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THE IMPACT OF THE COVID-19 PANDEMIC ON THE CROSS- SECTORAL INFORMATION FLOW IN THE U.S.

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Abstract: *In the past decades a connection between the financial services and technology sector has evolved into a dynamic and complex relationship. However, they were not spared from the far-reaching effects that the spread of the Covid-19 pandemic brought, each responding in a distinctive manner. This paper examines the alterations in the bidirectional information flow between the financial services and technology sectors provoked by the virus outbreak by employing the concept of transfer entropy. The results document an asymmetric and modest information flow in distribution tails prior to the pandemic, with the technology sector predominating. However, as we move towards central values, the transfer intensity decreases dramatically, even reaching negative values in the flow from the financial services sector. Following the pandemic declaration, while the technology sector maintains its superior position in information transfer, its the strength, shape, and symmetry are notably altered, with transmission doubling from the financial services sector, suggesting cross-sectoral contagion in market downturns and instability of the information transfer.*

Keywords: *Transfer Entropy, Covid-19, Industry Sectors.*

JEL Classification: C13, G01, G14.

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1 Introduction

The relationship between the financial services and technology sector is complex and multifaceted with each sector influencing the other in diverse ways. One key area in which the two sectors affect each other is through the development of new technologies. Financial institutions are frequently early adopters and incorporators of emerging technologies, which enable them to streamline operations, reduce costs and improve customer experience. The connection between the financial services and technology sectors is not one-sided, though. As financial institutions have increasingly embraced new technologies, they have also created unique opportunities for technology companies, resulting in the rise of technologically enabled financial innovation disrupting traditional banking practices.

As the Covid-19 pandemic emerged, industry sectors all over the world have encountered their largest one-day falls on record, exhibited increased volatility, and even faced negative returns (Singh et al., 2020; Zhang, Hu & Ji, 2020). Although the majority stabilized in the following months, the adverse impact of the pandemic was more striking and long-lasting in the financial services sector. In the prompt aftermath of the pandemic declaration in 2020, it was expected to partially absorb the shock to the corporate sector, which delayed its recovery (Demirguc-Kunt, Pedraza & Ruiz, 2021). On the other hand, there is factual evidence of the technology sector reacting in a milder, even opposite manner, despite being generally distinguished by high volatility (Gharbi, Sahut & Teulon, 2014). In fact, as the Covid-19 spread, technology stocks have been blossoming and earning high positive monthly returns of over 20% (Mazur, Dang & Vega, 2020).

Under such circumstances, this paper aims to scrutinize the effect of the pandemic on the information flux between two selected industry sectors in the U.S.: technology and financial services, by comparing its strength, shape, and symmetry before and during/ after the Covid-19 crisis, without imposing the assumption about data linearity[2]. To quantify the bidirectional information flow, both Shannon's (STE) and Rényi's (RTE) transfer entropies are estimated for log returns of the two selected sectors for both subperiods. While the former considers the whole underlying empirical distribution between two stochastic processes, the latter describes the information flow only between

[2] Instead, both linear and non-linear dependencies are accounted for, contrary to popular in elementary statistical concepts such as Granger causality or linear correlation.

certain pre-decided parts of two distributions involved. In particular, the fact that one may separately scrutinize information fluxes between tails or central-peak parts of asset price distributions by calibrating the zooming parameter q (Jizba, Kleinert & Shefaat, 2012).

Results confirm a modest information flow preceding the Covid-19 pandemic with a predominate flow from the technology sector witnessed primarily in distribution tails. As we approach central values, the transfer intensity abates dramatically, even reaching negative values in the direction from the financial services sector. Thus, additional knowledge of its historical returns can aggravate the uncertainty for future returns of the technology sector (Dimpfl and Peter, 2014). Following the pandemic declaration, the strength, shape, and symmetry of information transfer are noticeably altered while the superior position of the flow from the technology sector is preserved. Information transmission soars in both directions, more than doubles from the financial services sector. Furthermore, negative entropy estimates completely vanish as the decreasing RTE function stabilizes at STE positive estimates. The findings ratify the cross-sectoral contagion in market downturns as well as the instability of the information transfer proposed by previous research and provide their extensions to the most recent events (Aloui, Aissa & Nguyen, 2011; Laughlin, Aguirre & Grundfest, 2013; Wang et al., 2017).

The structure of the rest of this paper is as follows. The second section is focused on the presentation of data used in the empirical analysis and the description of methodology. Next section interprets the obtained results on the comparison of the transfer entropy between the financial services and technology sector in both directions. The final section summarizes the main findings and offers conclusions.

2 Data and methodology

To compare changes in information flows between the financial and the technology sector induced by the Covid-19 pandemic in the U.S., closing daily prices of two stock market indices are used. NASDAQ Computer (US:TECH), containing securities classified as "Technology" according to the Industry Classification Benchmark (ICB), is selected as a representative of the technology sector. Also, NASDAQ Financial- 100 US (US:FIN) is picked to describe the financial services sector, gathering companies listed as "Financial

Services" in the ICB. All data are fetched from Yahoo Finance.

The breakpoint in the time series analysis is the declaration of the Covid-19 pandemics by the WHO on March 11, 2020 (Cucinotta and Vanelli, 2020). The subperiod since the virus outbreak until the most recent past, March 31, 2023, constitutes the Covid/ post-Covid period. The pre-Covid period is considered from February 10, 2017[3] until March 10, 2020.

Prior to the empirical analysis, observation days with missing data for at least one index are filtered out, which yields 769 observations in each category. Then, log returns are computed to induce stationarity, which is a necessary precondition in the information transfer quantification. Next, the two types of model- free transfer entropy; STE and RTE, are calculated for a wide range of returns' distribution quantiles to capture the information flow between centre and tail observations in both subperiods. Finally, differences between the technology and financial services sector are inspected to compare how the information transfer evolved in response to the Covid-19 outbreak in the respective sectors.

2.1 Transfer Entropy

Correlation or model based techniques such as the Granger causality have been widely used to illustrate and explain the linear statistical dependencies in different engineering and science applications. Nonetheless, for the analysis of nonlinear dependencies commonly present in financial data, information-theoretic quantities such as the transfer entropy (TE), have been proven superior (Gençağa, 2018).

Let *Z* be a stationary Markov process of order *j*. The likelihood of observing *Z* at time *t+1* in state *z* conditional on *j* previous observations is $p\ (z_{t+1}|z_t, \ldots, z_{t-j+1}) = p\ (z_{t+1}|z_t, \ldots, z_{t-j})$. In the bivariate case, the information transfer from process *Y* to process *Z* is recommended to be measured by computing the deviation from the generalized Markov property $p\ (z_{t+1}|z_t^{(j)}) = p\ (z_{t+1}|z_t^{(j)}, y_t^{(k)})$ developed on the Kullback Leibler distance, the STE. It is defined in Schreiber (2000) as:

[3] The beginning of the pre-Covid subperiod is chosen with the aim of having equal representation across both samples.

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$$T_{Y\to Z}(k,j) = \sum\nolimits_{Z,Y} p(z_{t+1}, z_t^{(j)}, y_t^{(k)}) \times log \frac{p(z_{t+1}|z_t^{(j)}, y_t^{(k)})}{p(z_{t+1}|z_t^{(j)})} \tag{1}$$

which highlights that STE is an asymmetric measure. Precisely, the Equation (1) calculates the information flow from Markov process *Y* to *Z*. To paraphrase, STE measures the supplementary information about the future values of *Z*, which can be acquired by the inspection of *Y*'s past observations, beyond what uncertainty reduction is achieved by only knowing the past *Z* states. The specification of the information transfer in the opposite direction, $T_{Z\to Y}$ *(j,k)*, is analogous.

Nevertheless, TE can also be based on RTE. (Jizba, Kleinert & Shefaat, 2012). Unlike STE, it is dependent on various attainable outcomes of *Y*. For $q\to 1$ RTE converges to STE. In case of less probable events, i.e.,$0<q<1$, tail outcomes are featured more. Contrarily, for $q\geq 1$ the escort distribution accentuates central observations. This fact raises substantial interest in the universe of financial data, as they exhibit special characteristics such as leptokurtic distribution and tail dependence (Rényi, 1970; Grammig and Peter, 2013).

Employing the escort distribution $\Phi_q(l)=p^q(j)/\Sigma p^q(l)$ for $q>0$, RTE is derived in Jizba, Kleinert and Shefaat (2012) as:

$$R_{Y\to Z}(k,j) = \frac{1}{1-q} log \frac{\sum_z \Phi\, q(z_t^{(j)})p^q(z_{t+1}|z_t^{(j)})}{\sum_{z,y} \Phi\, q(z_t^{(j)}, y_t^{(k)})p^q(z_{t+1}|z_t^{(j)}, y_t^{(k)})} \tag{2}$$

Equivalent to STE, R_(Y→Z) (k,j) captures the asymmetric flow of information from process Y to Z. The opposite direction is defined correspondingly. However, opposed to the STE, its zero value does not imply that processes Y and Z are independent, since it only relates to the specific value of q used in the calculation. Moreover, unlike STE, RTE can reach negative values, which signifies that additional knowledge of historical values of Y can soar the uncertainty for future values of Z. To put it simply, observations of Y can lead to higher probability of tail event of Z than would be anticipated when observing only Z. Since extreme events are considered more explanatory than median observations, RTE is rendered an appealing mechanism to study information movements and flows between financial time series (Dimpfl and Peter, 2014).

3 Results and discussion

The log returns of both analysed indices for the full sample period are portrayed in Figure 1, providing first hints at their behavioural changes induced by the spread of the Covid-19 pandemic. Prior to its outbreak, all returns are relatively stable oscillating around zero with rare short-term fluctuations. Plots propose higher volatility in the technology than in the financial services sector. This is expected, since the technology sector is characterized with exceptional volatility (Gharbi, Sahut & Teulon, 2014)[4].

The start of the pandemic, marked with the red dashed line, causes notable turbulences in returns of both sectors, reaching their maxima, minima, or both shortly after the pandemic declaration. Even in the subsequent months, selected indices remained highly volatile with frequent negative returns, mirroring the reaction of the global stock market. Even though the global market stabilized in the end, returns of the technology sector still experience intermittent jumps and falls well into the 2023 (Singh et al., 2020).

To improve the understanding of idiosyncrasies between the technology and financial services sector in terms of their reaction to the virus outbreak, this section is further split into two subsections with the break point being the WHO pandemic declaration on March 11, 2020.

[4] For example, the aggregate idiosyncratic volatility of firms included in the NASDAQ, preponderated with high-technology stocks, surpasses the volatility of the S&P 500 Index and is four times higher than in NYSE/AMEX companies.

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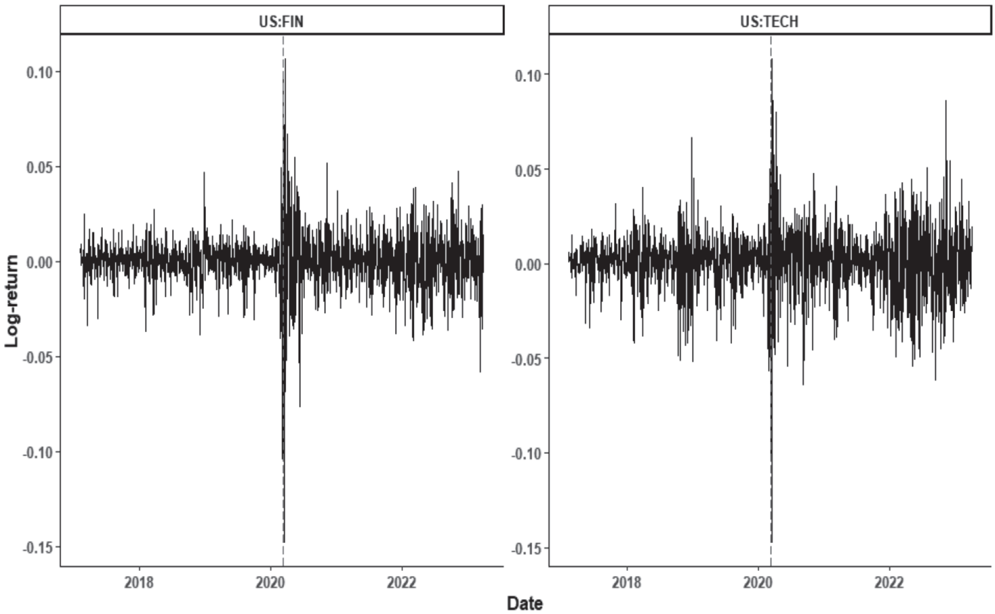
Figure 1: Log returns of both indices for the entire observed period of February 10, 2017- March 31, 2023



Note: The red dashed line indicates the start of Covid-19 pandemic declared by the WHO

Source: Cucinotta and Vanelli (2020)

3.1 Pre-Covid period

Confirming findings from Figure 1, Table 1 suggests that log returns of both indices are close to zero before the pandemic begins. Regardless, the mean return of the technology sector is ten times higher than of the financial services sector. As the traditional finance theory claims, high return tends to be accompanied by high risk, which is confirmed by the higher volatility, measured with standard deviation (St. Dev.). Since maximum returns are moderately higher in the technology sector, it appears that its increased volatility is more pronounced in positive returns. To the contrary, minimum returns are lower in the financial services sector, which renders the range of both sectors roughly the same.

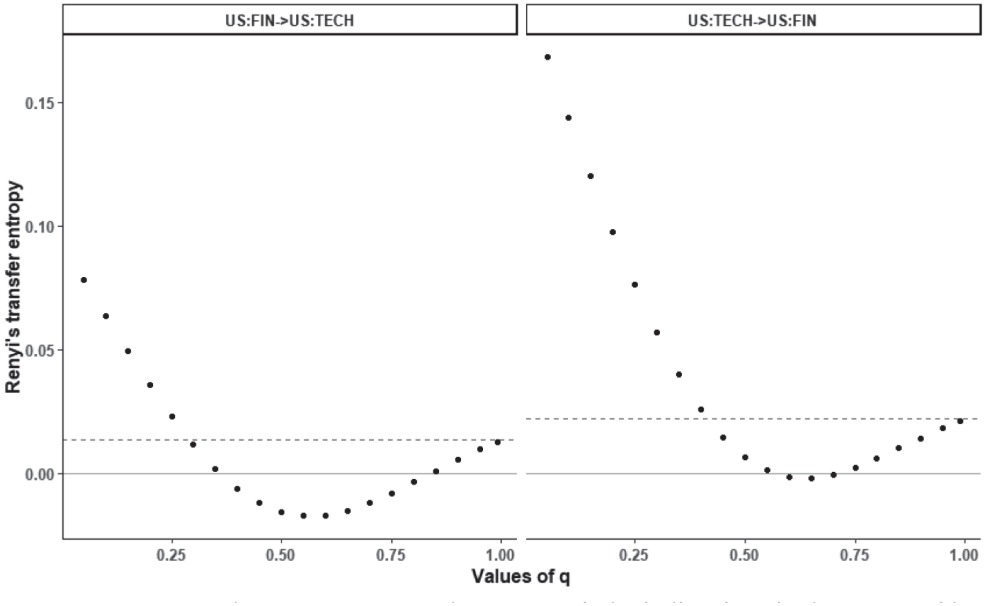
Table 1: Summary statistics for log returns of both US:TECH and US:FIN indices for the pre-Covid period of February 10, 2017- March 10, 2020

Index	N	Mean	St.Dev.	Min	Pctl(25)	Pctl(75	Max
US:TECH	768	0.0010	0.014	-0.078	-0.004	0.007	0.067
US:FIN	768	0.0001	0.010	-0.104	-0.004	0.005	0.049

Source: author

The TE estimates for the pre-Covid period are visualized in Figure 2. The RTE as a function of *q* is convex for all values of *q* considered in both directions of the information transfer. As *q* approaches 0, the weight put on the transition probabilities of the distribution tails grows. For the lowest *q'*s, the RTE estimates are the highest in both directions, which supports the claim that it is tail events, not central observations that are crucial when it comes to information transfer. On their peak for *q=0.05*, RTE in both directions reach their maxima, almost 0.1 for the information transfer from the financial sector to the technology sector, and even more than 50% more in the inverse direction. The information flow is therefore not symmetrical.

Figure 2: RTE between US:FIN and US:TECH in both directions in the pre-Covid period for different values of q $\in$[0.05; 1]



Note: The red dotted line is the estimate of STE.

Source: author

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As q increases, bidirectional information transfer declines fast with a sharper drop in the transfer from the technology sector to the financial services. The strength of the information transmission finally ceases to weaken as $q \to 0.55$ for US:FIN to US:TECH and $q \to 0.65$ for the opposite direction. After a short interval of plateauing, the RTE estimates establish a pattern of slow increase until they converge to STE estimates as $q \to 1$, which agrees with the theoretical background formulated in the previous section. The values of STE with slightly higher information flow from the technology to the financial sector are non-zero in both directions of transmission, suggesting that the sectors do not become fully independent as we drift to the centre of observations.

It is also noteworthy to draw our attention to the negative values of RTE asymmetrically presented in the information transfer depicted in Figure 2. Although RTE only dips into the negative territory in the transmission from the technology sector, it reaches negative values for approximately a half of the quantiles of the probability distributions represented by the parameter q in the opposite direction. As a result, the knowledge of historical observations of both indices broadens the tail part of the probability density function of the technology sector more than only its previous observations would do. Strictly speaking, additional knowledge of historical values of the US:FIN reveals a greater risk in the next time step of the US:TECH than would be anticipated by knowing merely the historical data of the US:TECH (Jizba, Kleinert & Shefaat, 2012).

Overall, results for the pre-Covid period show a remarkable information transmission between the technology and financial services sector in the U.S. with a distinct information surplus flowing from the technology sector.

3.2 Covid and post-Covid period

Even though returns of both U.S. sectors plummeted after the pandemic initiation, the downturn does not seem to materialize in their mean returns, disclosed in Table 2, which remain at their pre-pandemic levels. The instability of both sectors intensifies. Though the technology sector remains more volatile, the volatility gap shrinks exceedingly since the standard deviation almost doubles in returns of the financial services sector. The market downturn is reflected in minimum and maximum returns as well, which increased in absolute terms and reached similar values for both sectors. In fact, the minimum return observed became almost twice as small in the technology sector. At the same time, the maximum recorded return more than doubled in the financial services sector.

Altogether, there is an indication that the co-movement of sectors' returns largely increased which validates the previous research on the behaviour of asset returns in crises (Sandoval and Franca, 2012).

Table 2: Summary statistics for log returns of both US:TECH and US:FIN indices for the Covid/post- Covid period of March 11, 2020-March 31, 2023

Index	N	Mean	St.Dev.	Min	Pctl(25)	Pctl(75	Max
US:TECH	768	0.0010	0.021	-0.147	-0.010	0.012	0.108
US:FIN	768	0.0001	0.019	-0.148	-0.010	0.010	0.106

Source: author

As summary statistics for log returns become more alike in the Covid/ post-Covid period, the information flow measured by the RTE in Figure 3 does not seem to feature notable differences with respect to the direction considered. At the first sight, albeit still asymmetrical, RTE estimates are a convex, decreasing function of q in both transmission directions with the weakening rate of decay in higher values of q. Despite the sizeable pace of decrease, information transfers never become negative, reaching their minimum at slightly positive STE estimates. However, a closer inspection of the US:FIN→US:TECH transfer reveals that the entropy strength stagnates for a moment as q approaches its third quartile and begins to slowly increase in the end until they attain the STE estimate.

Contrarily, the RTE as a function of q is strongly monotonically decreasing in the information transfer from the technology sector at a faster rate than in the opposite direction.

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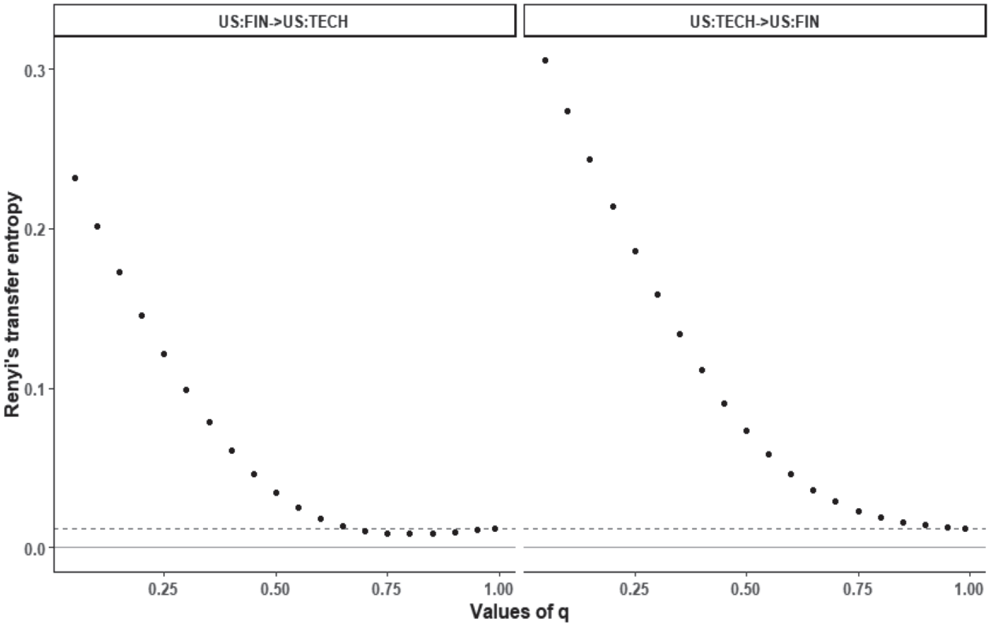
Figure 3: RTE between US:FIN and US:TECH in both directions in the Covid period for different values of q ∈[0.05; 1]



Note: The red dotted line is the estimate of STE

Source: Author

Another prominent feature highlighted in Figure 3 is the sharp increase in RTE. The previously dominant flow from the technology sector retains its leading position by surpassing 0.3, while the information flow from the financial services sector is more than doubled reaching values beyond 0.2 for smallest values of the parameter q. Again, the RTE estimates exhibit the highest values in both directions for the lowest q's, indicating that the information transmission between the two sectors is mostly driven by rare, outlier events rather than by the more central observations.

In a nutshell, the Covid-19 outbreak had a profound impact on the bidirectional information transfer between the U.S. technology and financial services sector. Although the information surplus spilling from the technology sector is maintained, the shape, symmetry, and strength of RTE as a function of q is affected. In both directions, shapes of the RTE functions start to approach each other and cease to reach negative values for any q, stabilizing at STE estimates marginally above zero. Simultaneously, the information stream is boosted, even more than doubled in the direction from the financial services sector. This discovery contributes to the body of research documenting the market interactions escalation in crises and extends it by validation on recent events (Dimpfl and Peter, 2014).

4 Conclusion

Changes in statistical coherence between financial time series in adverse market conditions or downturns have inspired many studies (Aloui, Aissa & Nguyen, 2011; Sandoval and Franca, 2012; Dimpfl and Peter, 2014). On a similar note, this article investigates shifts in the bidirectional information flow between the technology and financial services sector in the U.S. provoked by the recent Covid-19 pandemic. With intentions of accommodating the non-linear dynamics as well as leptokurtic distributions commonly featured in financial returns, the flexible concept of transfer entropy is utilized.

Prior to the viral outbreak, a modest information flux is documented in returns distribution tails with dominant flow from the technology sector. This finding suggests the presence of low probability events or extreme values in the data that are vital for information transfer. However, as we approach central values, the information transmission sharply diminishes, even turns negative in the flow from the financial services sector. In such cases, the knowledge of its past returns unveils greater risk than observed by only knowing the history of the technology sector alone.

After the pandemic declaration, the global financial markets faced tremendous fluctuations, which reflected on the information flow between the analysed sectors. While the superior position of the transfer from the technology sector is preserved, the entropy characteristics such as its strength, shape and symmetry are notably altered. The information transfer intensifies in both directions for tail events and ends up to more than double in the flow from the financial services sector. Negative values of transfer entropy fully disappear as the decreasing function of q stabilizes at Shannon's entropy positive estimates.

Altogether, reported evidence could be advantageous to investors aiming to mitigate risks in their portfolios. If a fast deterioration in either of the sectors is observed, they should consider the relocation of the portfolio containing related assets, as the influence is high in this case, due to the corresponding transfer entropy estimates being high for outlier observations. Moreover, estimates exhibit the increasing tendency in unfavourable market conditions, which supports the previous research on spillover and contagion between financial markets in market downturns (Aloui, Aissa & Nguyen, 2011; Wang et al., 2017).

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