42	1.89	2.24	6.90	2.18	2.40	3.93	2.90	2.90	3.63	5.45	5.95	3.77
KRDMD=1	4.56	2.52	3.50	4.94	4.54	4.43	4.88	2.66	30.47	3.51	3.65	3.66	2.35	1.42	5.67	2.00	2.92	1.85	4.89	5.57	3.48
PETKM=1	3.79	2.71	2.98	3.10	3.89	2.80	3.90	2.61	4.44	35.46	3.43	2.73	6.58	2.22	4.23	1.56	3.42	2.76	3.65	3.76	3.23
PGSUS=1	3.41	3.15	2.80	1.72	3.85	3.37	3.28	3.22	3.95	3.54	38.82	2.85	2.98	1.25	8.05	2.70	1.99	1.59	3.93	3.56	3.06
SAHOL=1	8.45	2.77	4.85	2.83	8.03	5.96	7.24	5.63	2.50	1.75	1.86	19.80	1.95	2.27	4.34	1.47	3.03	1.38	7.08	6.81	4.01
SISE=1	3.01	2.20	3.33	2.84	3.28	3.04	3.61	3.21	2.96	6.78	3.05	3.23	39.73	1.55	3.60	2.51	3.12	2.22	3.72	3.03	3.01
TCELL=1	4.64	3.20	2.90	2.18	4.78	3.58	3.72	3.37	1.95	2.37	2.65	3.89	1.74	38.84	2.90	1.98	5.19	1.35	4.73	4.04	3.06
THYAO=1	6.41	1.96	4.48	2.71	6.78	5.77	5.99	3.38	4.55	2.77	5.75	4.70	2.39	1.76	21.84	1.42	2.60	1.70	6.57	6.48	3.91
TOASO=1	3.27	4.61	2.58	2.04	3.38	2.87	3.28	4.89	2.98	2.42	2.63	2.95	2.92	2.18	2.91	42.25	2.49	2.12	3.34	3.91	2.89
TTKOM=1	4.37	3.31	3.97	1.41	5.64	4.11	5.03	3.26	2.86	2.92	2.01	3.75	2.50	4.62	3.26	2.07	33.19	1.50	5.16	5.03	3.34
TUPRS=1	3.09	2.30	2.66	2.39	3.75	2.41	3.39	6.03	2.86	4.03	1.90	3.00	2.69	1.49	3.00	2.44	2.08	44.07	3.12	3.31	2.80
VAKBN=1	8.56	2.25	4.82	2.18	9.47	8.02	8.72	3.54	3.06	1.78	2.06	5.82	1.87	2.12	5.00	1.36	3.27	1.26	16.62	8.23	4.17
YKBNK=1	8.37	2.27	4.65	2.19	9.30	6.65	9.11	4.07	3.25	1.84	1.94	5.85	1.63	1.83	5.10	1.61	3.25	1.42	8.54	17.13	4.14
TO	5.53	2.57	3.60	2.40	5.87	4.67	5.52	3.60	3.05	2.55	2.37	4.44	2.28	1.99	4.19	1.78	2.88	1.67	5.57	5.38	**71.92**
NET	1.36	-0.74	-0.21	-0.93	1.66	0.62	1.35	-0.18	-0.42	-0.67	-0.69	0.43	-0.73	-1.07	0.28	-1.10	-0.46	-1.13	1.40	1.23	

Notes: The results of this table are built on a TVP-VAR framework which has a lag length of order one with a 10-step-ahead generalized forecast error variance decomposition (BIC).

APPENDIX E

DIRECTIONAL AND NET CONNECTEDNESS FOR 1-MONTH FUTURES PRICES

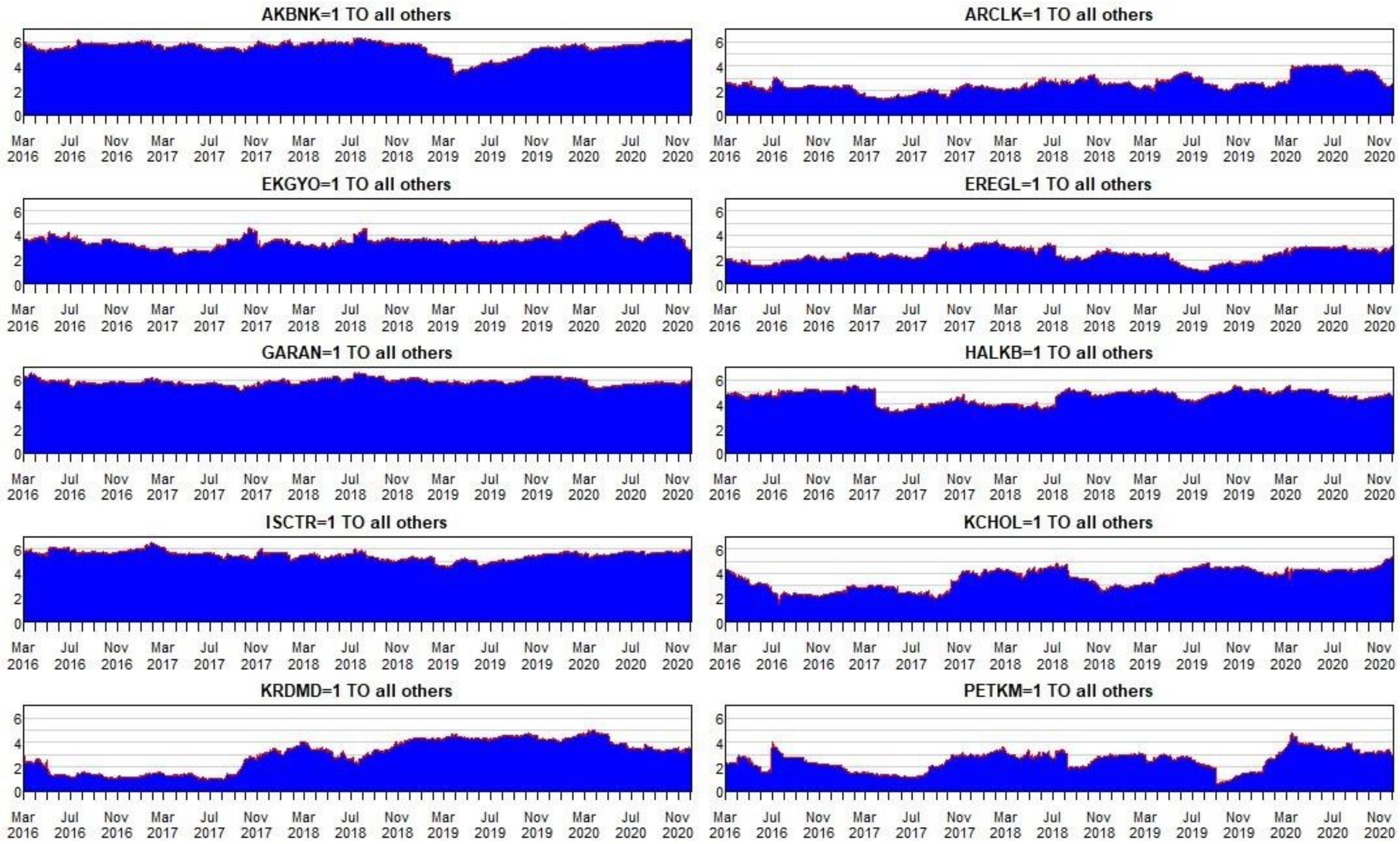

Figure E1. Total directional connectedness to others (Part 1)

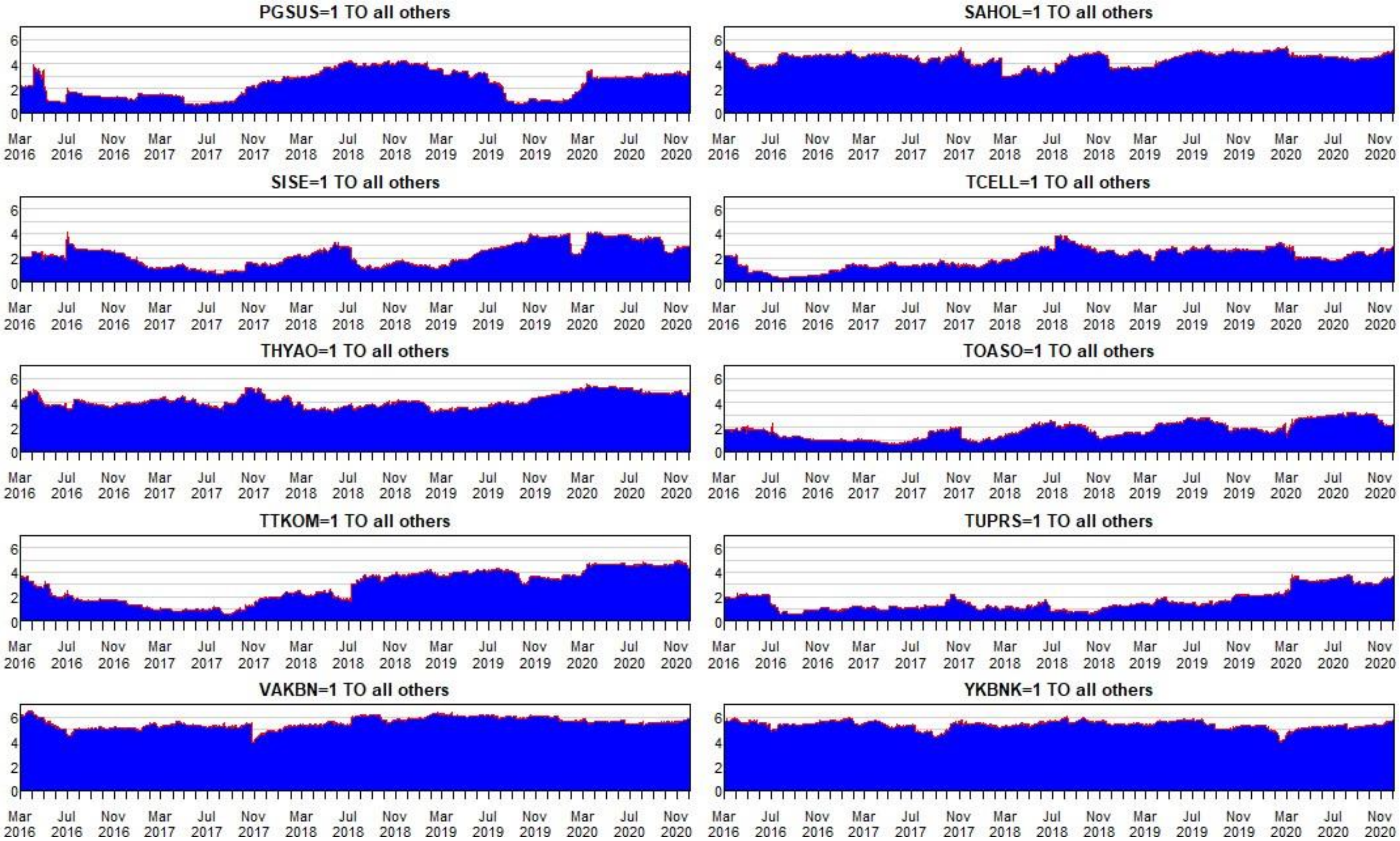

Figure E2. Total directional connectedness to others (Part 2)

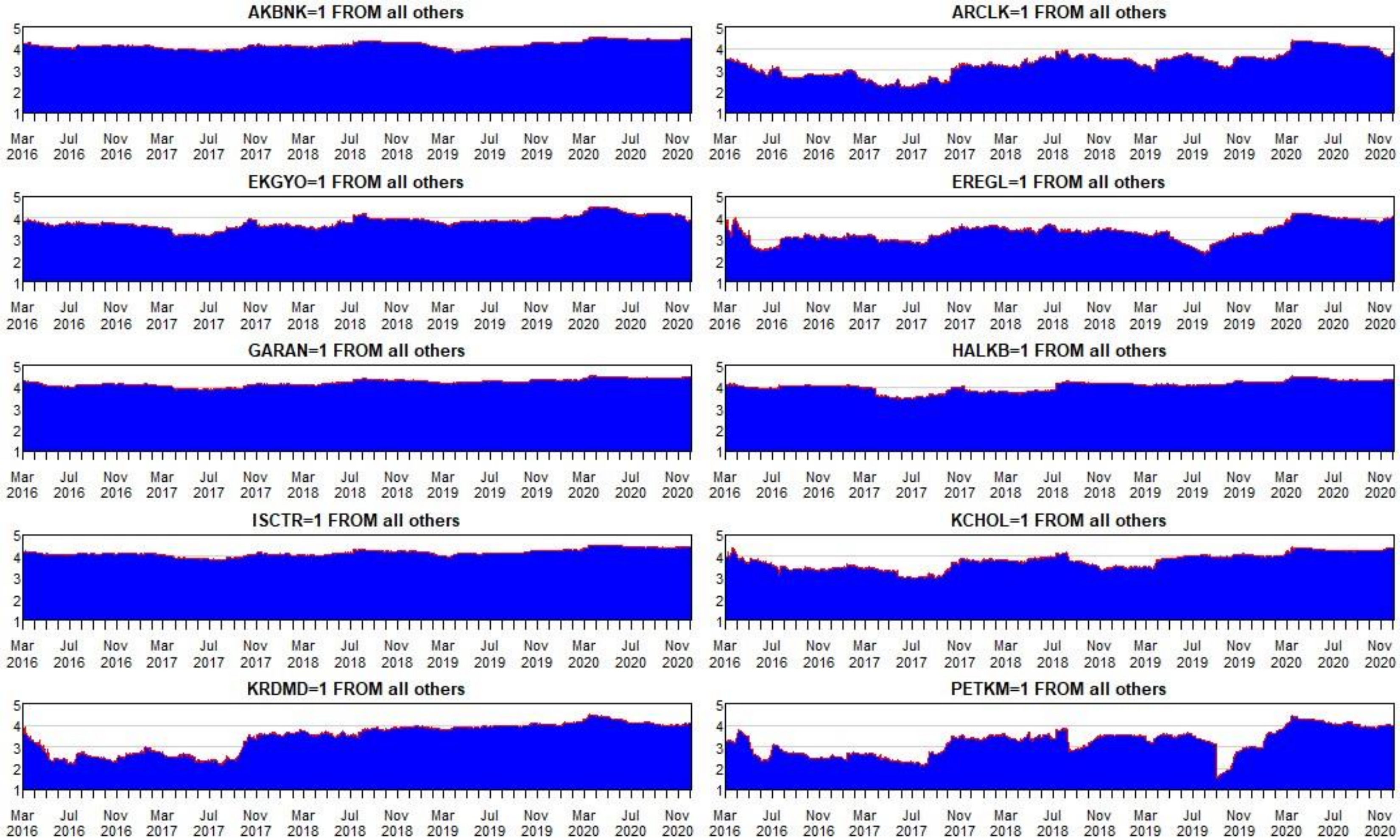

Figure E3. Total directional connectedness from others (Part 1)

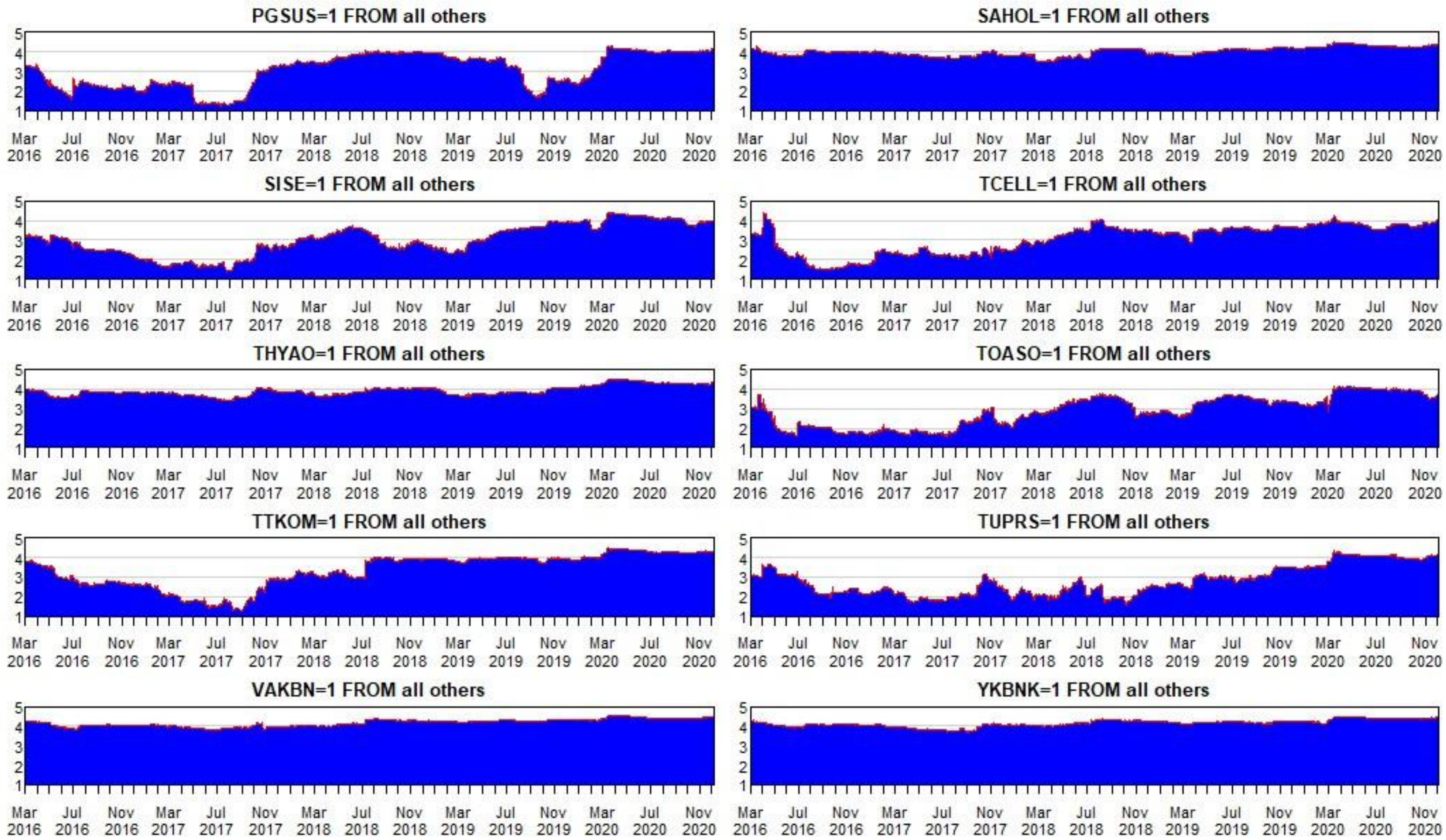

Figure E4. Total directional connectedness from others (Part 2)

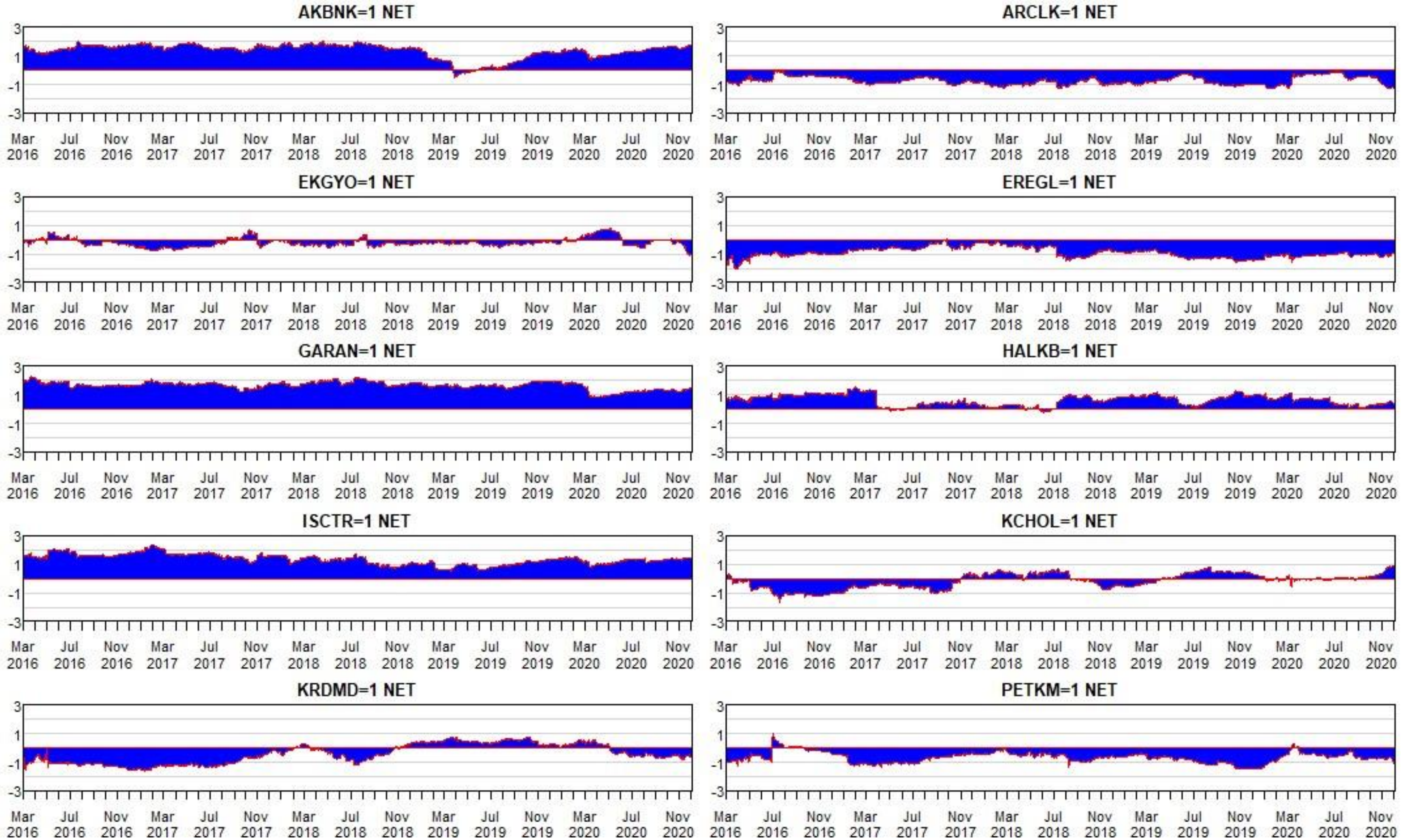

Figure E5. Net total directional connectedness (Part 1)

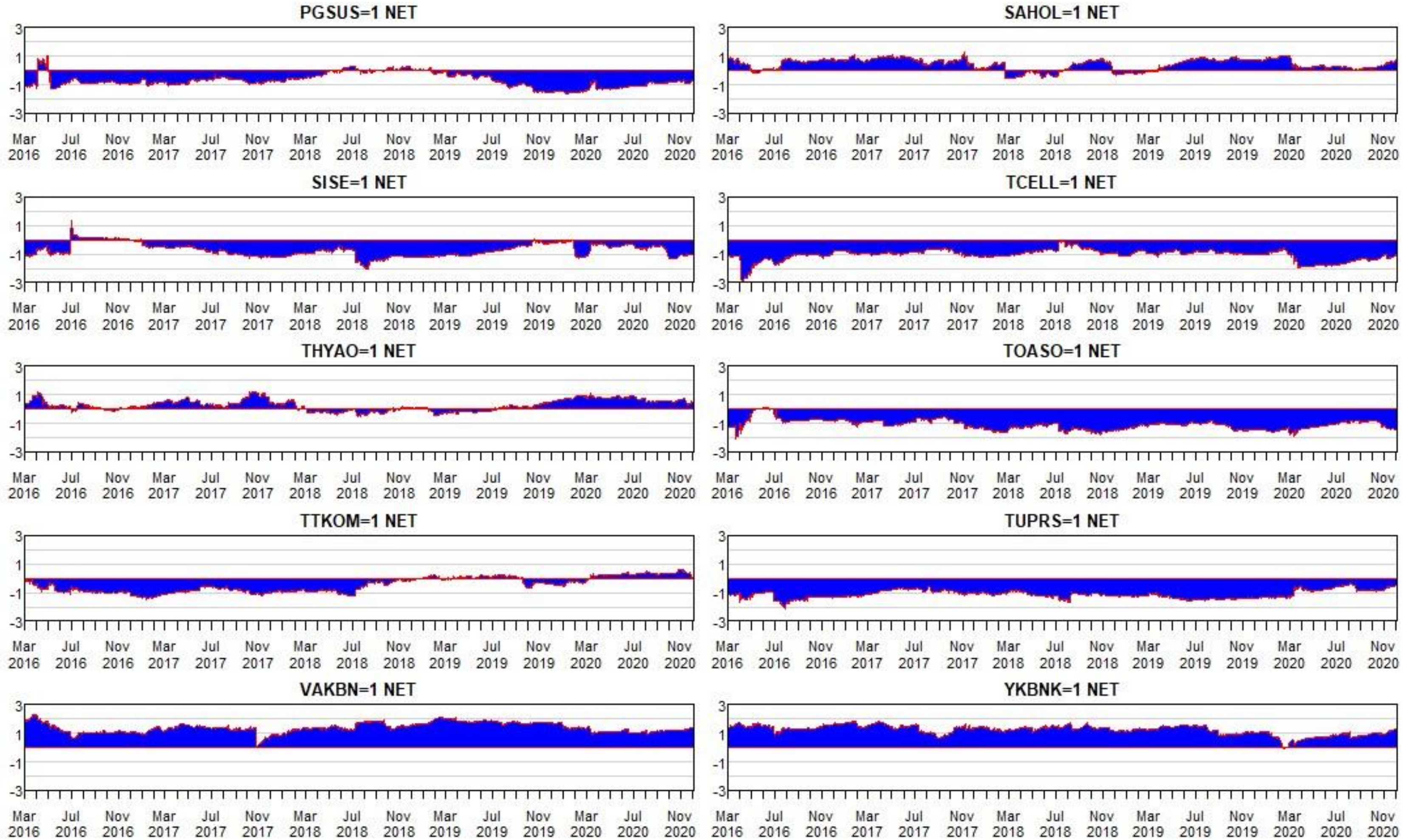

Figure E6. Net total directional connectedness (Part 2)

APPENDIX F

DYNAMIC CONNECTEDNESS TABLE FOR SPOT AND 1-MONTH FUTURES PRICES

	AKBNK	ARCLK	EKGYO	EREGL	GARAN	HALKB	ISCTR	KCHOL	KRDMD	PETKM	PGSUS	SAHOL	SISE	TCELL	THYAO	TOASO	TTKOM	TUPRS	VAKBN	YKBNK	AKBNK=1	ARCLK=1	EKGYO=1	EREGL=1	GARAN=1	HALKB=1	ISCTR=1	KCHOL=1	KRDMD=1	PETKM=1	PGSUS=1	SAHOL=1	SISE=1	TCELL=1	THYAO=1	TOASO=1	TTKOM=1	TUPRS=1	VAKBN=1	YKBNK=1	FROM
AKBNK	7.67	1.55	2.25	1.10	5.77	3.58	4.53	2.58	1.70	1.21	1.52	3.80	1.40	1.36	2.29	1.18	1.77	0.78	4.83	4.31	5.52	1.03	1.85	1.01	5.48	3.06	4.23	1.82	1.20	0.73	0.85	3.18	0.74	1.18	2.14	0.73	1.29	0.64	4.19	3.94	2.31
ARCLK	2.93	14.64	1.95	1.36	3.00	2.45	2.73	3.85	1.70	1.59	1.61	2.96	2.17	1.78	1.81	2.65	1.97	0.91	2.87	2.43	2.53	8.97	1.72	1.17	2.81	2.19	2.40	2.52	1.30	1.23	1.20	2.22	1.06	1.31	1.69	1.49	1.42	0.67	2.62	2.13	2.13
EKGYO	3.25	1.54	11.15	1.37	3.40	3.37	3.13	2.13	2.08	1.64	2.08	2.70	1.95	1.06	2.72	1.29	1.77	1.12	3.52	3.38	2.95	1.07	8.28	1.23	3.36	3.21	2.96	1.62	1.56	1.09	1.22	2.46	1.15	0.90	2.56	0.86	1.38	0.81	3.41	3.25	2.22
EREGL	2.35	1.52	2.09	16.56	2.28	2.15	2.44	2.25	4.27	2.00	1.49	2.43	2.63	1.04	2.31	1.91	1.38	1.09	2.59	2.14	1.98	0.97	1.68	11.07	2.25	1.90	2.45	1.58	3.09	1.41	1.13	2.00	1.40	0.94	2.19	0.98	0.88	0.82	2.18	2.15	2.09
GARAN	5.64	1.55	2.30	1.06	7.52	3.45	4.56	2.46	1.70	1.26	1.54	3.29	1.29	1.29	2.29	1.12	1.93	0.75	4.74	4.36	4.68	1.15	1.97	0.98	7.02	3.17	4.35	1.74	1.16	0.80	0.90	2.87	0.69	1.12	2.16	0.71	1.45	0.62	4.29	4.07	2.31
HALKB	4.20	1.51	2.75	1.20	4.15	9.04	3.85	2.06	1.94	1.48	1.64	2.66	1.36	1.37	2.56	0.97	1.80	0.73	4.77	3.80	3.54	1.14	2.39	1.23	4.04	8.17	3.77	1.45	1.49	0.87	0.89	2.53	0.78	0.97	2.43	0.68	1.34	0.56	4.24	3.66	2.27
ISCTR	4.78	1.52	2.29	1.20	4.91	3.48	8.12	2.50	1.82	1.36	1.64	3.36	1.37	1.17	2.22	0.99	1.81	0.79	4.72	4.32	4.05	1.04	1.91	1.36	4.79	3.28	7.02	1.76	1.28	0.85	0.90	2.75	0.84	0.85	2.06	0.64	1.35	0.59	4.21	4.08	2.30
KCHOL	3.45	2.78	2.00	1.43	3.37	2.40	3.16	10.52	1.72	1.49	1.71	3.76	1.99	1.53	2.12	2.21	1.71	1.79	3.20	3.33	2.88	1.89	1.84	1.23	3.20	2.19	2.99	7.52	1.33	0.92	1.05	3.28	1.13	1.09	2.10	1.33	1.26	1.34	2.87	2.92	2.24
KRDMD	2.74	1.49	2.29	3.14	2.79	2.61	2.79	2.04	12.51	2.16	2.43	2.03	1.85	0.90	3.14	1.26	1.85	0.97	2.80	2.94	2.55	1.25	2.08	3.00	2.76	2.48	2.85	1.46	8.03	1.60	1.59	1.79	1.07	0.76	3.03	0.90	1.46	0.84	2.79	3.01	2.19
PETKM	2.45	1.64	2.19	1.78	2.57	2.49	2.65	2.17	2.59	15.50	1.90	1.95	2.14	1.51	2.70	1.42	2.06	1.45	2.63	2.52	2.28	1.32	1.97	1.78	2.61	2.25	2.74	1.49	2.05	8.30	1.14	1.87	1.33	1.29	2.61	0.62	1.85	1.38	2.45	2.37	2.11
PGSUS	2.55	1.51	2.43	1.13	2.62	2.33	2.57	2.18	2.43	1.62	14.32	1.87	1.59	0.77	5.92	0.97	1.26	0.98	2.68	2.65	2.49	1.13	1.99	1.31	2.64	2.18	2.63	1.72	1.91	1.45	8.89	1.75	1.04	0.63	5.78	0.87	1.00	0.91	2.65	2.64	2.14
SAHOL	4.71	1.93	2.35	1.39	4.17	2.81	3.94	3.48	1.53	1.24	1.38	9.39	1.54	1.55	2.10	1.48	1.96	1.01	3.67	3.63	3.94	1.16	2.18	1.25	4.06	2.67	3.67	2.59	0.97	0.84	0.84	7.11	0.90	1.18	1.96	0.67	1.33	0.61	3.41	3.38	2.27
SISE	2.61	2.19	2.59	2.36	2.44	2.15	2.44	2.87	2.19	2.09	1.73	2.40	15.35	1.29	2.59	2.28	1.70	1.32	2.75	2.35	2.25	1.09	2.43	2.08	2.41	1.89	2.49	1.90	1.51	1.43	1.01	1.93	8.47	1.07	2.42	1.02	1.21	1.11	2.40	2.18	2.12
TCELL	3.03	2.00	1.82	1.11	2.94	2.73	2.47	2.55	1.34	1.65	1.10	2.83	1.60	17.68	1.73	1.33	3.64	1.07	2.53	2.16	2.75	1.39	1.58	1.13	2.93	2.23	2.26	1.55	1.16	1.30	0.70	2.43	1.10	10.25	1.56	0.80	2.55	0.58	2.28	2.15	2.06
THYAO	3.11	1.36	2.52	1.45	3.22	2.91	2.94	2.08	2.65	1.90	4.64	2.28	1.81	0.97	10.50	0.83	1.60	1.20	3.34	2.89	2.83	1.01	2.01	1.31	3.18	2.67	2.93	1.49	2.06	1.25	2.80	1.99	1.15	0.78	9.74	0.65	1.15	0.76	3.08	2.94	2.24
TOASO	2.76	3.25	2.09	2.01	2.60	1.89	2.18	3.88	1.82	1.58	1.24	2.80	2.66	1.39	1.43	18.40	1.55	1.25	2.37	2.53	2.32	2.17	1.89	1.52	2.46	1.66	2.15	2.72	1.48	1.11	0.98	2.28	1.16	0.91	1.34	7.61	1.20	0.84	2.13	2.40	2.04
TTKOM	2.99	1.82	2.03	1.10	3.35	2.63	2.91	2.28	1.99	1.94	1.51	2.68	1.61	3.06	2.19	1.20	14.03	1.09	3.20	2.86	2.95	1.41	1.90	1.17	3.12	2.38	2.99	1.44	1.48	1.29	0.87	2.20	0.92	2.19	1.99	0.84	8.11	0.71	2.77	2.78	2.15
TUPRS	2.06	1.38	1.85	1.38	2.09	1.60	1.92	3.68	1.51	2.05	1.34	2.10	1.80	1.37	2.17	1.46	1.52	22.01	2.06	1.81	1.89	1.08	1.72	1.60	2.00	1.41	1.94	2.84	1.21	1.81	0.93	1.44	1.25	1.33	2.09	0.79	0.94	12.62	2.01	1.93	1.95
VAKBN	4.86	1.54	2.45	1.24	4.86	4.06	4.49	2.42	1.75	1.33	1.62	2.97	1.49	1.14	2.46	1.02	1.90	0.77	7.73	4.49	3.87	1.09	2.12	1.13	4.69	3.66	4.32	1.63	1.37	0.78	0.88	2.58	0.83	1.03	2.34	0.62	1.52	0.54	6.41	4.00	2.31
YKBNK	4.66	1.40	2.50	1.08	4.80	3.47	4.45	2.69	1.94	1.34	1.72	3.15	1.38	1.00	2.29	1.18	1.79	0.77	4.79	8.23	3.69	0.91	2.30	1.05	4.65	3.12	4.35	1.91	1.39	0.72	0.94	2.70	0.72	0.71	2.20	0.75	1.43	0.67	4.14	6.99	2.29
AKBNK=1	6.01	1.44	2.17	1.01	5.17	3.28	4.15	2.30	1.71	1.26	1.59	3.42	1.28	1.35	2.25	1.13	1.87	0.83	4.17	3.73	8.24	1.31	2.27	1.13	5.40	3.25	4.38	2.04	1.36	1.00	0.93	3.39	0.78	1.07	2.33	0.69	1.39	0.65	4.28	3.98	2.29
ARCLK=1	2.37	10.64	1.57	1.14	2.62	2.10	2.23	3.06	1.59	1.47	1.38	2.16	1.33	1.56	1.56	2.23	1.94	0.80	2.31	1.81	2.73	18.76	1.76	1.16	2.64	2.09	2.20	2.56	1.53	1.54	1.56	2.44	1.11	1.38	1.58	1.52	1.83	0.99	2.45	2.29	2.03
EKGYO=1	2.81	1.45	8.87	1.24	3.04	3.16	2.79	2.05	1.94	1.60	1.83	2.67	1.90	1.14	2.44	1.24	1.83	1.08	3.28	3.25	3.22	1.25	11.43	1.41	3.28	3.35	2.99	1.77	1.66	1.24	1.18	2.77	1.25	0.80	2.51	0.83	1.71	0.83	3.52	3.39	2.21
EREGL=1	2.09	1.39	1.86	11.34	2.08	2.23	2.70	1.93	4.12	2.11	1.74	2.12	2.38	1.10	2.10	1.67	1.48	1.28	2.33	2.03	2.18	1.08	1.91	16.68	2.11	2.11	3.04	1.41	2.94	1.63	1.09	2.23	1.45	0.91	2.06	0.79	0.96	1.02	2.14	2.22	2.08
GARAN=1	5.34	1.45	2.26	1.05	6.98	3.36	4.42	2.33	1.67	1.25	1.55	3.18	1.28	1.28	2.25	1.07	1.82	0.71	4.54	4.19	4.87	1.16	2.12	1.00	7.47	3.33	4.55	1.86	1.22	0.87	0.95	3.05	0.76	1.05	2.31	0.71	1.55	0.71	4.35	4.13	2.31
HALKB=1	3.71	1.39	2.71	1.17	3.94	8.44	3.75	1.96	1.93	1.39	1.62	2.60	1.25	1.19	2.40	0.91	1.79	0.69	4.46	3.53	3.64	1.19	2.64	1.25	4.14	9.28	3.87	1.70	1.57	0.89	0.95	2.72	0.85	0.94	2.53	0.70	1.42	0.60	4.51	3.76	2.27
ISCTR=1	4.42	1.36	2.15	1.23	4.65	3.39	6.98	2.35	1.83	1.39	1.66	3.10	1.40	1.06	2.19	1.00	1.86	0.79	4.51	4.21	4.21	1.05	2.03	1.52	4.88	3.35	7.98	1.89	1.42	0.90	0.96	2.94	0.90	0.88	2.16	0.62	1.48	0.68	4.32	4.31	2.30
KCHOL=1	3.03	2.22	1.78	1.38	2.88	2.24	2.88	8.66	1.51	1.39	1.67	3.52	1.63	1.28	1.78	2.01	1.50	1.70	2.74	3.08	3.07	1.94	1.89	1.32	3.06	2.47	3.07	12.47	1.22	0.95	1.18	3.58	1.18	1.10	2.00	1.45	1.42	1.75	2.93	3.04	2.19
KRDMD=1	2.21	1.34	1.82	2.69	2.23	2.23	2.33	1.93	9.38	2.13	2.23	1.56	1.56	1.02	2.86	1.23	1.59	0.97	2.51	2.60	2.41	1.38	2.06	2.60	2.41	2.29	2.71	1.40	16.65	1.70	1.89	1.84	1.16	0.74	3.05	1.01	1.47	1.00	2.65	3.14	2.08
PETKM=1	1.87	1.56	1.64	1.51	2.24	1.69	2.06	1.61	2.47	10.03	1.96	1.53	1.82	1.39	2.24	1.13	1.84	1.35	2.04	1.93	2.28	1.58	1.75	1.63	2.39	1.65	2.29	1.42	2.25	19.94	1.72	1.46	3.80	1.30	2.28	0.71	1.87	1.42	2.22	2.15	2.00
PGSUS=1	1.88	1.69	1.84	1.18	1.95	1.68	1.80	1.95	2.13	1.25	11.09	1.39	1.17	0.74	4.27	1.11	1.09	0.81	1.89	1.84	1.93	2.09	1.64	1.04	2.10	1.80	1.97	1.95	2.12	1.90	22.86	1.52	1.62	0.66	4.38	1.53	1.06	0.86	2.16	2.06	1.93
SAHOL=1	4.22	1.64	2.30	1.31	3.87	2.80	3.48	3.25	1.53	1.26	1.45	7.65	1.44	1.42	1.96	1.34	1.76	0.80	3.38	3.27	4.13	1.40	2.44	1.40	4.13	2.91	3.69	2.90	1.18	0.88	0.92	9.83	1.01	1.08	2.07	0.73	1.42	0.67	3.59	3.49	2.25
SISE=1	1.69	1.54	1.76	1.73	1.73	1.61	1.81	1.94	1.58	1.68	1.43	1.60	10.23	1.30	1.88	1.45	1.29	1.12	1.99	1.63	1.69	1.23	1.87	1.77	1.92	1.71	2.05	1.90	1.50	4.25	1.74	1.76	24.41	0.88	2.00	1.42	1.63	1.37	2.18	1.75	1.89
TCELL=1	2.89	1.64	1.66	1.08	2.92	1.98	1.84	1.77	1.12	1.55	1.01	2.23	1.63	11.37	1.48	1.19	2.95	1.68	2.64	1.78	2.56	1.50	1.51	0.98	2.62	1.83	1.89	1.68	1.00	1.45	1.53	1.86	1.05	21.65	1.43	1.01	2.57	0.68	2.63	2.13	1.96
THYAO=1	2.91	1.29	2.41	1.40	3.04	2.78	2.72	2.09	2.57	1.84	4.59	2.14	1.72	0.90	9.85	0.78	1.48	1.18	3.18	2.80	2.97	1.01	2.17	1.30	3.27	2.84	2.89	1.69	2.20	1.30	2.85	2.15	1.19	0.78	10.57	0.69	1.27	0.85	3.25	3.10	2.24
TOASO=1	2.29	2.92	1.61	1.36	1.97	1.58	1.82	2.62	1.62	1.13	1.43	1.64	1.97	1.01	1.45	9.96	1.31	0.83	1.82	2.01	1.86	2.44	1.36	1.02	1.98	1.59	1.87	2.69	1.53	1.41	1.54	1.65	1.71	1.02	1.56	25.32	1.35	1.49	2.00	2.25	1.87
TTKOM=1	2.24	1.44	1.77	0.72	2.72	2.14	2.25	1.86	1.71	1.94	1.42	1.87	1.31	2.91	1.67	1.11	9.79	0.77	2.79	2.48	2.37	1.71	2.25	0.76	2.97	2.09	2.57	1.77	1.44	1.65	1.16	1.97	1.38	2.40	1.83	1.06	19.34	0.77	2.85	2.73	2.02
TUPRS=1	1.82	1.15	1.44	1.19	1.83	1.28	1.63	3.32	1.48	2.08	1.49	1.43	1.59	0.88	1.49	1.08	1.12	13.56	1.59	1.78	1.63	1.43	1.48	1.36	2.13	1.39	2.02	3.20	1.57	2.26	0.96	1.57	1.63	0.77	1.68	1.66	1.04	25.37	1.75	1.88	1.87
VAKBN=1	4.37	1.47	2.45	1.17	4.57	3.76	4.15	2.21	1.82	1.29	1.70	2.87	1.35	1.09	2.34	1.00	1.76	0.81	6.71	4.02	4.16	1.17	2.36	1.13	4.66	3.87	4.30	1.83	1.50	0.92	1.01	2.85	0.92	1.05	2.45	0.70	1.57	0.62	7.95	4.07	2.30
YKBNK=1	4.28	1.26	2.39	1.09	4.50	3.35	4.19	2.37	1.97	1.27	1.73	2.95	1.29	1.00	2.31	1.15	1.75	0.83	4.33	7.13	3.95	1.10	2.39	1.14	4.58	3.34	4.45	2.01	1.59	0.85	1.03	2.89	0.79	0.83	2.43	0.81	1.54	0.70	4.23	8.21	2.29
TO	3.19	1.84	2.23	1.60	3.26	2.69	3.00	2.54	2.11	1.76	1.96	2.59	1.83	1.51	2.44	1.51	1.92	1.31	3.18	2.95	2.94	1.48	2.09	1.56	3.28	2.58	3.06	2.01	1.70	1.43	1.37	2.40	1.31	1.25	2.43	1.05	1.57	1.13	3.06	2.97	**86.12**
NET	0.88	-0.29	0.01	-0.49	0.94	0.42	0.71	0.31	-0.08	-0.36	-0.18	0.33	-0.29	-0.54	0.21	-0.53	-0.23	-0.64	0.88	0.66	0.65	-0.55	-0.12	-0.52	0.97	0.31	0.76	-0.18	-0.39	-0.57	-0.56	0.15	-0.58	-0.70	0.19	-0.81	-0.45	-0.73	0.76	0.68	

Notes: The results of this table are built on a TVP-VAR framework which has a lag length of order one with a 10-step-ahead generalized forecast error variance decomposition (BIC).

APPENDIX G

DIRECTIONAL AND NET CONNECTEDNESS FOR SPOT AND 1-MONTH FUTURES PRICES

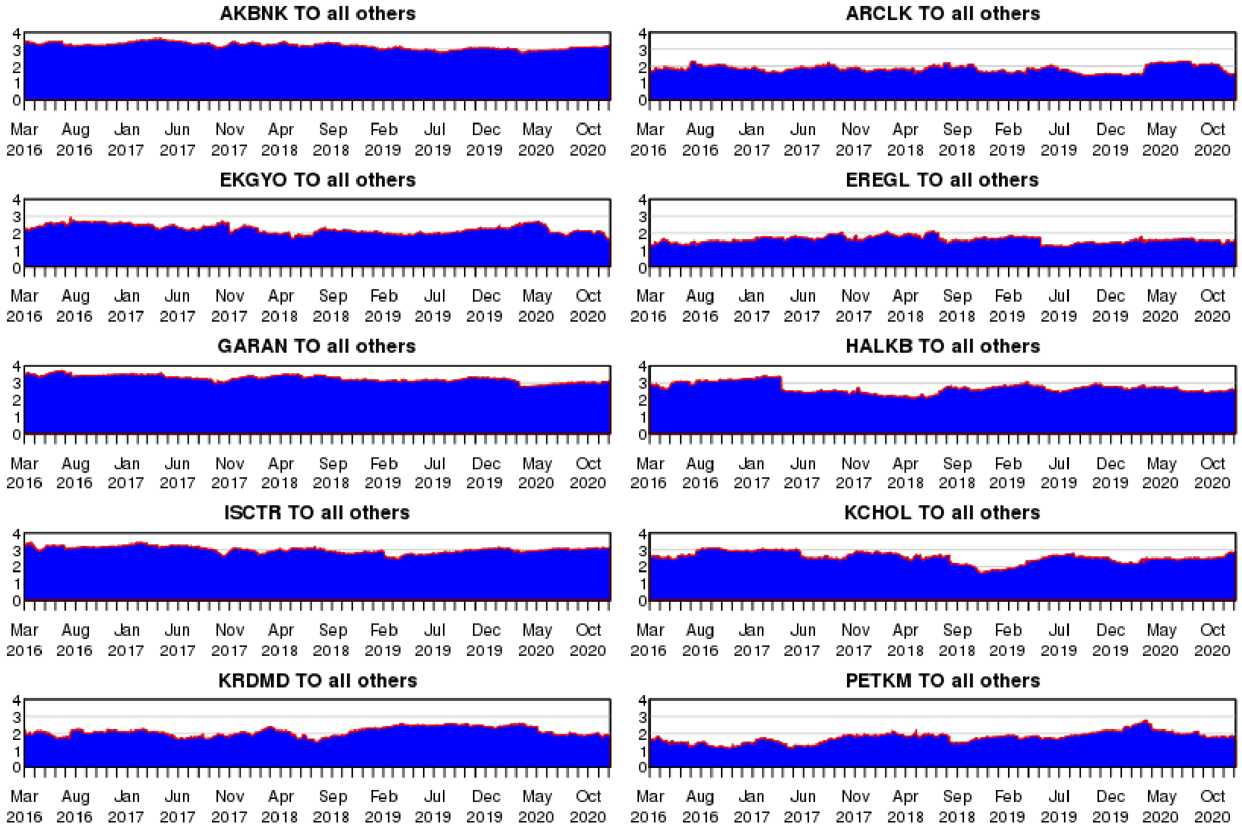

Figure G1. Total directional connectedness to others (Part 1)

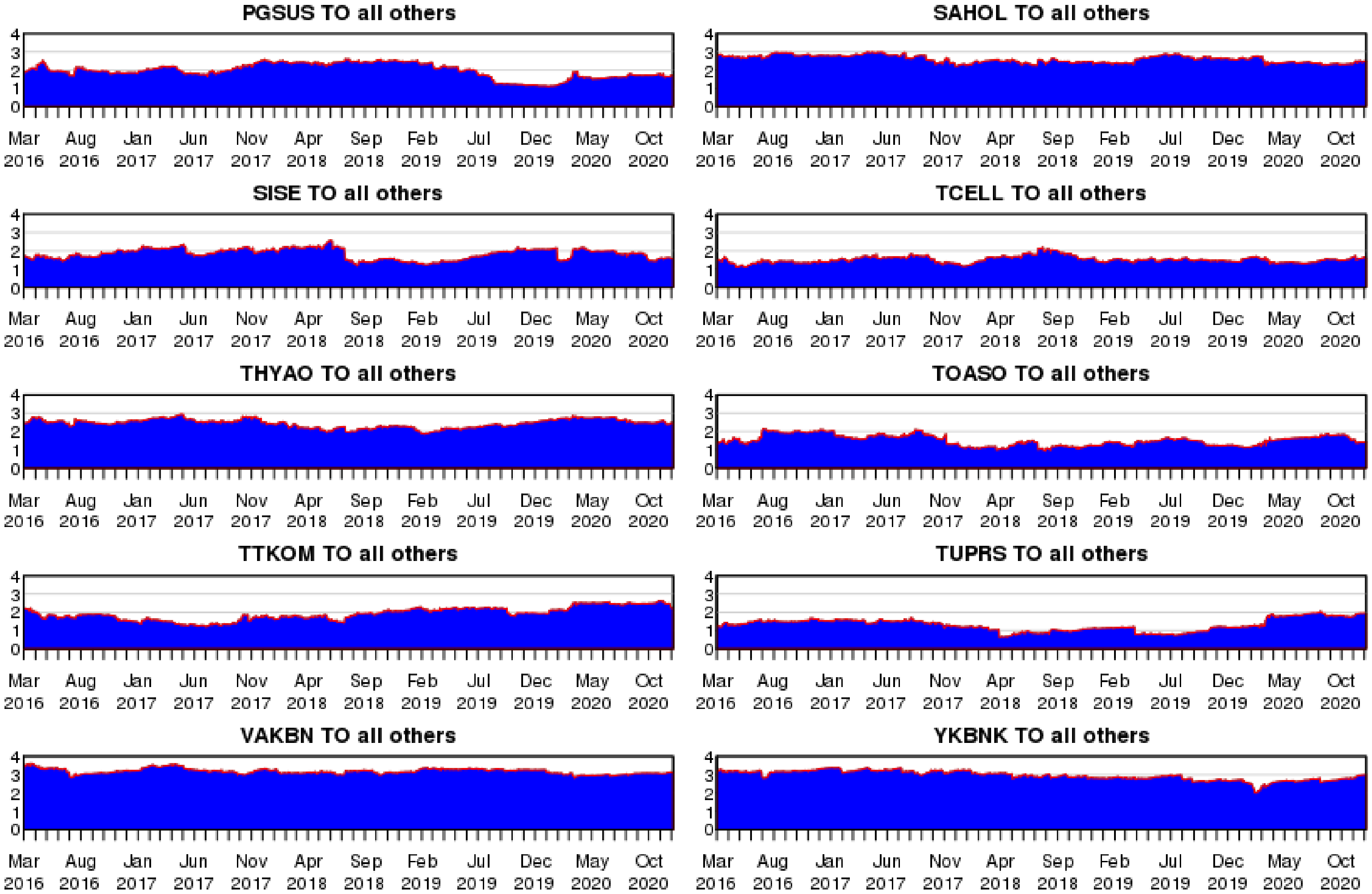

Figure G2. Total directional connectedness to others (Part 2)

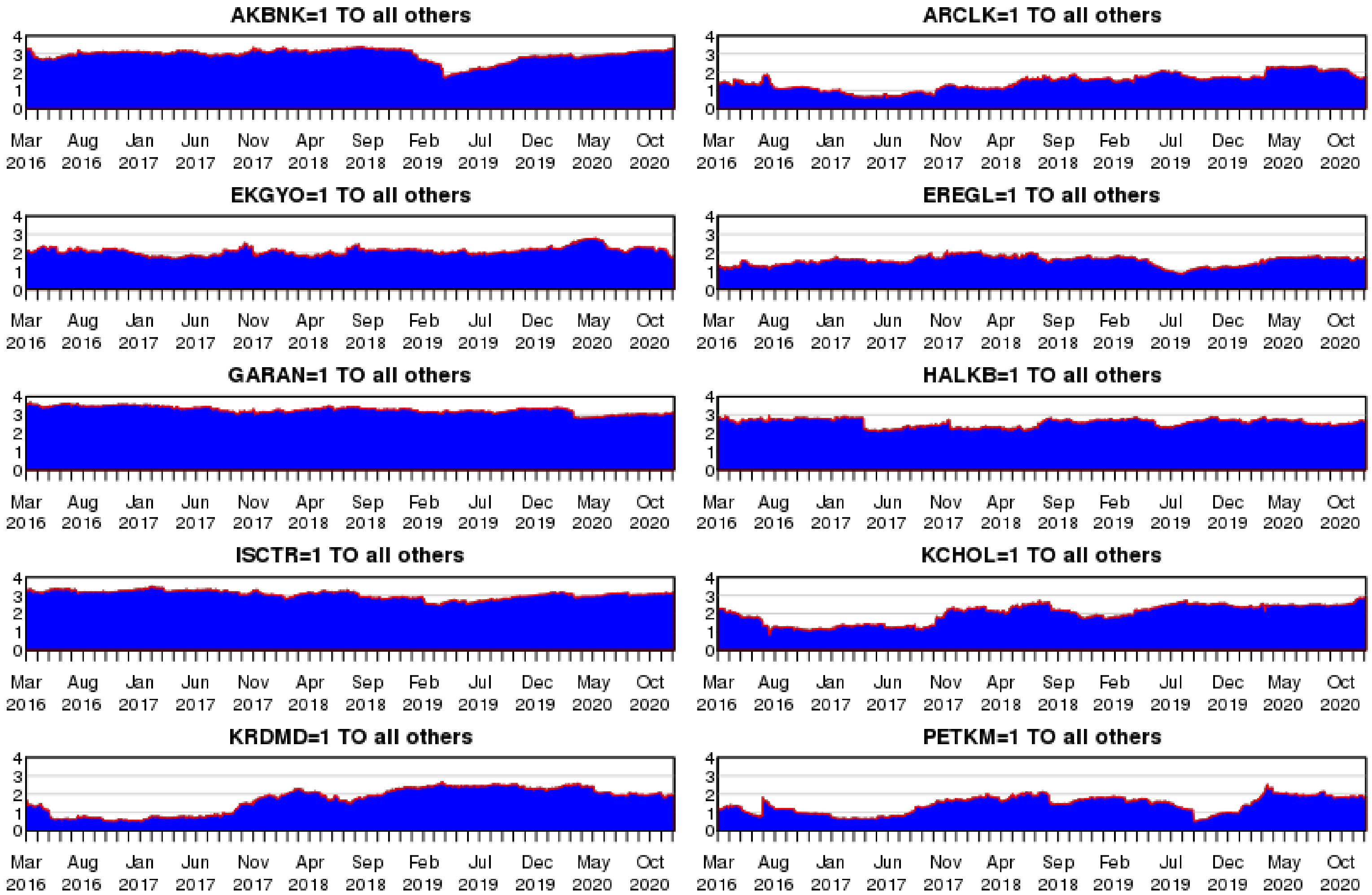

Figure G3. Total directional connectedness to others (Part 3)

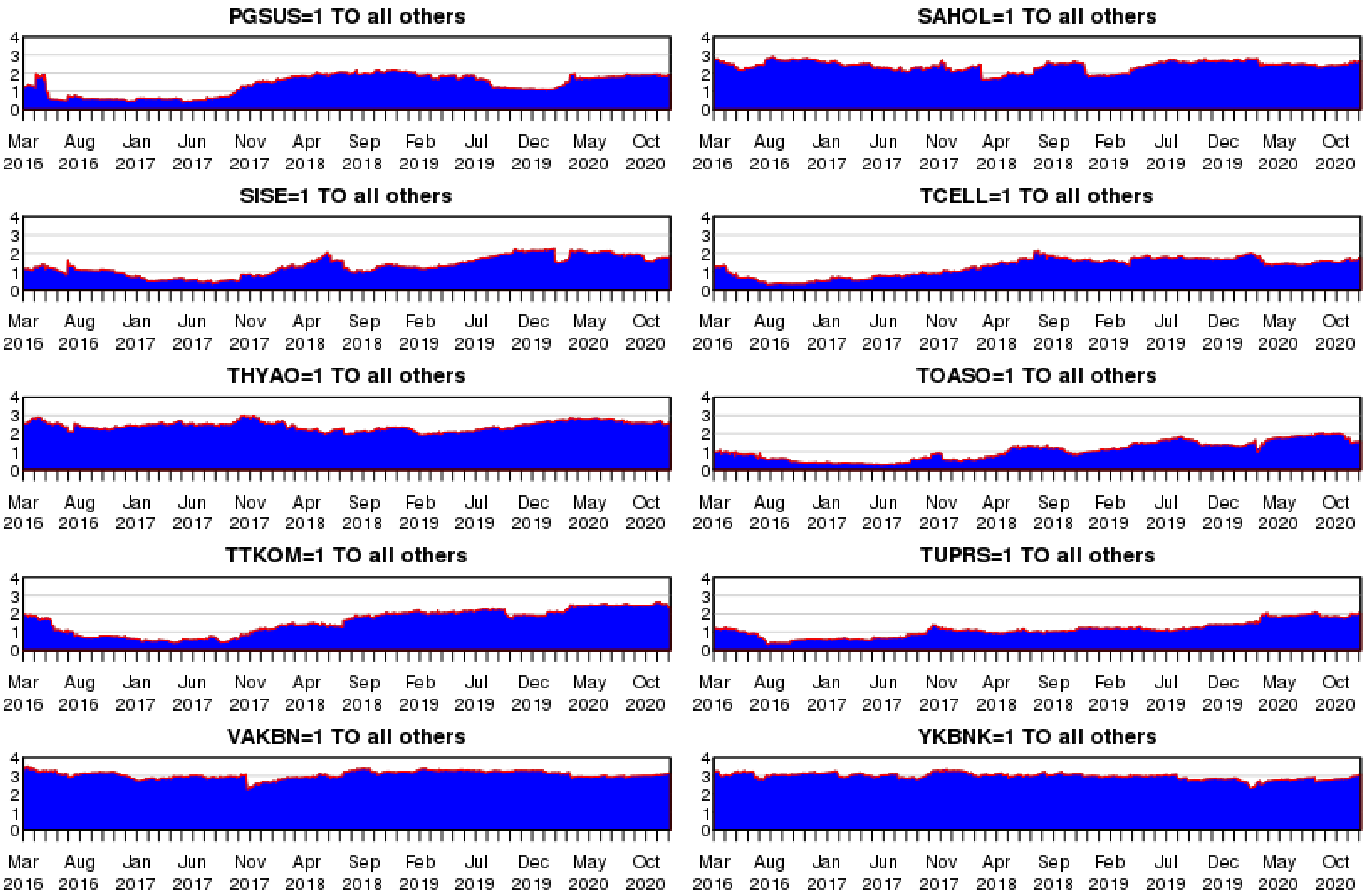

Figure G4. Total directional connectedness to others (Part 4)

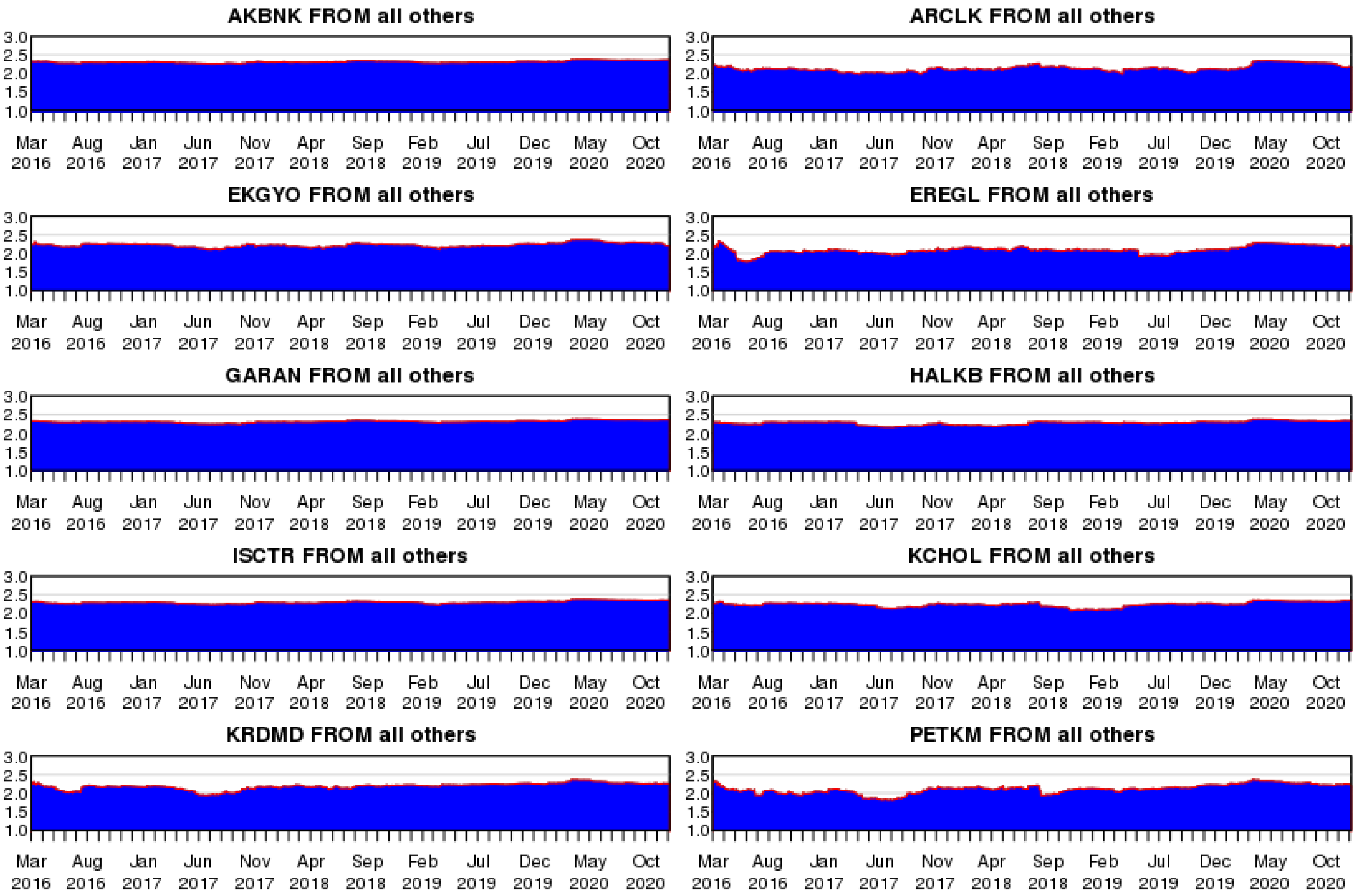

Figure G5. Total directional connectedness from others (Part 1)

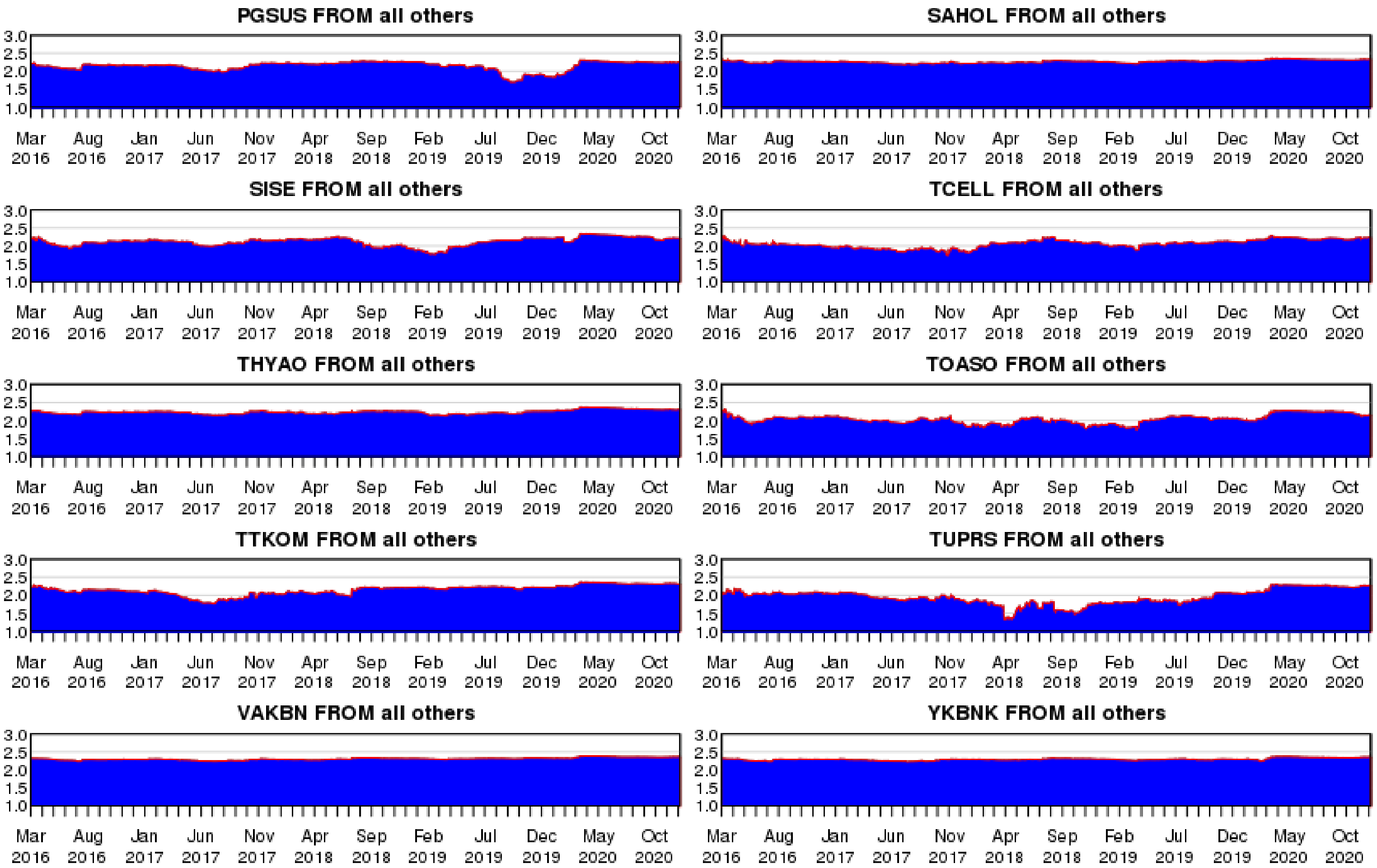

Figure G6. Total directional connectedness from others (Part 2)

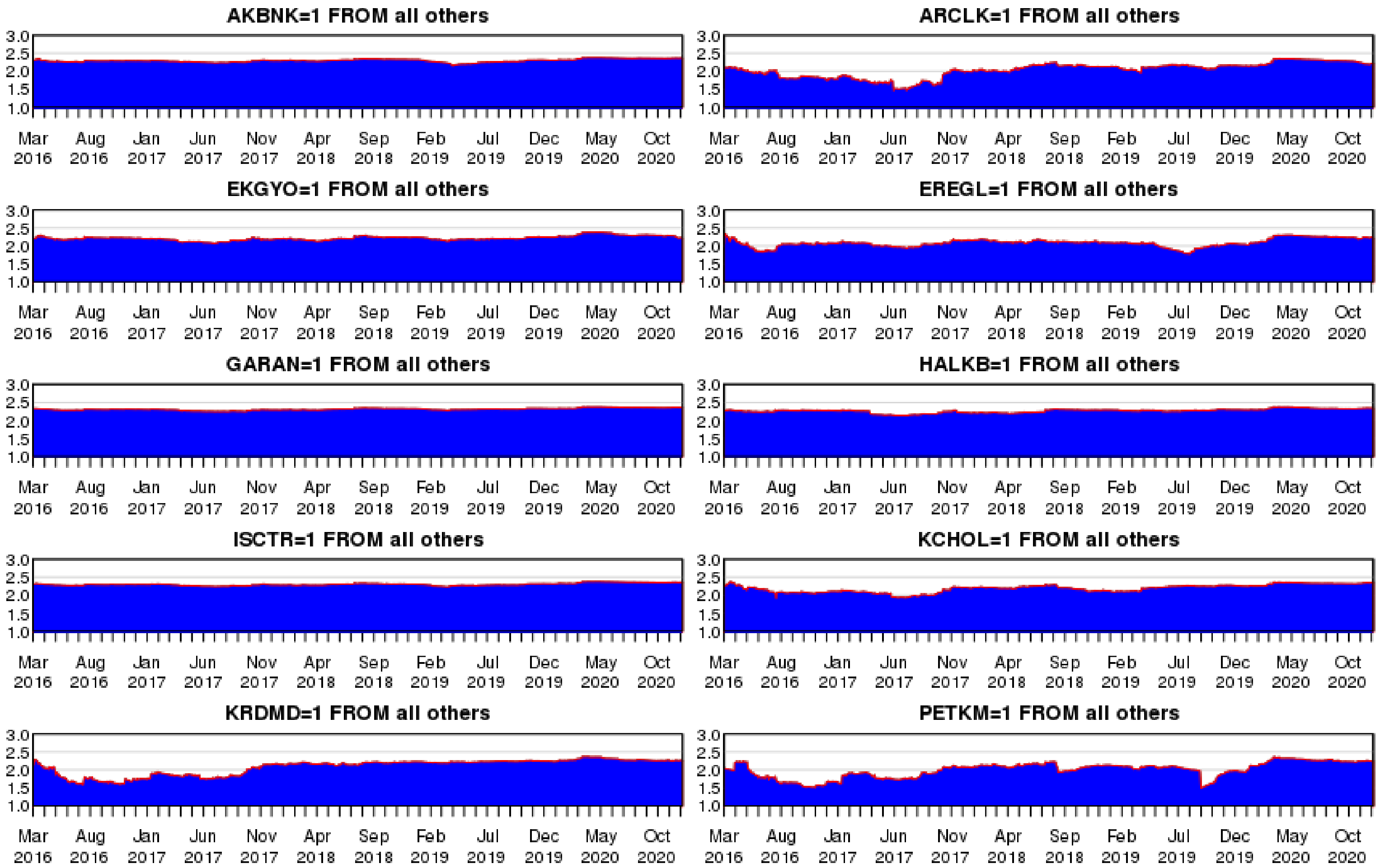

Figure G7. Total directional connectedness from others (Part 3)

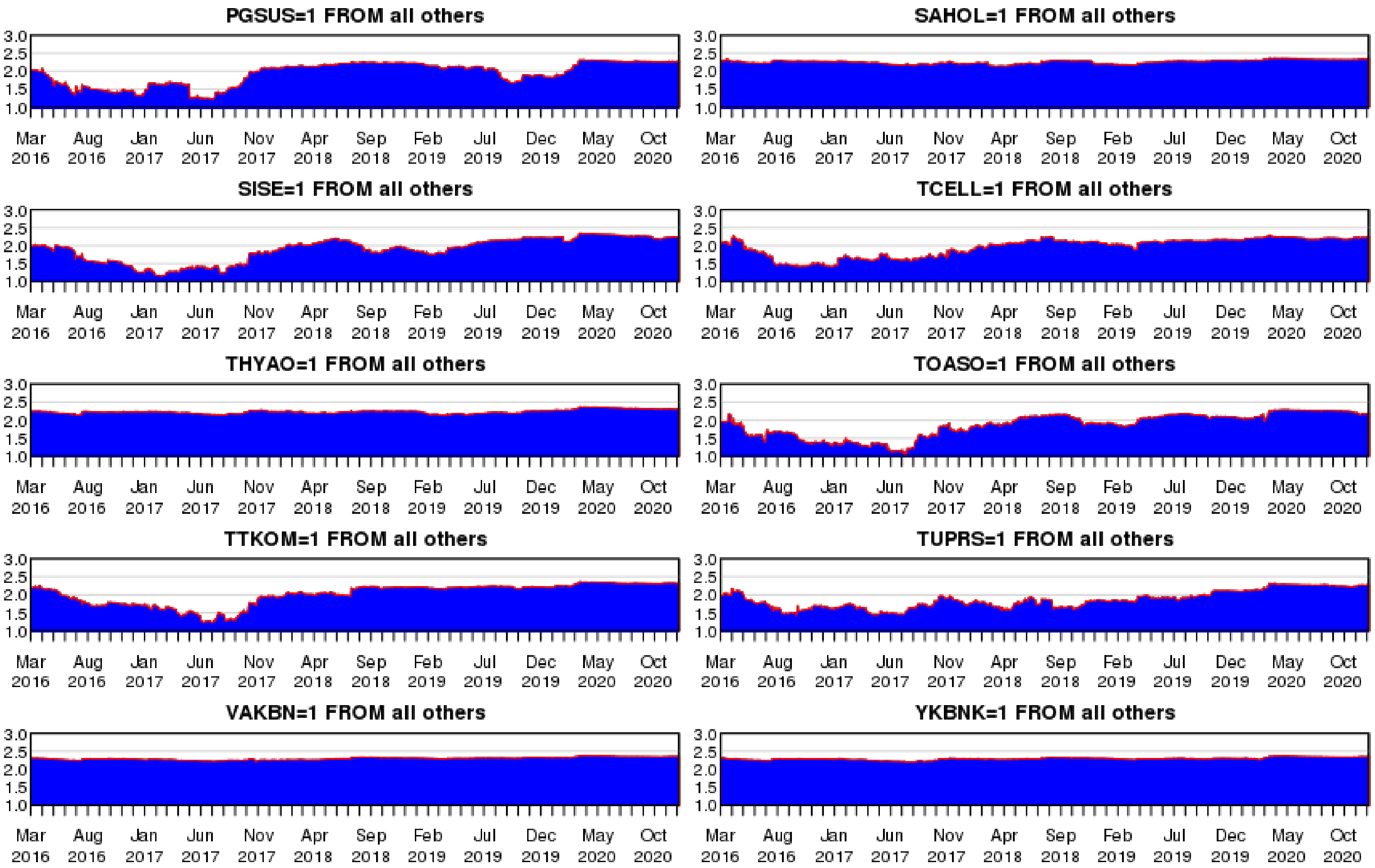

Figure G8. Total directional connectedness from others (Part 4)

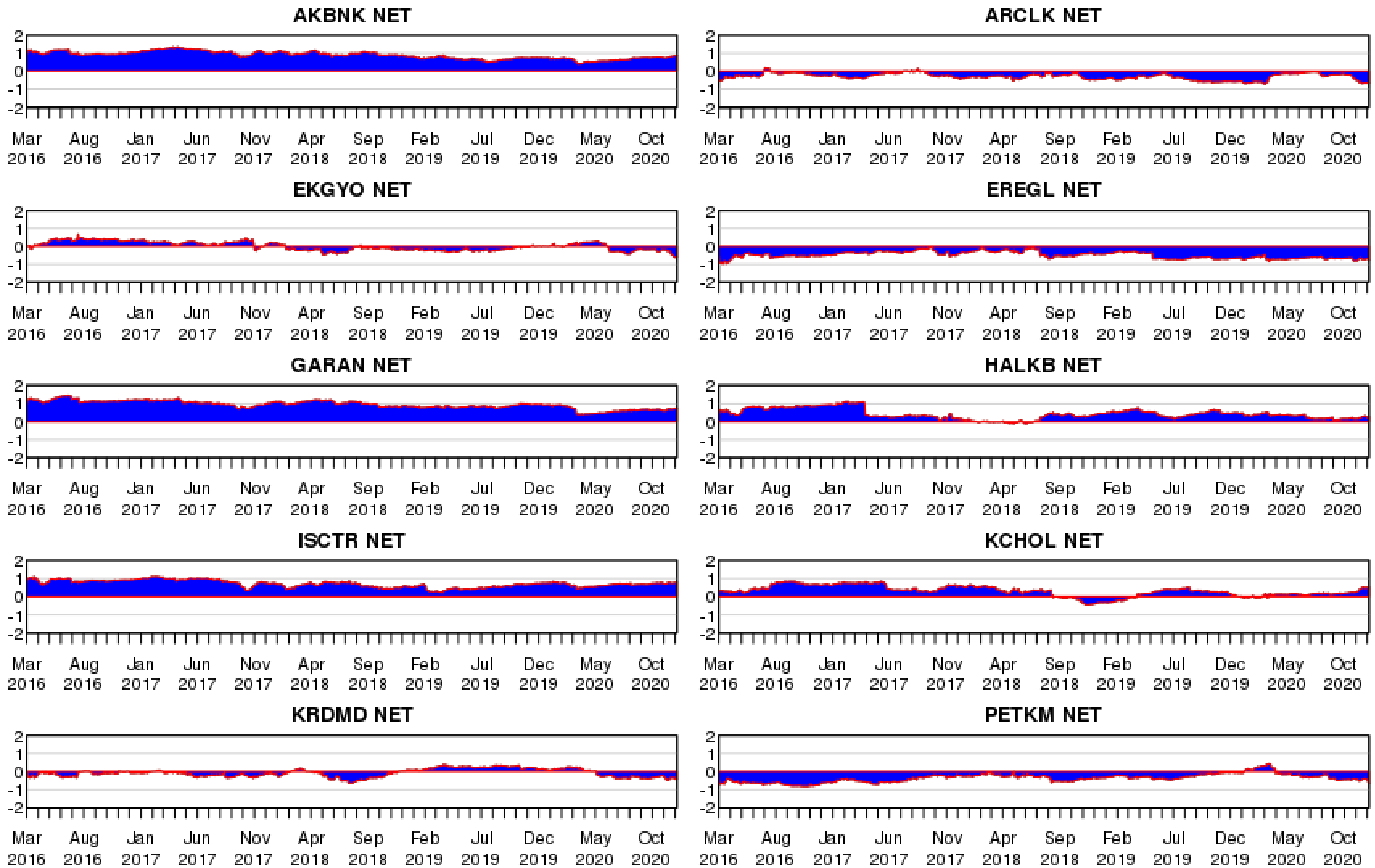

Figure G9. Net total directional connectedness (Part 1)

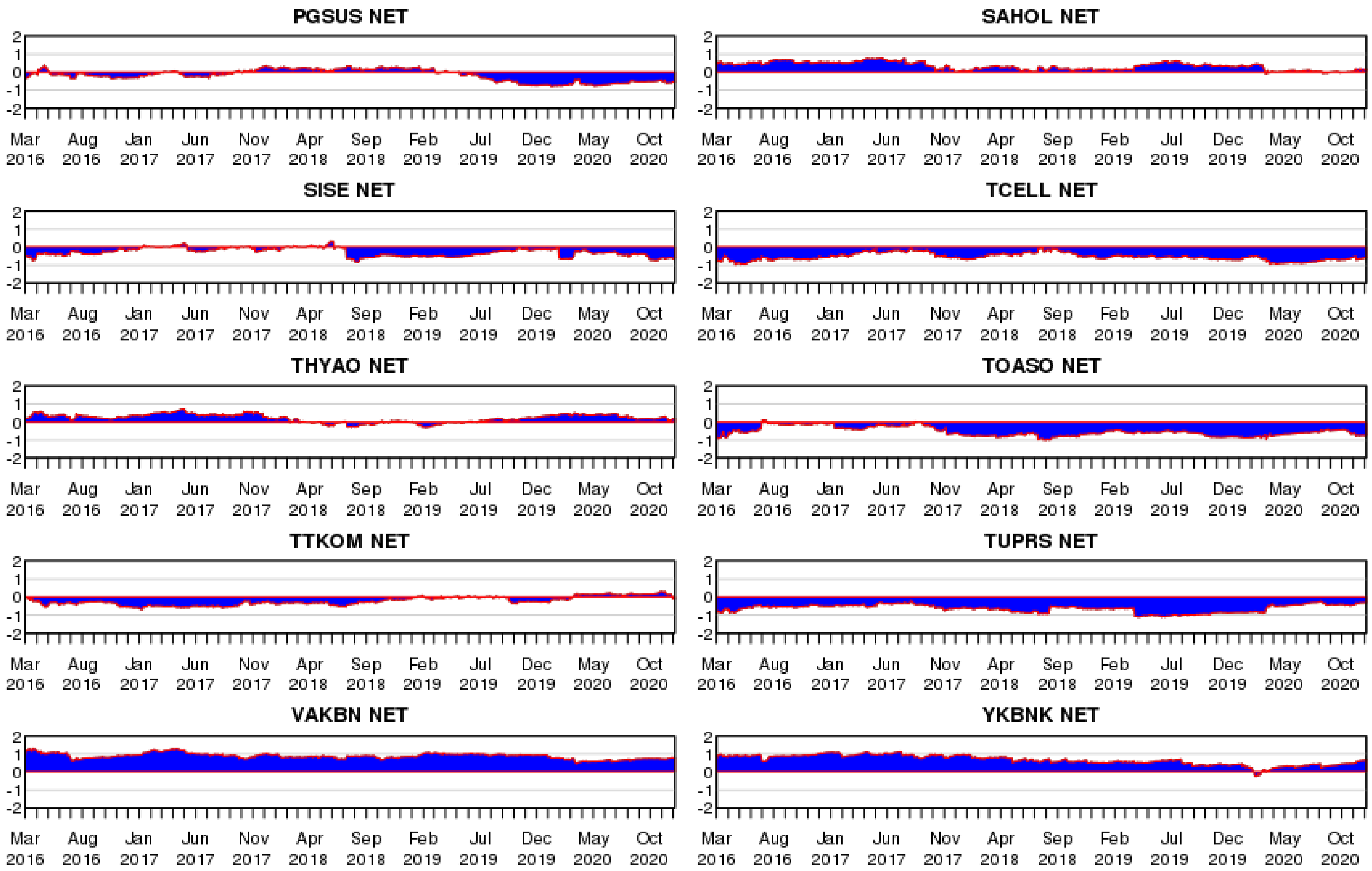

Figure G10. Net total directional connectedness (Part 2)

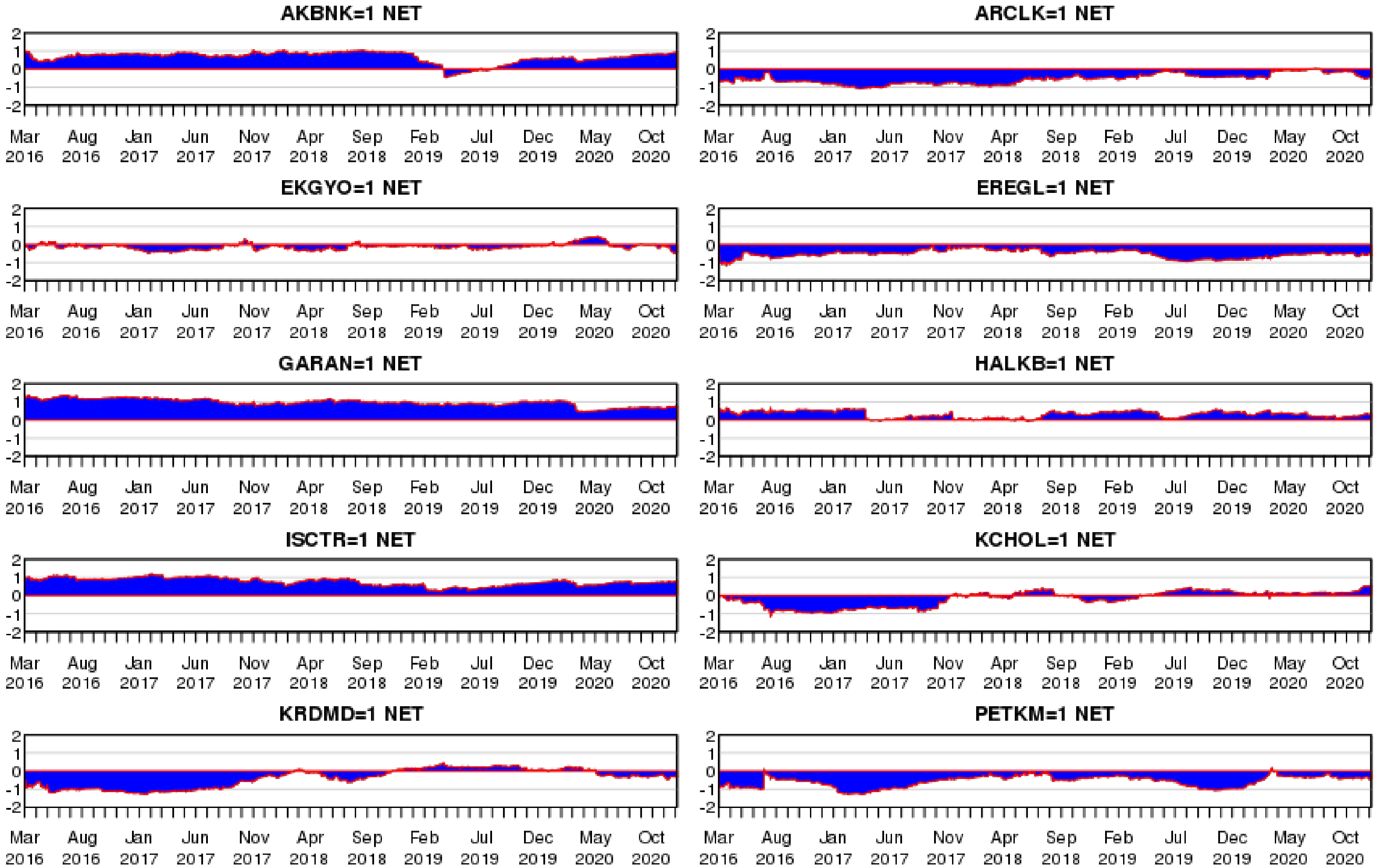

Figure G11. Net total directional connectedness (Part 3)

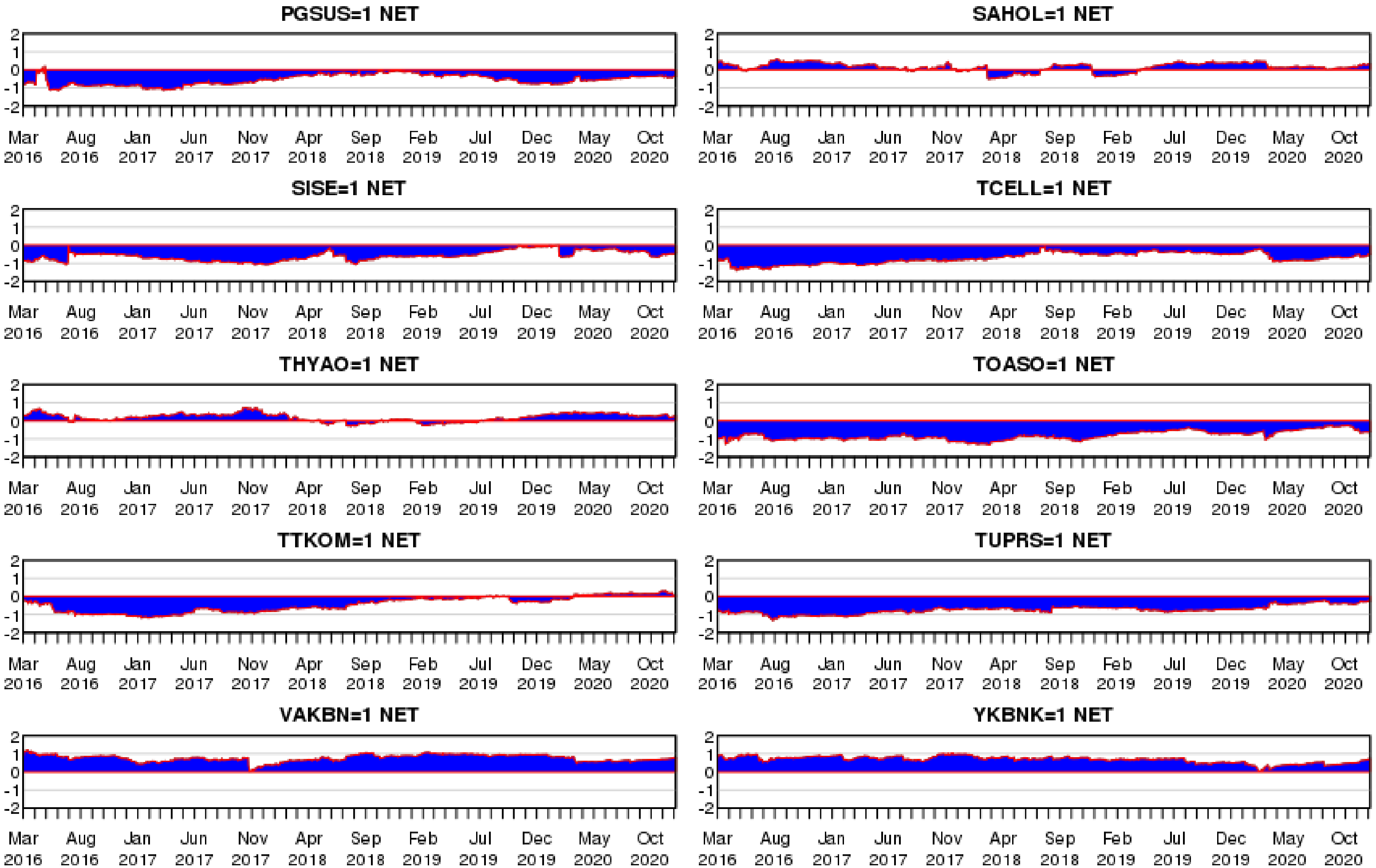

Figure G12. Net total directional connectedness (Part 4)

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