



Connectedness and spillovers in the innovation network of green transportation

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ARTICLE INFO

Keywords:

Green transportation

Connectedness

Spillovers

ABSTRACT

Greener alternatives for fuelling automobiles, such as hydrogen transport and electric vehicles, have shown considerable promise in transportation. Many others are sceptical of the growing enthusiasm for these new technologies, believing that energy storage technologies and management are insufficient for a complete shift. Such a network of variables and smart grid technologies that can help with the transition may reveal some systemic hazards linked with financial institutions, company risk and failure, and so on. This study attempts to characterise spillovers and connections between the indices of green transportation, smart grid, innovative materials, energy storage, and energy management globally. To do this, we employ a novel strategy developed by Balcilar et al. (2021) as well as a robustness check using the well-known Diebold and Yilmaz (2012) method. The study highlights the sub-systemic sector's connections, giving policymakers insights into instruments to support financial market sustainability and stability. It would be critical to separate the impact of these indicators, but given the intrinsic relationship, this would be nearly impossible. The transportation innovation network is not rigid and established in its interconnection. The role of indicators shifts from transmitting to absorbing shocks regularly, and policymakers who want to encourage long-term solutions must be aware of this.

1. Introduction

In recent times, the debate around the energy transition has moved from whether it is necessary to how it will be done, how to minimise the negative socioeconomic impact, and which economic sectors may be the front runners paving the way. The selection of sectors and industries highly depends on technological readiness and cost structures. Among these sectors, transportation has shown great potential through greener alternatives for fossil fuelled vehicles, i.e., hydrogen transport and electric vehicles. Increasing enthusiasm for these new technologies is seen sceptically by many, arguing that energy storage technologies and management are not sufficient for a complete transition. Such a network of variables, along with the smart grid technologies that can enhance the transition, might demonstrate certain systemic risks associated with financial institutions, businesses risk and failure etc. (Balcilar et al., 2021). Connectedness is the approach that allows researchers to comprehend the underlying risks in these networks. In other words,

connectedness "measures the degree of interrelations and the interdependencies among the components of a system" (Maggi et al., 2020). Yu et al. (2018) stress that the usefulness of the connectedness approach lies in the fact that it can provide early warnings regarding future crises.

According to modern portfolio theory, comprehending the connectedness of financial theory attains an intriguing assimilation of effective risk management and diversification strands while all this information is transmitted in portfolios. It is interesting to analyse the financial system influenced by several strands of system-wide connectedness and systemic risk (Baruník and Křehlík, 2018; Yousof et al., 2023). Hence, connectedness performs a vital aspect of risk management, more precisely in default connectedness, return connectedness and portfolio diversification. Moreover, applying the connectedness model gives us an inclusive picture of systematic risk through a network of covariates. It estimates the ratio of linkages between the parts of a system (Maggi et al., 2020; Balcilar et al., 2021). These models allow us to identify the individual net transmitters and receivers of systemic shocks and detect

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<https://doi.org/10.1016/j.enpol.2023.113686>

Received 2 December 2022; Received in revised form 14 June 2023; Accepted 18 June 2023

Available online 23 June 2023

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the system-wide connectedness and contagion build-up effects. The time-varying parameter vector autoregression extended applied in this study common connectedness framework based on these frameworks; therefore, a connectedness model allows us to capture the interrelations of estimated variables which belong to a general system.

In recent years, the study of connectedness and spillovers was mainly adapted to investigate the connectedness of financial markets and their associated risk (see [Diebold and Yilmaz, 2009; 2012, 2014; Baruník and Krehlík, 2018](#)). This has evolved into a growing literature considering the connectedness of various other variables, from studies investigating the connectedness in uncertainty (see, for example, [Gabauer and Gupta, 2018](#); or [Jiang et al., 2019](#)) to studies evaluating the transmissions from transport prices to commodity, currency, and stock markets ([Lin et al., 2019](#)), and the studies overviewed below linked to the energy sphere. Finally, the choice of indicators puts in a policy framework all the factors that affect and influence the green transportation innovation system.

In the light of above-mentioned discussions on the importance of spillovers and connectedness applications, this study stresses to characterise spillovers and connectedness between the indices of green transportation, smart grid, advanced materials, energy storage, and energy management internationally from October 15th, 2010, to February 4th, 2022. A crucial part of promoting sustainability and reducing carbon emissions is the interaction between green mobility, the smart grid, cutting-edge materials, energy storage, and energy management. Aiming to lower greenhouse gas emissions and increase energy efficiency, green transportation includes environmentally friendly practices and technology including electric cars, hybrids, biofuels, and effective public transit systems. In order to maximize power generation, transmission, and consumption, the smart grid, an intelligent electrical distribution network, incorporates cutting-edge technologies like sensors, meters, and communication systems. This allows for the seamless integration of renewable energy sources and electric vehicles. Innovative materials help create lightweight, energy-efficient automobiles that use less fuel and emit fewer emissions because to their unique compositions and sustainable qualities.

Lithium-ion batteries and hydrogen fuel cells are two types of energy storage devices that are essential for the broad use of renewable energy sources as well as supporting the infrastructure for electric vehicle charging. Energy storage systems offer a consistent supply of power and improve grid stability by storing extra energy from intermittent renewable sources. Finally, resource allocation, load forecasting, and demand response are all improved by energy management systems, allowing for effective energy use and a decrease in carbon emissions. The interaction of these factors fosters sustainability, improves energy efficiency, and creates a robust energy ecosystem that is favourable to a more environmentally friendly future.

The contributions of this study to the literature are in four ways. This is the first attempt to understand the linkage between green transportation and a number of relevant sub-sectors. Second, we apply a novel technique of [Balcilar et al. \(2021\)](#) and a robustness check through the well-known method of [Diebold and Yilmaz \(2009, 2012, 2014\)](#) (collectively referred to as DY hereafter). Third, the study considers the connectedness of indices tracking the stock prices of the companies involved in financial markets, which can provide valuable information to portfolio managers and venture capitalists when evaluating a potential investment. Fourth, the study provides intuitions to policymakers on instruments to promote sustainability in transportation.

The next section presents a summary of existing literature, followed by a description of the methodology and dataset used. Next, we discuss the empirical results before we conclude.

2. Literature review

The literature on green transportation is limited to technical papers discussing implementation (see [Chang et al., 2018; Fang et al., 2020; Rabbani et al., 2020](#)), requirements and feasibility (see [Panday and](#)

[Bansal, 2014; Todorovic and Simic, 2019](#)), and prices or demand studies (see, [Agrawal et al., 2010; Bordin and Tomasgard, 2021](#)). To our knowledge, there has been no study to date that has investigated the comovements/connectedness, or spillovers (or the stocks of the companies in this market) between green transportation and other financial instruments in their value chain (or indices tracking these stock prices). The closest related study, using the same methodology, is that of [Tiwari et al. \(2022a\)](#). As such, this is the gap that we are trying to fill, and given that the main contribution is of this paper is not only the area of green transportation, but the methodology used, we focus the rest of the literature review on studies in the energy sphere investigating connectedness and/or spillovers, as this methodology is not well known or documented outside the financial literature, as opposed to the literature on green transportation.

[Tiwari et al. \(2022a\)](#) use the DY approach, as well as a time-varying parameter – vector autoregressive (TVP-VAR) and least absolute shrinkage and selection operator – vector autoregressive (LASSO-VAR) models to evaluate how energy-sector stocks are connected over a nearly 27-year period (4 July 1994 to 21 April 2020) for 20 regional blocks. They find (with the DY methodology) that the most significant net contributor of volatility is CCARBNS (top commodity-exporting countries)¹ region, then the G12 and G7 countries. The biggest net receiver of volatility was the Southeast Asian region. Their VAR models support the results from DY. Interestingly, they find that during the global financial crisis (GFC) and the COVID-19 pandemic, energy stock markets had extremely high spillover levels, and more concerningly, world policy uncertainty influenced volatility spillovers.

[Farid et al. \(2021\)](#) investigate volatility transmissions between energy, stocks and precious metals using the DY approach and intraday data. They focus their analysis on determining what the effect of the COVID-19 pandemic was by looking at volatility just before and during the pandemic. They find that volatility connectedness peaked during the pandemic (supported by the study of [Tiwari et al. \(2022a\)](#)). [Chen et al. \(2022\)](#) combine the DY approach with the quantile method to study the excessive spillovers in analysing the spillovers between markets for fossil energy, clean energy, and metals. They find that there are approximately 30pp. more spillovers at the tail estimates compared to the mean/median. They also find that the spillovers between the three markets are asymmetric due to differences in spillovers at the tails during extremely positive and negative events. Unsurprisingly, they find that clean energy spillovers change from net receivers to net transmitters after the signing of the Paris Agreement.

[Bagheri et al. \(2021\)](#) use and extend the [Baruník and Krehlík \(2018, BK hereafter\)](#) methodology (which is based on the DY methodology and extends it to the estimate spillovers in the frequency domain) by incorporating a hierarchical vector autoregressive (HVAR) model to obtain a better perspective of energy markets. They find that connectedness increases dramatically during crisis periods for energy and financial markets. They find that spillovers are mainly driven by short-term factors and are highly speculative. Utilising both DY and BK methodologies to evaluate spillovers of green bonds and commodities in both the time- and frequency domains, [Naeem et al. \(2021\)](#) find evidence of asymmetric spillovers. They find that gold and silver have the strongest connectedness with green bonds, which is also time-invariant, while crude oil has a strong long-term connectedness with S&P green bonds, commodities, including oil and natural gas (energy). When considering asymmetric spillovers, they find that positive (negative) returns spillovers are more robust in the short-run (long-run).

Another study utilising DY and BK methodologies, [Iqbal et al. \(2022\)](#), investigates spillovers in sustainable investments. They also find asymmetric return spillovers across regions in the short and long run. They find that Germany, France, the Netherlands, and the UK are net transmitters. Looking at asymmetries, they find that negative returns transmit

¹ The acronym for the country group is used only in [Tiwari et al. \(2022a\)](#).

more intensely than positive returns; this effect is also exaggerated during crises. Li et al. (2021), using DY and BK, find spillovers for both returns and volatility are more robust in the short run, which mainly cause the overall spillover effects between oil, gold, and the geopolitical risks in BRICS countries. They find the most important spillover relationship between oil and gold, while China's geopolitical risks have the greatest effect on gold, oil, and other BRICS countries' geopolitical risks. Tiwari et al. (2022b) use a TVP-VAR approach to measure spillovers and connectedness between green bonds, renewable energy stocks, and carbon markets. They find heterogeneity in dynamic total connectedness over time, dependent on economic events. Clean energy markets are the main net transmitter, while green bonds and wind are the net receivers of shocks. Balcilar et al. (2021) created a new TVP-VAR approach based on Antonakakis et al. (2020), the same model we used in our study, to investigate the connectedness of agricultural commodities and crude oil futures. They find heterogeneity in the dynamic connectedness and depend on economic events, with peaks in connectedness during periods of crisis. Crude oil is one of the main net transmitters in the overall system and is connected to most commodities, acting as a receiver for some and transmitter for others, which change over time.

Two studies closer to our study are those of Lui and Hamori (2020) and Geng et al. (2021). The former investigates (using both DY and BK) the spillover transmissions from fossil energies and key financial variables to renewable stock markets in the US and Europe, accounting for time-varying effects. They find spillovers in the US are higher than in Europe, and the stock market transmits the most to renewable stocks, far exceeding fossil fuels. Lui and Hamori (2020) also find evidence of time-varying spillovers, specifically in extreme events (like the 2016 Brexit referendum). In the frequency domain, they find that return (volatility) spillovers are primarily in high (low) frequencies or the short-run (long run). Geng et al. (2021) model (using DY) the return and volatility spillover networks of new energy companies and find a very high degree of connectedness, particularly in their volatility. They also find asymmetric spillovers, with bad news (negative shocks) contributing more to the global new energy stock market risk.

This study aims to do the same as the studies listed above, by establishing the connectedness between key areas in financial markets but considering a different set of indices, namely green transportation, advanced materials, energy management, energy storage and smart grid.

3. Methodology and data

3.1. Data description

This research paper uses daily prices from October 15th, 2010, to February 4th, 2022, applying a time-varying parameter vector autoregression extended joint connectedness model to investigate the spillovers and connectedness among the Nasdaq indices for green transportation, advanced materials, energy management, energy storage and smart grid, with descriptions provided in Table 1.

Concerning the indices, energy storage is mainly applied in electric vehicles (EVs), micro-grid and renewable energy systems. It is also worth mentioning that energy storage is a vital asset of the smart grid, the latter has a game-changing role in accelerating the sustainable and green energy projects. Hence, energy storage and smart grid are the key to the green transportation market. Furthermore, advanced materials have shown great potential through greener alternatives for fuelling vehicles, and they are more eco-friendly emerging higher production efficiency. Lastly, energy management can enhance the energy-efficiency, hence the reduction of greenhouse gas emissions. All the data is collected from DataStream.² Fig. 1 visually represents these indices, which exhibit the non-stationary properties one expects from

stock market data, as such, we use the returns (first differences) for these indices, which is shown in Fig. 2.

Table 2 presents a summary statistic of the estimated data and provides a preliminary investigation of the contagion among the variables.

3.2. Methodology

Recently, Antonakakis et al. (2020) created a time-varying parameter vector autoregression (TVP-VAR) model and Lastrapes and Wiesen (L&W) (2020) developed a joint connectedness approach. Balcilar et al. (2021) combined these two models and built a TVP-VAR extended joint connectedness framework. By and large, a scaling parameter λ_t was proposed by L&W (2020) to estimate joint connectedness equivalent of $S_{i \rightarrow \bullet, t}^{gen, to}$.³ This scaling parameter λ_t can be computed as follows:

$$g\widetilde{SOT}_{ij,t} = \lambda_t gSOT_{ij,t} \tag{1}$$

$$\lambda_t = \frac{jSOI_t}{\frac{1}{K} \sum_{i=1}^K \sum_{j \neq i}^K gSOT_{ij,t}} = \frac{jSOI_t}{gSOI_t} \tag{2}$$

The aforementioned function can estimate total directional connectedness (TDC) and net total directional connectedness (NTDC). The TDC and NTDC estimators are given as follows:

$$calculation\ of\ TDC = > S_{i \rightarrow \bullet, t}^{int, to} = \sum_{j=1, j \neq i}^K g\widetilde{SOT}_{ij,t} \tag{3}$$

$$calculation\ of\ NTDC = > S_{i,t}^{int, net} = S_{i \rightarrow \bullet, t}^{int, to} - S_{i \leftarrow \bullet, t}^{int, from} \tag{4}$$

However, the above functions cannot assess net directional pairwise spillover. The proposed model of Balcilar et al. (2021) calculates the net directional pairwise spillover by generalised the scaling parameter λ_t of L&D (2020). So, the scaling parameter λ_t for an extended joint connectedness model is given as follows:

$$\lambda_i = \frac{S_{i \leftarrow \bullet, t}^{int, from}}{S_{i \rightarrow \bullet, t}^{gen, from}} \tag{5}$$

$$\lambda = \frac{1}{K} \sum_{i=1}^K \lambda_i \tag{6}$$

Hence, the calculation of net total and pairwise directional connectedness by Balcilar et al. (2021) takes the following form:

$$S_{i,t}^{int, net} = S_{i \rightarrow \bullet, t}^{int, to} - S_{i \leftarrow \bullet, t}^{int, from} \tag{7}$$

$$S_{i,t}^{int, net} = gSOT_{ji,t} - gSOT_{ij,t} \tag{8}$$

4. Empirical results

This section reports the results of the method of Balcilar et al. (2021). All results are based on a TVP-VAR model with a lag length of order one (BIC) and a 20-step-ahead generalised forecast error variance decomposition. As in Balcilar et al. (2021), we first consider the total connectedness index (TCI) average, which examines the connectedness of the entire sample. We then consider how the TCI evolves by reviewing the dynamic total connectedness before looking at the net total and pairwise connectedness. Examining the dynamic total connectedness allows us to determine the response of the indices to various economic and political events. In contrast, the latter two will enable us to see how individual indices behave regarding net transmitters or net receivers and how they interact and influence each other, i.e., the spillovers.

Table 3 presents the averaged joint connectedness between the

² <https://www.refinitiv.com/en/>.

³ For more details, please see Lastrapes and Wiesen (2021).

Table 1
Variable description.

| Variable | Nasdaq index | Description |
|----------------------|---|---|
| Green transportation | Nasdaq OMX Green Transportation | Is a primary sector index, part of the Green Economy Index, and is designed to track companies specifically focussing on efficiency gains and pollution reduction associated with the transportation industry (automobiles, trains, and others). |
| Advanced materials | Nasdaq OMX Advanced Materials | Is a primary sector index, part of the Green Economy Index, and is designed to track companies specifically focussing on producing materials with advanced properties that enable renewable technologies, or reduce the dependence on petroleum-based products. |
| Energy management | Nasdaq OMX Energy Management | Is a subsector index of the Green Economy Index and is designed to track companies that focus on providing solutions to help reduce energy consumption (e.g., efficient motors, micro turbines, process controls, and appliances). |
| Energy storage | Nasdaq OMX Energy Storage | Is a subsector index of the Green Economy Index and is designed to track companies that focus on providing solutions that increase the ability of energy storage when needed (batteries). |
| Smart grid | Nasdaq OMX Clean Edge Smart Grid Infrastructure | Is designed as a transparent and liquid benchmark for the smart grid and electric infrastructure sector, i.e., companies focussing on electric grid; electric meters, devices, and networks; energy storage and management; and enabling software. |

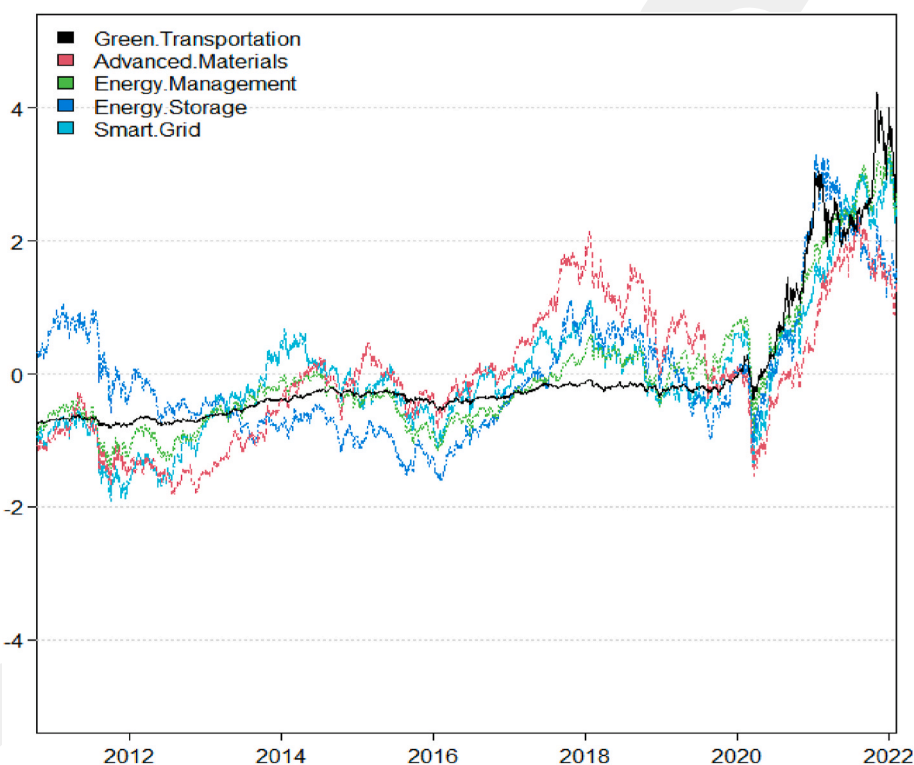


Fig. 1. Time series plot of the variables
Note: Y-axis represents index values.

various indices and the total transmissions and receptions for each index's returns (hereafter referred to as just indices). The diagonal elements represent their total transmissions, while the off diagonals represent the total "to" or "from" connections. 60.16% of the forecast error variance in TCI in the network of indices can be explained by these indices. In comparison, the other approximately 40% can be attributed to idiosyncratic effects (exogenous to the network analysed). Furthermore, Green Transportation, Advanced Materials, and Energy Storage indices act as the net transmitters, while Energy Management and Smart Grid act as net receivers of shocks (innovations) in the market.

We now shift our attention to the dynamic total connectedness, which, unlike average connectedness, only highlights underlying interrelations and shows the evolution of these interrelations over time. This is particularly of interest to investors and policymakers to understand the dynamics of these markets (and indices) and how policies and exogenous economic conditions influence them. The dynamic connectedness shows (Fig. 3) that there was a particular rise in connectedness during 2012 (which likely corresponds to the European sovereign debt crisis), to a lesser extent around the adoption of the Paris Agreement (12

December 2015) and when it entered into force (4 November 2016). Another considerable rise in connectedness was during the recent COVID-19 pandemic, as seen around March 2020. The connectedness analysis does not distinguish between good and bad events. Still, it merely shows when there were significant co-movements in the indices (derived from the underlying company stock market data).

On the other hand, the dynamic net total connectedness in Fig. 4 shows how the various indices' roles in the networks evolve over time (i.e., changing from net receivers to net transmitters and vice versa, the dynamic spillovers). Although Table 3 identified Green Transportation as a net transmitter, there are sustained periods where it is a net receiver, the longest of which is from 2012 to 2015 and again between the end of 2017 and the end of 2019. On the other hand, the Advanced Material and Energy Storage indices are transmitters for nearly the entire period, similar to the Smart Grid index, being a net receiver for almost the whole period. The Energy Management index is a net receiver for nearly the entire period, apart from the end of 2017 to the end of 2019.

In Fig. 5, we only consider the relationships with the Green Transportation index for pairwise connectedness to determine its importance

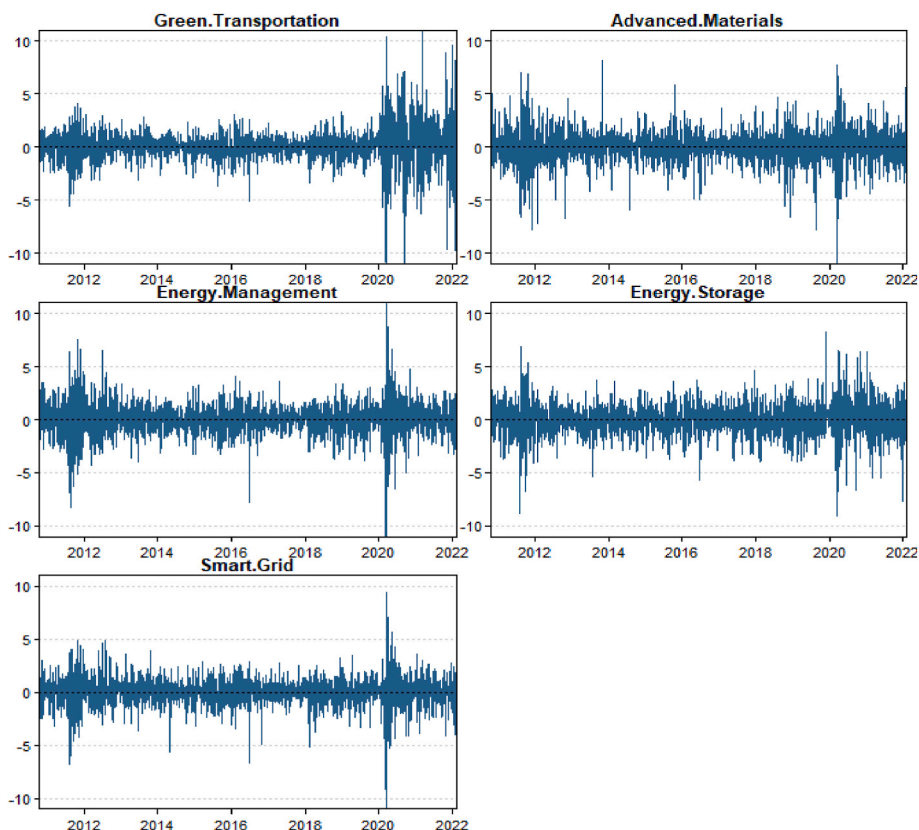


Fig. 2. Returns plot of the variables
Note: Y-axis represents index values.

Table 2
Summary statistics.

| | Green Transportation | Advanced Materials | Energy Management | Energy Storage | Smart Grid |
|--|----------------------|--------------------|-------------------|----------------|--------------|
| Mean | 0.066 | 0.020 | 0.030 | 0.008 | 0.022 |
| Variance | 2.246 | 2.159 | 2.160 | 2.123 | 1.557 |
| Skewness | -0.352*** | -0.540*** | -0.414*** | -0.261*** | -0.831*** |
| Ex.Kurtosis | 12.000*** | 6.629*** | 10.740*** | 3.764*** | 11.261*** |
| JB | 17531.447*** | 5474.330*** | 14078.691*** | 1751.678*** | 15721.612*** |
| ERS | -22.032*** | -22.642*** | -21.577*** | -22.929*** | -13.932*** |
| Q(20) | 35.676*** | 26.000*** | 60.496*** | 47.947*** | 46.281*** |
| Q ² (20) | 1082.684*** | 1151.798*** | 1790.980*** | 663.101*** | 806.269*** |
| Non-parametric Kendall rank correlation | | | | | |
| | Green Transportation | Advanced Materials | Energy Management | Energy Storage | Smart Grid |
| Green Transportation | 1.000 | | | | |
| Advanced Materials | 0.398*** | 1.000 | | | |
| Energy Management | 0.469*** | 0.510*** | 1.000 | | |
| Energy Storage | 0.415*** | 0.408*** | 0.464*** | 1.000 | |
| Smart Grid | 0.391*** | 0.433*** | 0.550*** | 0.400*** | 1.000 |

Notes: ***, ** and * show significance at 1%, 5% and 10%, respectively; Skewness: D’Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit-root test with constant; Q(20) and Q²(20): Fisher and Gallagher (2012) weighted portmanteau test.

within this network of indices. It is important to note that Green Transportation can act as both a transmitter and receiver of shocks, which tend to change over time. Green Transportation mainly received shocks from Advanced Materials and Energy Storage, while it mainly transmitted shocks to Energy Management and Smart Grid. The relatively low values indicate that it does not simply transmit or receive shocks but is equally responsive to innovations. This study’s results strongly contradict the findings of Alagoz et al. (2012), who identified energy storage as a significant determinant of smart grid.

Moreover, energy storage is applied in electric vehicles (EVs), micro-grid and renewable energy systems. It is also worth mentioning that EVs

reduce CO, CO₂, NO, and SO₂ gas and alleviate fossil fuel and environmental inducements. Hence, EVs are the key to the green transportation market (Hasan et al., 2021).

4.1. Robustness checks with DY

For robustness, we redo the analysis using DY. Table 4 produces a similar TCI value of 61.12%, as opposed to 60.16%. However, DY reports that only Energy Management is a net transmitter of shocks, while all the other indices are net receivers, on average.

The dynamic total connectedness in Fig. 6 shows the events with

Table 3
Averaged joint connected table.

| | Green Transportation | Advanced Materials | Energy Management | Energy Storage | Smart Grid | FROM |
|----------------------|----------------------|--------------------|-------------------|----------------|------------|--------|
| Green Transportation | 43.13 | 12.33 | 18.03 | 14.34 | 12.18 | 56.87 |
| Advanced Materials | 12.03 | 46.25 | 17.41 | 11.77 | 12.55 | 53.75 |
| Energy Management | 18.31 | 18.12 | 25.30 | 16.73 | 21.55 | 74.70 |
| Energy Storage | 13.94 | 11.62 | 15.98 | 46.50 | 11.96 | 53.50 |
| Smart Grid | 12.85 | 13.92 | 22.17 | 13.04 | 38.02 | 61.98 |
| TO | 57.12 | 55.98 | 73.58 | 55.88 | 58.23 | 300.80 |
| NET | 0.25 | 2.23 | -1.12 | 2.39 | -3.75 | TCI |
| NPDC | 2.00 | 3.00 | 1.00 | 4.00 | 0.00 | 60.16 |

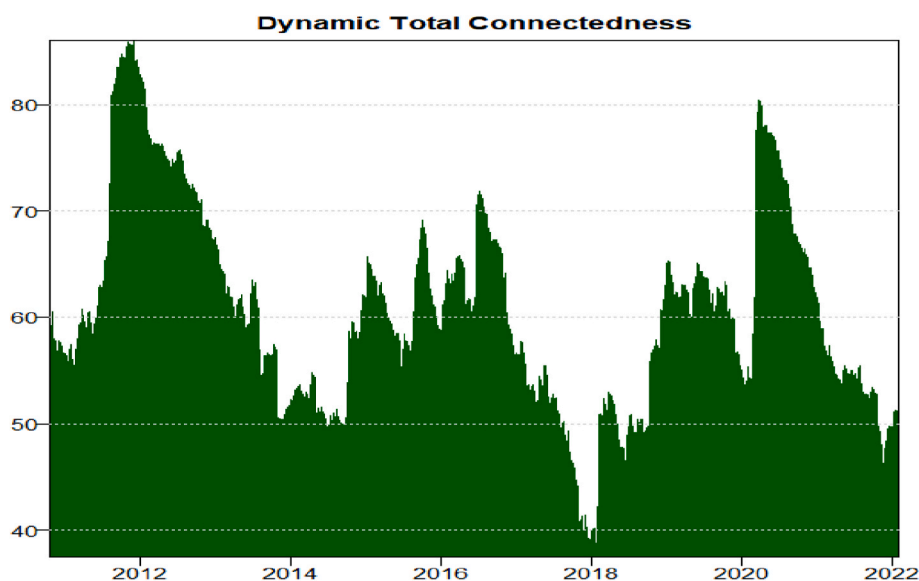


Fig. 3. Dynamic total connectedness

Note: Y-axis represents total connectedness index values.

significant rises in connectedness in 2012, 2015–2017, 2019, and 2020 much more than in Fig. 3. Overall, the results in Fig. 6 are similar to that of Fig. 3, albeit quantitatively slightly different. From a direct comparison, the DY methodology seems to be more sensitive to heightened periods of connectedness, as opposed to Balcilar et al. (2021). The “best” methodology would depend on the reasons for the study, as a study aiming to identify periods of heightened connectedness, would benefit more from using DY, than that of Balcilar et al. (2021).

Fig. 7 shows the dynamic net total connectedness, contrasting the results from Fig. 4. Fig. 7 reiterates the average results from Table 3, with Energy Management acting as a net transmitter for nearly the entire sample period. Green Transportation seemed to work as a net transmitter until 2017, after which it changed to a predominantly net receiver, while Smart Grid was a net transmitter before 2013 and predominantly a net receiver after 2013. Advanced Materials and Energy Storage indices have short periods where they act as net transmitters. However, they are predominantly net receivers of shocks.

Considering the pairwise connectedness shown in Fig. 8, the results are again different from those observed in Fig. 5. Green Transportation acted as the net transmitter before the middle of 2018 for Advanced Materials and Energy Storage and as a net receiver of shocks from these indices afterwards. For the Green Transportation and Smart Grid pair, the former acted as a net transmitter prior to 2020. From 2013 onwards, Green Transportation only received shocks from Energy Management. The size of the dynamic connectedness values in Fig. 8 is also much larger than those in Fig. 5, possibly indicating that the DY methodology is much more sensitive to the connectedness of the variables, likely relating to outliers, as noted in Balcilar et al. (2021).

5. Conclusion and policy implications

With the growing need for a more sustainable (and environmentally friendly) economy, more and more companies are being created by inventors that want to make a difference. These companies will require capital from outside sources (investors) at some point in their lifetimes. It is, therefore, essential to consider how these various companies influence each other, specifically when they tend to be more (or less) connected. At the heart of this is the transportation sector, which transitions towards using greener alternatives while playing a role in the sustainability of all other economic sectors. The innovation system of transport depends on, while at the same time affecting, the technological advancements of the energy sector, such as the promotion of smart grids, use of advanced materials, energy management and storage.

This study concludes the connectedness between the indices for Green Transportation, Advanced Materials, Energy Management, Energy Storage, and Smart Grids, with time-varying intensity, as well as the roles of each indicator over time. They could be net transmitters in one period and net receivers in the next time period. Overall, this system of 5 indices explains approximately 60% of the innovations to the market are from the market itself, while the other ~40% are from exogenous economic and political factors.

The findings show that the market valuation of these companies (measured with indices grouping the relevant companies according to their primary source of income into five groups) co-move (as can be seen from the average connectedness) during specific periods and that the degree to which the co-move change over time (as showcased by the dynamic total connectedness). This holds important implications for investors and portfolio managers, specifically relating to the timing of

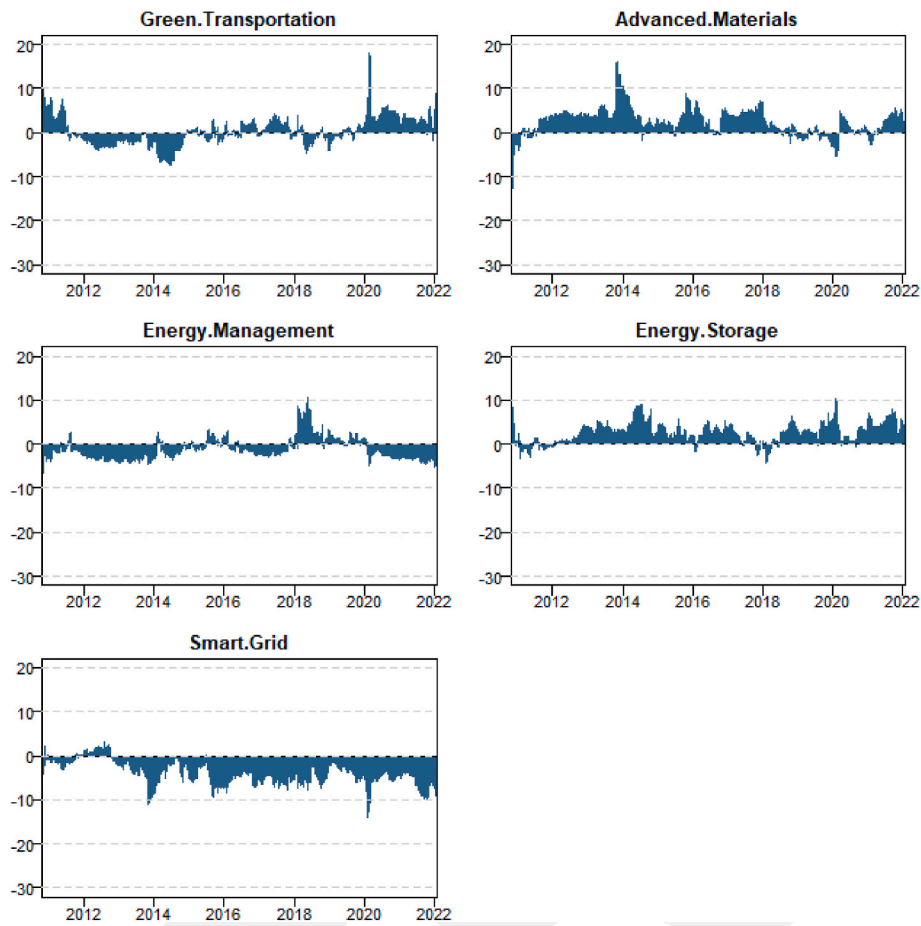


Fig. 4. Dynamic net total directional connectedness
 Note: Y-axis represents total connectedness index values.

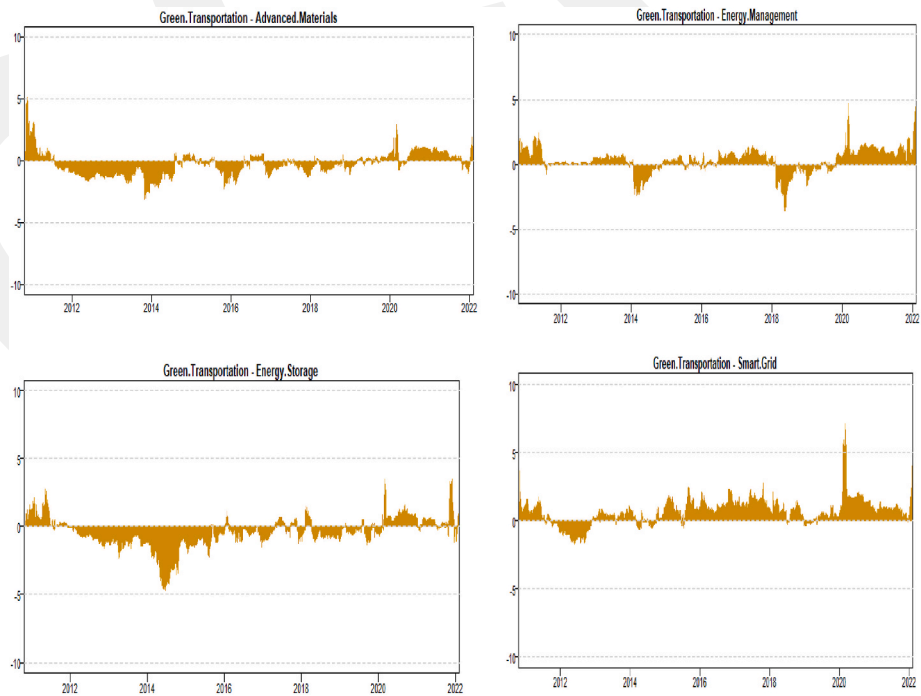


Fig. 5. Dynamic net pairwise directional connectedness
 Note: Y-axis represents total connectedness index values.

Table 4
Robustness averaged Joint Connected Table.

| | Green Transportation | Advanced Materials | Energy Management | Energy Storage | Smart Grid | FROM |
|----------------------|----------------------|--------------------|-------------------|----------------|------------|--------|
| Green Transportation | 40.86 | 13.13 | 18.82 | 14.94 | 12.25 | 59.14 |
| Advanced Materials | 13.54 | 40.65 | 19.15 | 13.07 | 13.60 | 59.35 |
| Energy Management | 16.31 | 15.90 | 33.80 | 15.01 | 18.98 | 66.20 |
| Energy Storage | 15.44 | 12.91 | 18.10 | 40.55 | 13.00 | 59.45 |
| Smart Grid | 12.63 | 13.73 | 22.27 | 12.85 | 38.52 | 61.48 |
| TO | 57.91 | 55.66 | 78.34 | 55.87 | 57.83 | 305.61 |
| NET | -1.23 | -3.69 | 12.14 | -3.58 | -3.65 | TCI |
| NPDC | 3.00 | 1.00 | 4.00 | 1.00 | 1.00 | 61.12 |

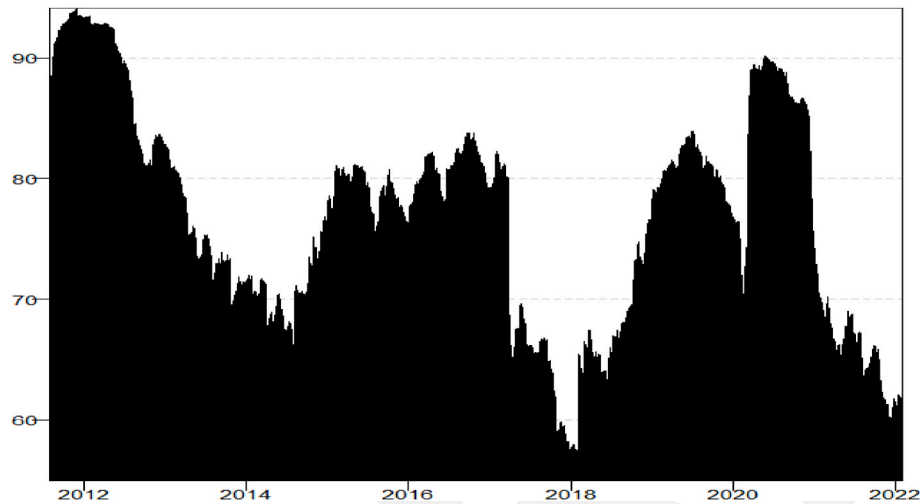


Fig. 6. Dynamic Total Connectedness
Note: Y-axis represents total connectedness index values.

their investments (and disinvestments), but also for managing their risk profiles, as a portfolio can be seen as sufficiently diversified when it is evaluated in times where the connectedness is relatively low. Once these changes, the portfolios will be less diversified, which increases their risk. They, in particular, would want to take into account the periods where there was a high degree of connectedness likely due to exogenous market conditions (bullish markets in 2012 after the GFC and the bearish markets at the start of the recent COVID-19 pandemic, in line with Lui and Hamori (2020); Bagheri et al. (2021); Fabri et al. (2021); and Tiwari et al. (2022a;b)), as this could point to the risks associated with these investments, as can be seen by the high volatility around these periods in Fig. 2. There are also important links between Green Transportation and the other indices, as shown in the pairwise connectedness analysis, with varying intensity over time, and the role (spillover) of each index can change from a net transmitter to a net receiver (and vice versa). Considering the pairwise connectedness of variables and the patterns they form are essential, as this provides additional information that would otherwise not be shown in the total connectedness analysis.

These results have important policy implications, specifically for the global effort to promote green transportation and reduce the sector's reliance on fossil fuels and the associated emissions. It would be essential to disconnect the impact of these indicators from each other, but this would be near impossible given the inherent link. The innovation network of transportation is not rigid and set in its interconnectedness. The role of the indicators constantly changes from transmitting to absorbing shocks, and the policymaking to promote sustainable solutions must be cognisant of this fact. Also, important findings of this analysis are the fact that external shocks such as the EU sovereign debt crisis, the Paris Agreement and the COVID-19 pandemic affect the relationship of stakeholders and indicators in the transportation sector,

either in the magnitude of the connectedness or their role as absorbers or transmitters of the external shocks. It is, therefore, more important for policymakers to consider the possible effect of a proposed policy on the target market, the related markets, the current economic climate, and the impact on the connectedness between these indices.

The results of this study have important ramifications for investment and financial policymaking. The observed co-movement of market values across businesses classified into several indices according to their main revenue streams emphasizes the interdependencies and interconnection within these industries during particular time periods. To guide their decision-making processes, policymakers must take into account the dynamic character of these interactions, which is reflected in the shifting degree of co-movement over time. Due to their insights into the timing of investments and disinvestments, these findings are particularly pertinent for investors and portfolio managers. Periods of relatively low connectivity are critical to take into account when assessing portfolio diversity since they make portfolios appear more diversified.

On the other hand, changes in co-movement patterns may lead to less diversified portfolios and higher risk exposure. Investors should be aware of times with high levels of connectivity that may be caused by external market events, such as the bullish markets following the Global Financial Crisis (GFC) in 2012 and the negative markets at the start of the most current COVID-19 pandemic. The increased volatility seen during those times demonstrates how this increased connection signals the associated dangers present in these financial contexts. The pairwise connectivity analysis of the analysis demonstrates significant correlations between Green Transportation and other indices.

Each index's function may change over time from being a net transmitter to a net receiver, and vice versa, based on the strength and direction of spillover effects. These pairwise connection dynamics and the patterns they create should be carefully considered by policymakers

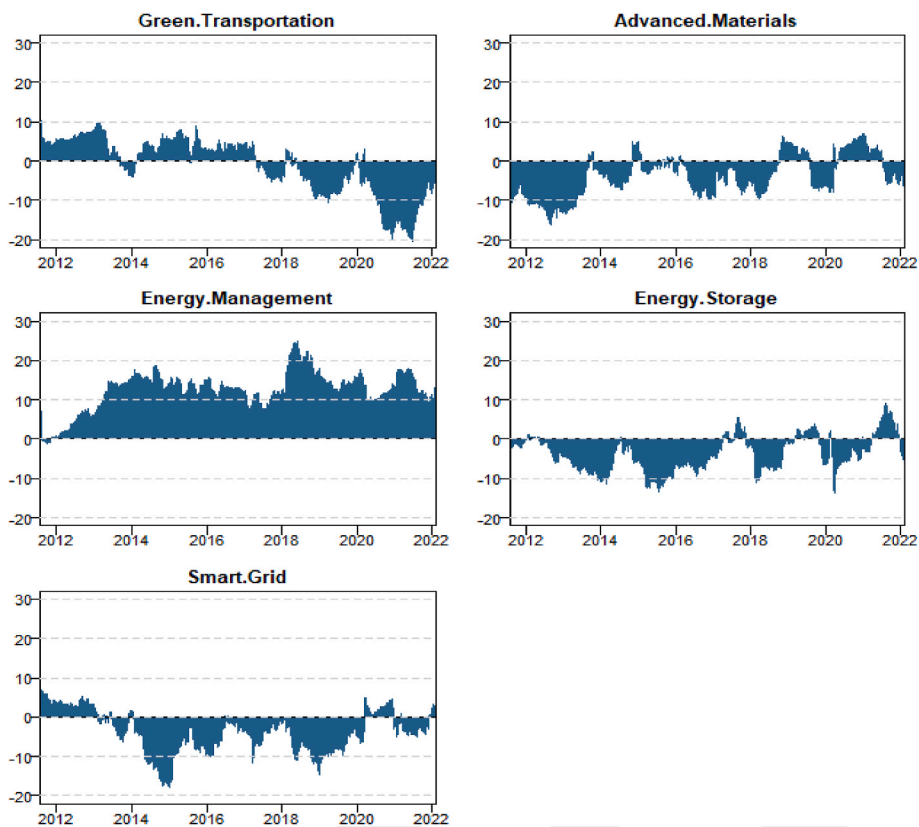


Fig. 7. Dynamic net total directional connectedness
 Note: Y-axis represents total connectedness index values.

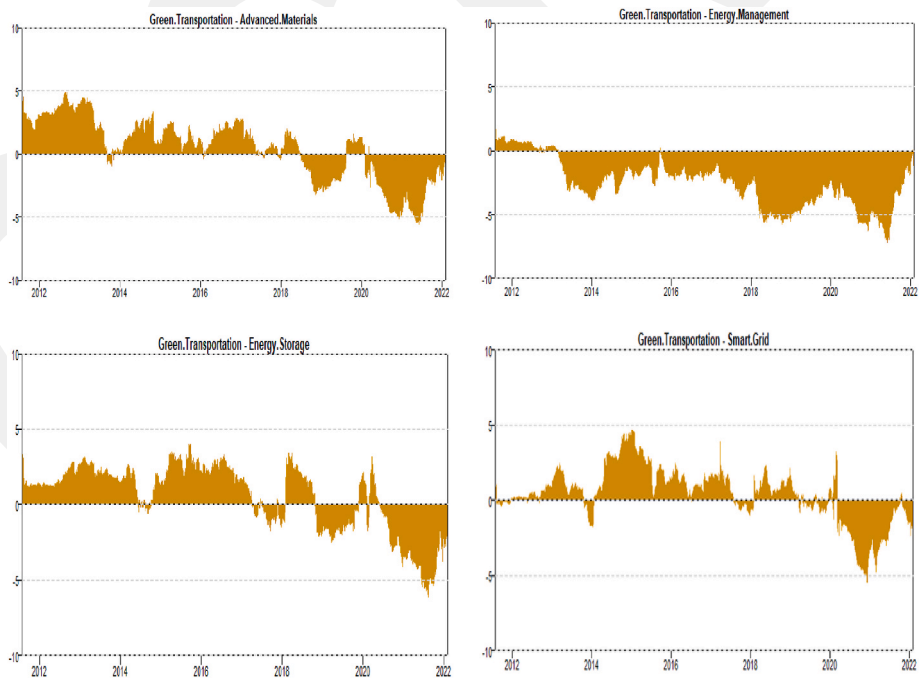


Fig. 8. Dynamic net pairwise directional connectedness
 Note: Y-axis represents total connectedness index values.

as they offer important additional information that may not be obvious from the total connectedness study alone. Regulators and policymakers can make more informed choices to guarantee the stability and resilience of financial markets and encourage sustainable investment

practices by incorporating these results into the policymaking processes. Finally, the spillovers and connections between green transportation, smart grid, innovative materials, energy storage, and energy management are integral to creating a sustainable and efficient energy system.

These interconnected indices work together to reduce carbon emissions, promote renewable energy adoption, enhance energy efficiency, and improve the overall reliability and resilience of the grid. Electric vehicles (EVs) are a prime example of this integration, as they rely on energy storage technologies and require smart grid infrastructure for charging. Similarly, in the context of energy storage, innovative materials can enhance the performance and lifespan of batteries, supercapacitors, and other storage technologies, enabling better integration with renewable energy sources. Moreover, according to this article's outcomes, EVs are a crucial hedge for technology investments for investors seeking exposure to the green transportation sector. EVs reduce the CO, CO₂, NO, and SO₂ gas and alleviate fossil fuel and environmental inducements. Hence, policymakers can urge investors to invest in the above technologies. A technical investor with interest in the transportation market is likely to find new signals in the findings of this study that can help them make recent decisions on alternatives for internal combustion engines.

Future research can investigate the connectedness of the volatility of these indices, which, as alluded to in the discussion, seem to all rise around the same time. This would be useful for investors and portfolio managers, as volatility is a measure of the perceived risk in the market.

CRedit authorship contribution statement

R. Inglese-Lotz: Writing – original draft, Writing – review & editing. **Eyup Dogan:** Conceptualization, Formal analysis, Methodology. **J. Nel:** Formal analysis, Visualization. **Panayiotis Tzeremes:** Methodology, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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