Borsa Istanbul Sectoral Connectedness Analysis

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ABSTRACT

This study examines the volatility connectedness among banks, industrials, and services subindices of Borsa Istanbul using the Diebold-Yılmaz connectedness index methodology. The findings indicate that the banks index typically acts as a net receiver of connectedness from industrials and services indices. If the banks index is considered a proxy for the financial side of the Turkish economy while the other two represent the real side, this result aligns with earlier observations on the connectedness between the real and financial sides of economies. Specifically, it suggests that when a proxy for the real side incorporates financial variables, the real side tends to be a net source of connectedness most of the time. As shock propagators, industrials play a dominant role, and the banks index often moves in the opposite direction to the other two sectors.

Key Words: *Real and Financial Sectors, Financial Connectedness, Volatility, Borsa Istanbul.*

JEL Classification: *C32, E44, G10.*

Borsa İstanbul Sektörel Bağlanmışlık Analizi

ÖZ

Bu çalışma, Diebold-Yılmaz bağlanmışlık endeksi metodolojisi kapsamında Borsa İstanbul'un banka, sanayi ve hizmet alt endeksleri arasındaki volatilite bağlanmışlığını incelemektedir. Bulgular, bankalar endeksinin tipik olarak sanayi ve hizmetler endekslerinden net bir bağlanmışlık alıcısı olarak hareket ettiğini göstermektedir. Bankalar endeksinin Türkiye ekonomisinin finansal tarafını, diğer ikisinin ise reel tarafını temsil ettiği düşünülürse, bu sonuç ekonomilerin reel ve finansal tarafları arasındaki bağlanmışlığa ilişkin daha önceki gözlemlerle de uyumludur. Özellikle, reel taraf için kullanılan temsili değişken finansal değişkenleri içerdiğinde, reel tarafın çoğu zaman net bir bağlantılılık kaynağı olma eğiliminde olduğu gözlemlenmektedir. Şok yayıcı olarak, sanayi sektörü baskın bir rol oynamakta ve bankalar endeksi genellikle diğer iki sektörün tersi yönünde hareket etmektedir.

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JEL sınıflandırması*: C32, E44, G10.*

INTRODUCTION

The exploration of connectedness among various asset classes, indices, commodities, and other real and financial variables through a network theoretic perspective has emerged as a highly dynamic research domain in the past decade, particularly following the introduction of the Diebold-Yılmaz Connectedness Index (DYCI) methodology in a series of papers by Diebold and Yılmaz (2009, 2012, 2014). However, research on connectedness between the subindices of an exchange, within this domain, has been relatively scarce. Among the limited

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examples exploring international exchanges, relevant studies include Costa et al. (2022) for the U.S. market, Chatziantoniou et al. (2022) for the Indian market, Chirila (2022) for the Polish market, and Yin et al. (2020) for the Chinese market. These papers employ either the standard DYCI approach or one of its extensions based on time-varying parameter vector autoregressive (TVP-VAR) model à la Antonakakis et al. (2020). Though they use different number of sectors within various exchanges and contexts, they usually agree on the importance of financials and industrials as net connectedness sources over time. In the context of the Turkish stock exchange, Borsa Istanbul (BIST), the existing literature predominantly employs the Granger causality test, cointegration, and variants of GARCH-based methods to investigate interactions among BIST subindices. Noteworthy contributions to this body of research include studies by Berument et al. (2005), Duran and Şahin (2006), Eyüboğlu and Eyüboğlu (2019), Kamışlı and Sevil (2018), Kocaarslan (2020), Şenol (2020), and Topaloğlu (2020). The only paper that we are aware, which uses DYCI methodology is Ekinci and Gençyürek (2019). They use TVP-VAR based approach and explore volatility connectedness between seven BIST subsectors (finance, industry, technology, tourism, transportation, food, and retail-trade). They conclude that industrial and financial sectors lead in spilling over volatility to other sectors under consideration.

This paper focuses on BIST as the primary subject of investigation, analyzing the volatility connectedness among a chosen set of its subindices—specifically, banks, industrials, and services—utilizing a standard DYCI approach and its extensions as detailed in Schmidbauer et al. (2013, 2016, 2017). Our three-variable model is parsimonious enough, and in line with earlier literature, important subindices are selected so that possible indirect spillover effects between multiple subindices are excluded by design. Besides, this selection of subindices is by no means arbitrary and they are chosen such that, as an important by-product, they allow us to reflect on connectedness between the real (as proxied by industrials and services sectors) and the financial (as represented by banks sector) sides of the Turkish economy. This is accomplished as explained in the following.

Uluceviz and Yılmaz (2020, 2021) have conducted connectedness analyses between the real and financial sides of developed economies, including the U.S. and Switzerland, within the DYCI framework. In a nutshell, their approach is, first, to construct a real activity index from real variables only and then use the constructed index along with financial variables to explore how real and financial sides of these economies interact in a DYCI framework. Their findings suggest that when the real activity index is crafted solely from real variables, devoid of financial variables, the financial side of the economy predominantly serves as a pronounced net transmitter of shocks to the real side. However, when a commonly used proxy for real activity, typically constructed using both real and financial variables, is employed, the direction of connectedness tends to be from the real side to the financial side. As a result, by selecting industrials and services sectors as representatives of the real, and banks as the representative of the financial sides of the Turkish economy, we approach Uluceviz and Yılmaz (2020, 2021) domain.

Consequently, we find that while Industrials and Services indices, representing real side of the economy move more or less in tandem, the banking sector consistently exhibits a counter-directional movement compared to the other two sectors and serves as a net receiver of connectedness from the industrials and services sectors, particularly during periods of heightened volatility. This observation aligns to some extent with prior literature, as evident in works such as Chirila (2022) and Ekinci and Akyürek (2019). Furthermore, we can argue that our findings are in agreement with those of Uluceviz and Yılmaz (2020, 2021), suggesting that when variables representing the real side experience shocks from the financial side, the connectedness tends to flow from the real to the financial side.

As an extension, we analyse propagation values as computed in Schmidbauer et al. (2013, 2016, 2017). Propagation values serve as metrics for assessing the significance of nodes in a network as shock propagators, essentially quantifying the eigenvector centrality of network nodes (For additional perspectives on centrality measures within the network literature, refer to, for instance, Newman, 2010.) Propagation values of Banks with respect to Industrials and Services behave in a particular way. That is to say, banks' importance as shock propagators move in opposite direction with industrials and services about 70% of the time, respectively.

This type of analysis has a sound econometric and theoretical basis as documented in earlier literature, therefore, it would contribute to diversification efforts of portfolio managers and other investors alike by providing timely information on the dynamics of BIST subindices. This would result with more efficient management of funds during times of high volatility events such as: Taper tantrum of 2013, exhange rate attack on Turkish lira during August 2018 or declaration of Covid-19 pandemic in early 2020, among others.

The remainder of the paper is structured as follows: Section I offers a concise overview of the data utilized. Section II outlines our methodological approach. Section III presents our empirical findings, and Section IV provides a summary and conclusion for the paper.

I. DATA

In this paper, our primary raw data series comprise the daily open, high, low, and close values of BIST subindices, specifically Banks, Industrials, and Services. The data were obtained from Reuters Datastream using the tickers: XBANK.IS, XUSIN.IS, and XUHIZ.IS for the Banks, Industrials, and Services indices, respectively. After cleaning and combining raw data series, we compute Garman and Klass (1980) type range-based volatility of each subindex, as in Diebold and Yılmaz (2009). Our final sample spans a daily period from 2009-11-05 to 2022-06-23, comprising a total of 3160 days.

Volatilities are typically characterized by serial correlation and right skewness; however, taking the natural logarithm is known to approximate a normal distribution, as discussed by Diebold and Yılmaz (2014). Therefore, as a preprocessing step before estimation, we apply natural logarithms to daily volatilities.

II. METHODOLOGY

A.DYCI Methodology: A Tool For Network Connectedness Analysis

In this section, we provide a brief introduction to DYCI methodology, which was developed in Diebold and Yılmaz (2009, 2012, 2014), and its extension by Schmidbauer et al. (2013, 2016, 2017). To save space, we present only the equations pertinent to our empirical analysis (for a more comprehensive understanding, interested readers are encouraged to consult the referenced papers).

A covariance stationary N-variable $VAR(p)$ model, $x_t = \sum_{i=1}^{p} \emptyset_i \, x_{t-i} + \varepsilon_t$, $\varepsilon_t \sim iid\,(0, \Sigma)$, has a moving average (MA) representation of the form: $x_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i}$, where $N \times N$ coefficient matrices A_i conform the formula $A_i = \emptyset_1 A_{i-1} + \emptyset_2 A_{i-2} + \cdots + \emptyset_p A_{i-p}$, with A_0 an $N \times N$ identity matrix, and $A_i = 0$ for $i < 0$. These coefficient matrices drive the model dynamics. We are interested in the variance decompositions, which allow one to estimate the fraction of the H-step ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall i \neq j$, for each i. Calculation of variance decompositions necessitates ortogonal innovations which is normally attained through identification schemes such as Cholesky decomposition. But this leads to variable-ordering dependent results. To circumvent this, Diebold and Yılmaz (2012) utilize generalized VAR approach, due to Koop et al. (1996) and Pesaran and Shin (1998), which produce ordering invariant results.

Pesaran and Shin (1998) show that under the assumption of multivariate normal distribution of the error term, ε_t, the h-step generalized impulse response function scaled by the variance of the variable lead to node j's contribution to node i's h-step ahead generalized forecast error variance, $\theta_{ij}^{g}(h)$ for $h = 1, 2, \ldots$, as:

$$\theta_{ij}^{g}(h) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{h-1} (e_i' A_k \Sigma e_j)^2}{\sum_{k=0}^{H-1} (e_i' A_k \Sigma A_k' e_i)^2} \tag{1}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation, and e_j is the selection vector with one as the jth element and zeros otherwise. Normalizing each element of the variance decomposition matrix by respective row sum, one gets:

$$C_{i \leftarrow j}^{h} = \frac{\theta_{ij}^{g}(h)}{\sum_{j=1}^{N} \theta_{ij}^{g}(h)} \tag{2}$$

$C_{i\leftarrow j}^{h}$, is called pairwise directional connectedness. In the network literature, it is interpreted as adjacency matrix of a weighted directed network of nodes, denoted by C, and its ijth element is c_{ij}.

Normalized entries of the generalized variance decomposition matrix, in Eq. (2), is used to construct a summary measure of connectedness matrix C. Diebold and Yılmaz (2012) define the total connectedness index as:

$$C^{h} = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} C_{i\leftarrow j}^{h}}{\sum_{i,j=1}^{N} C_{i\leftarrow j}^{h}} = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} C_{i\leftarrow j}^{h}}{N} \tag{3}$$

Direct connectedness from node i (to node i) are given by the column (row) sums in C. It excludes nodes' connectedness to itself:

$$\text{from node } i \text{ to others: } C_{\bullet\leftarrow i} = \sum_{k=1, i\neq k}^{N} c_{ki} \tag{4}$$

$$\text{to node } i \text{ from others: } C_{i\leftarrow\bullet} = \sum_{k=1, k\neq i}^{N} c_{ik} \tag{5}$$

The difference between shocks, originated from and directed to node i, yield a measure of net directional connectedness transmitted from node i to all other nodes. It is designated as:

$$C_{i} = C_{\bullet\leftarrow i} - C_{\mathrm{i}\leftarrow\bullet} \tag{6}$$

B.Propagation Values

To extend DYCI framework, Schmidbauer et al. (2013, 2016, 2017) assume that all timely available information about the network throughout day t is contained in C. Furthermore, if an initial hypothetical shock of unit size hits node k on day t, it will propagate across the nodes of the network within day t as follows:

$$n_{s+1} = C.n_{s}, \qquad s = 0, 1, 2, \ldots \tag{7}$$

A hypothetical shock is designated as $n_0 = (0, \ldots, 0, 1, 0, \ldots, 0)$, where 1 is the kth element of n_0 (step s=0 represents the initialization). Iterating Eq. (7) and investigating steady-state properties (as $s \to \infty$) of the model, one gets:

$$\mathbf{v}' = \mathbf{v}'.C \tag{8}$$

When the left eigenvector $\mathbf{v} = (v_1, \ldots, v_N)'$ of C is normed so that $\sum_{k=1}^{N} v_k = 1$, v_k is termed as the propagation of node k. Intuitively, v_k represents node k's power as a network volatility creator. In social network analysis; a closely related concept, eigenvector centrality, is also widely used as mentioned in Bonacich (1987).

Empirically, we fit a standard VAR(4) model to $N = 3$ endogenous variables as in x_t vector below:

$$\mathbf{x_t} = \begin{bmatrix} Banks \\ Industrials \\ Services \end{bmatrix}_t . \tag{9}$$

The variable names in $\mathbf{x_t}$ vector coincide with respective BIST sectoral indices and they are consistent throughout the paper within relevant figures. Rolling data windows of size 250 (i.e., days $t - 249, \dots, t$ comprise each sample for day t) is used. We follow Diebold and Yılmaz (2012) and employ ordering-invariant impulse response function identification approach as suggested by Pesaran and Shin (1998). Forecasting $h = 20$ steps ahead, forecast error variance decomposition is appropriately settled. This procedure is then applied for every t, to obtain a sequence of connectedness matrices.

III. EMPIRICAL RESULTS

A.Dynamic Connectedness Analysis

In this section, we elaborate on system-wide, along with total and net directional connectedness results, and how they evolve over time. As we have noted above, we used a VAR(4) model with 250-day rolling data windows and $h = 20$ days ahead forecast horizon. These values yield relatively settled results and as a robustness check we investigated total connectedness index for various lag lengths[1].

In Fig. 1, we plot total connectedness index, which ranges from 29.4% to 53.1% over the whole analysis period. On 2013-01-25, total connectedness index reached all time low value of 29.4%. Then it slightly increased, and following a gradual drop, it reached yet another local minimum at 29.8% on 2013-05-30. This date resides within the week Fed chairman Bernanke appeared before the U.S. Congress' Joint Economic Committee where he revealed Federal Open Market Committee's (FOMC) intention to taper bond purchases. Bernanke's appearance resulted with increased bond yields and decreased stock prices globally[2]. Following this, connectedness index rose sharply and reached a new local maximum at around 50% in early 2014. Following ups and downs during the rest of 2014, it reaches a local minimum at 41% in late Jan 2015. Then a secular upward trend leads to all time high connectedness value of 53.1% in Oct 2016. This maximum value could be attributed to the aftermath of the failed coup attemp on 15 Jul 2016 in Türkiye. Gradual decrease down to 32% and realized local trough in Aug 2017 is reversed and resulted with a one year upward trend and a local maximum at 48.5% index value in Aug 2018. This increased connectedness could be associated to excessive volatility in Turkish lira

[1] In Fig. 6, we plot minimum and maximum values of connectedness index for models with VAR lag lengths $\in \{1, \cdots, 5\}$ and we observe that they move in line with the selected VAR(4) model results indicating robustness of our lag length selection.

[2] See https://www.reuters.com/article/us-usa-fed-2013-timeline-idUSKCN1P52A8, accessed on 2023-02-12.

prevailing at the time. Once markets are settled, a decrease in the connectedness index was observed until the end of 2019. With the outbreak of COVID-19 pandemic[3] and associated uncertainty in 2020, it has experienced a reversal in the downward trend and increased up to levels close to all time high values. It reached a local maximum in March 2020.

Due to the Covid-19 pandemic, economic activity ground to a virtual standstill worldwide, including in Türkiye. This was accompanied by sudden and sharp declines in the prices of most asset classes. In response to the economic downturn, central banks globally adopted extensive quantitative easing policies. These measures alleviated stress on economies and financial markets, leading to a subsequent rise in asset prices. The subsequent peak occurred locally in October 2020.

The introduction of newly developed COVID-19 vaccines brought about a change in economic prospects, causing the index to decline until March 2021. The tightening of monetary policies by global central banks, coupled with concerns about imminent inflation, prompted an upward trend in the index. The latest local peak was observed in early 2022, followed by a downward trajectory until the end of our sample.

Fig. 2 plots total and pairwise connectedness indices in a compact form. Indeed, all of our analysis hinges on this plot and relevant connectedness measures that are derived from it. In Fig. 2, we focus on the 3-by-3 subplot comprising of the first three rows and the columns, respectively. The diagonal elements in this subplot illustrate the own-shares of connectedness for each subindex, and they consistently remain high throughout the analysis period. This high own-shares of connectedness leaves a relatively small proportion available for spillover to other nodes in the network.

Fig. 3 shows total directional and net connectedness indices. First two panels of the plot (“to-others” and “from-others”) correspond to first three plots of fourth row and fourth column of Fig. 2, respectively. Third panel (“net”) of Fig. 3 is the net connectedness between “to-others” and “from-others” (Eq. 6), and hints us that the Banks index is a net connectedness receiver during most of our analysis period except some relatively short periods during 2015-2020 (first plot of the third row). Industrials and Services act as net sources of connectedness over most of our analysis period (second and third plots of third row of Fig. 3, respectively). In a broad sense, we can argue that Industrials index is the dominant net connectedness source over the analysis period.

Fig. 4 displays net directional connectedness from Banks to Industrials and Services sectors, respectively. Third panel of Fig. 3 and subplots of Fig. 4 can be used together to identify net connectedness dynamics in a more explicit way.

As an illustration, when examining the first plot of the third panel in Fig. 3 for the 2011-2013 period, it becomes evident that the net effect is predominantly negative throughout. This indicates that the Banks index serves as

[3] On 2020-03-11, the World Health Organization (WHO) declared the COVID-19 outbreak a pandemic.

a net receiver of connectedness during this specified time frame. To figure out sources of this negative connectedness, we revert to Fig. 4. Left panel of Fig. 4 hints us that Banks index is a net receiver from Industrials. However, right panel of the same plot shows us that Banks index is a net source of connectedness for the Services sector and in net terms, Banks index is a net receiver. For the 2013-2015 period, Fig. 3 shows that the net effect on Banks is dominantly negative where it reaches all time minimum connectedness. Similarly, in the left panel of Fig. 4, Banks index is a net receiver from Industrials. In the right panel of the same plot, we observe that Banks index is also receiving significant amount of net connectedness from Services index as well. As a result, Banks index is a net connectedness receiver during this time period. When we consider post-2020, from the aftermath of intense COVID-19 pandemic, until the end of our analysis: we observe that Banks index is a net connectedness receiver while Industrials index is a net connectedness source for the other two indices and Services index is a net source for almost all of the time ("Net" panel in Fig. 3). Precise sources of connectedness can be identified from Fig. 4. In Fig. 4, we observe that Banks index is a net receiver from both indices but with larger share being sourced from Services index.

B.Propagation Values

As a last step, we investigate shock propagating behaviour of each sector. This is accomplished through the lens of propagation values as defined in Eq. (8). Fig. 5 plots propagation values as a stacked plot where the sum of individual values, for each day, add up to 1. In this plot, the larger the value, the larger the importance of the node as a shock propagator. Propagation values for Banks vary within the range $[26.0\%, 36.8\%]$, while for Industrials and Services these ranges are $[29.4\%, 40.0\%]$ and $[27.8\%, 39.0\%]$, respectively.

The banking sector maintained a relatively stable trajectory until mid-2013; however, following Bernanke's taper tantrum speech in late May, and subsequent turmoil in financial markets, its significance experienced a notable decrease. After a local minimum in early 2014, it started to trend upwards, with ups and downs, reaching its all time high in early 2018. During early days of pandemic in 2020, its importance as a shock propagator decreased significantly until mid 2020 then with surged inflation domestically and globally, it rebounded and reached a local maximum in late 2021. After reaching a local minimum in early 2022, it stayed, approximately, at the same level until the end of our analysis period.

Industrials sector, after reaching its all time high in mid-2012, follows a secular downward trend and, with ups and downs, reaches its all time low in early 2015. Rebounding from its all time low, it reaches a local maximum in mid 2017, then local minimums in mid 2019 and late 2020. During the time when WHO declared Covid-19 outbreak a pandemic, it reaches a local maximum and finally, beginning 2021, it starts to trend up until the end of our analysis period.

The Services sector, after hitting its all-time low propagation value in the second half of 2012, exhibits an upward trend and reaches its peak value in 2013, causing a concurrent decrease in banks and industrials. Subsequently, there is a gradual decline until the end of 2018, followed by an upward trajectory. The abrupt surge in Services sector propagation values in early 2020 could be attributed to the Covid-19 pandemic, where companies in the services sector are anticipated to be most affected by changing economic conditions. Simultaneously, the banks index experiences significant drops, while industrials remain relatively stable for a certain period.

IV. SUMMARY AND CONCLUSIONS

This paper aims to understand volatility connectedness between Banks, Industrials and Services subindices of Borsa Istanbul within Diebold and Yılmaz (2009, 2012, 2014) connectedness index framework and its extensions as in Schmidbauer et al. (2013, 2016, 2017).

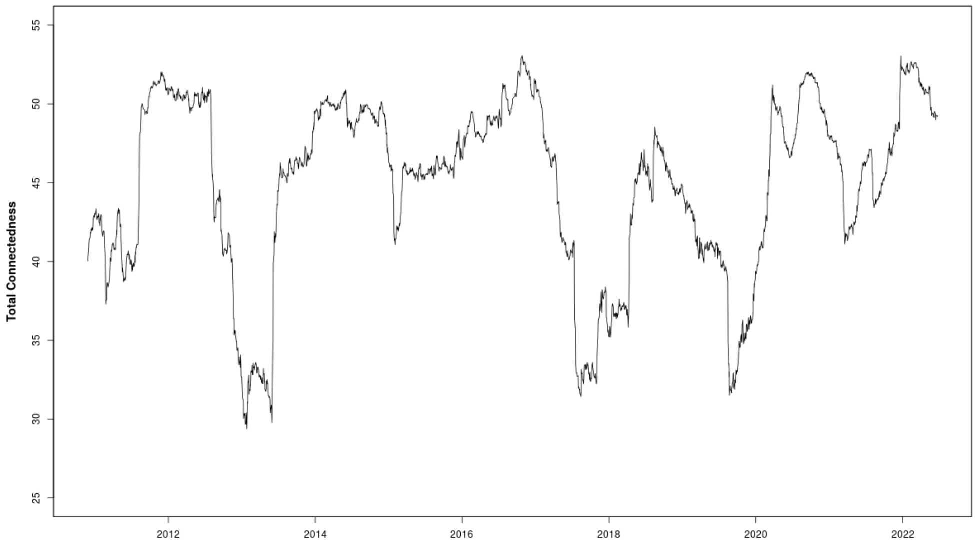
To accomplish this, we initially calculate range-based volatilities for each subindex and utilize them as input for the Diebold-Yılmaz analysis. Consequently, our findings indicate that the Banks index, potentially serving as a proxy for the financial side of the economy, exhibits distinct behavior compared to the Industrials and Services indices, which may be seen as representing the real side of the Turkish economy. Specifically, when the Banks index acts as a net receiver of connectedness, the Industrials and Services indices function as sources of connectedness towards it. In a similar vein, when we consider propagation values to quantify shock propagator characteristics of Banks index, we notice that it usually moves in opposite direction with the other two indices. Traces of domestic and local shocks that hit Borsa Istanbul are also apparent in the connectedness and propagation value plots. Global shocks such as (i) Bernanke's May 2013 taper tantrum announcement and (ii) COVID-19 pandemic have reflections in our analysis and they mostly impact banks negatively. Furthermore, domestic shocks such as 15 July 2016 failed coup attempt and August 2018 exchange rate attack on TRY are also evident.

To sum up, using standard DY connectedness framework analysis, we document how major subindices of Borsa Istanbul are affected from global and local shocks and how they interact with each other. We also observe that banks index move mostly in opposite direction with relative to Industrials and Services sectors.

These findings suggest that our approach could be valuable in the context of portfolio construction and management; however, further research is warranted in this direction.

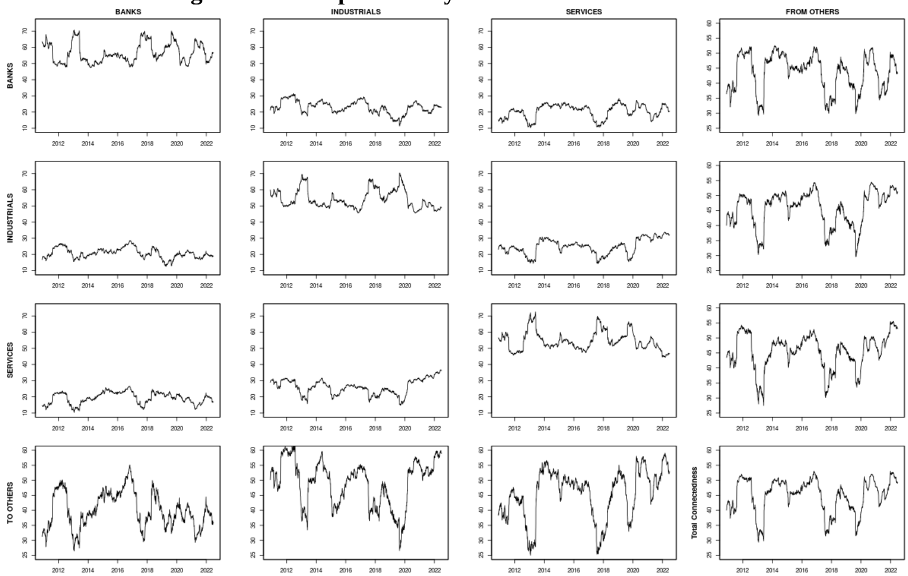
To the best of our knowledge, this study represents the first exploration into the interaction of Borsa Istanbul subindices within our proposed approach. The observed gap in this domain indicates the potential for high-quality research opportunities in the future.

Fig. 1 Total connectedness index



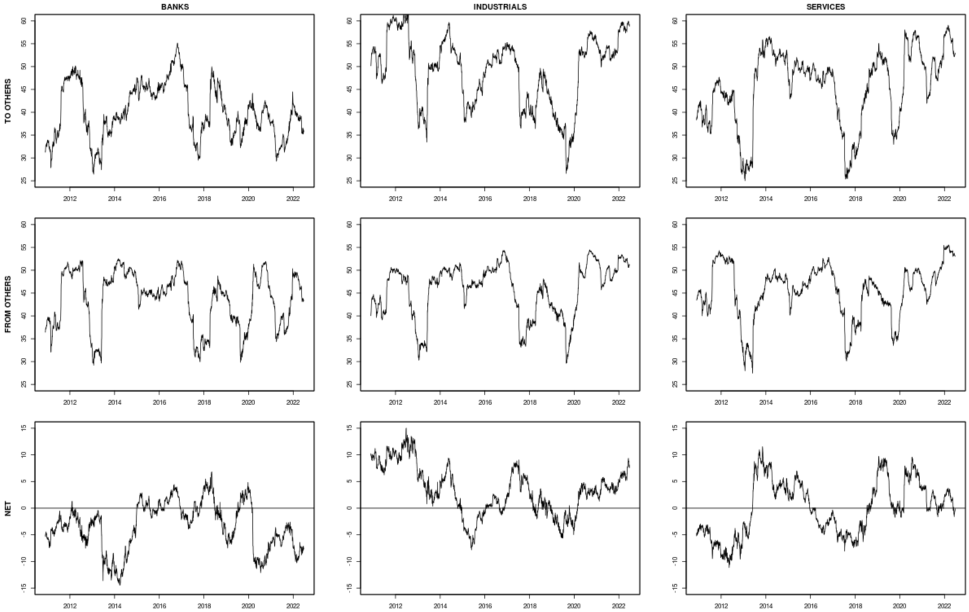
Source: Author's calculations.

Fig. 2 Total and pairwise dynamic connectedness indices



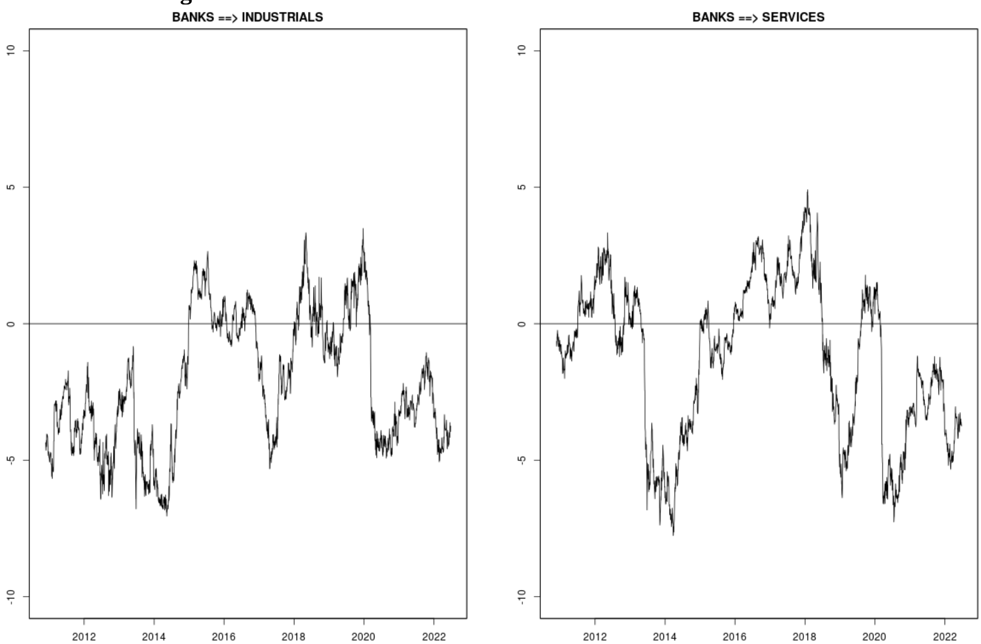
Source: Author's calculations.

Fig. 3 Dynamic total directional and net connectedness indices



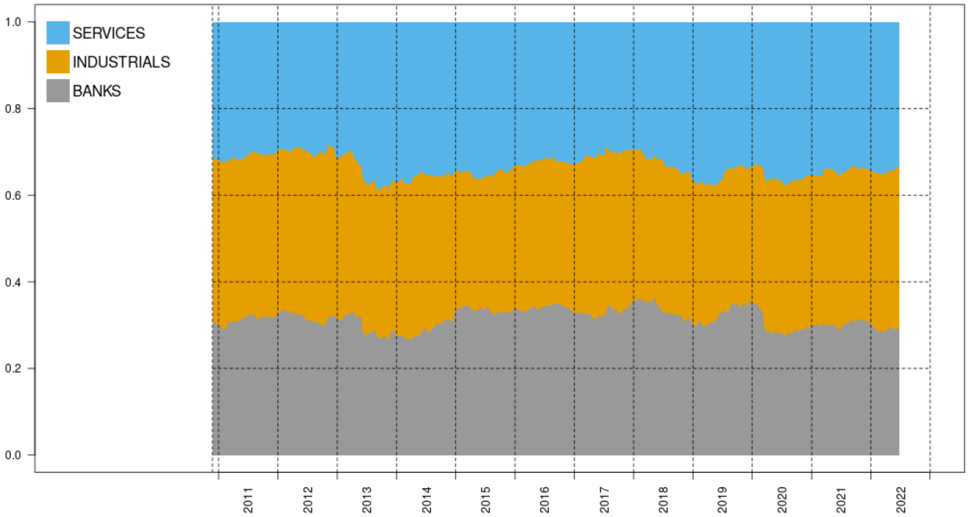
Source: Author's calculations.

Fig. 4 Net connectedness from Banks to Industrials and Services



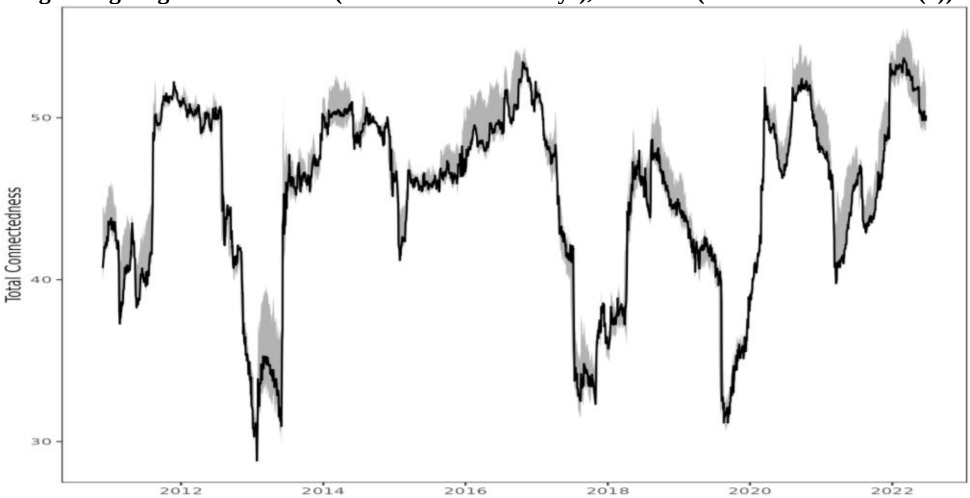
Source: Author's calculations.

Fig. 5 Propagation values



Source: Author's calculations.

Fig. 6 Lag length: shaded area (min & max of 1–5 days), solid line (selected model–VAR(4))



Source: Author's calculations.

Araştırma ve Yayın Etiği Beyanı

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