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Turbulence in the financial markets: Cross-country differences in market volatility in response to COVID-19 pandemic policies

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Abstract: *The current coronavirus pandemic has had far-reaching global effects on the health and wellbeing of individuals across each and every continent of the world. The economic and financial market response has been equally disastrous and turbulent with high levels of volatility observed across international financial markets. This study explores the temporal relation between the observed structural breaks, market volatility and government policy interventions for 28 countries and their respective market indices. We present results which indicate that the establishment of stay-at-home policies cause sharp discontinuities in 15 of the 28 markets (53.57%) and increase market efficiency in 30 of 49 stay-at-home policy establishment cases (61.22%). These results indicate a small, yet statistically significant degree of persistence and hence, predictability in international financial markets and their associated market indices in response to stay-at-home policies.*

Keywords: SARS-CoV-2, Financial Analysis, Market Volatility, Market Behaviour, Multi-Fractality, Stay-at-home policy

1 Introduction

Financial markets are increasingly referred to as complex systems by recognition of the vast interactivity between traders who are themselves, highly complex agents who both respond and contribute to the emergent market outcomes (Kuhlmann, 2014). Further, traders respond, adapt and learn from both endogenous (internal) feedback processes (e.g. herding behaviours) and exogenous (external) information (e.g. news and government policy) (Filimonov & Sornette, 2012). The current coronavirus pandemic is a prime example of an external factor which has had major implications for the recent performance of global financial markets. The COVID-19 outbreak has impacted almost all countries and has highlighted significant cross-country differences in their approach and success in controlling and containing the virus. Governments around the world have been quick to establish strict control measures such as travel restrictions, lockdowns, and other social distancing measures. But these responses have also an impact on the economy, the banking and insurance system or the global financial market, in particular due to COVID-19's unique global scope as a pandemic (Goodell, 2020).

The extensive COVID-19 media coverage has been shown to increase volatility in equity markets and sectors perceived to be most at-risk (Haroon & Rizvi, 2020), such as tourism, hospitality and retail. Global stock market risks have increased substantially and between-country differences have been observed which correlate to the severity of outbreak and policy interventions enacted (Zhang et al., 2020). Unexpected levels of uncertainty and high volatility have ensued (Açikgöz & Günay, 2020). Sharif et al. (2020) identified, for example, applying a wavelet-based approach to deal with issues such as a short sample period that the COVID-19 outbreak has a great influence on US geopolitical risk and economic uncertainty. The long-range dependence or volatility persistence (as a proxy for market efficiency) in various European financial markets has also been influenced (Aslam et al., 2020). Further, companies with the name "corona" have experienced abnormal losses and sustained periods of trading volatility despite not been connected or responsible for the outbreak (Corbet, Hu, et al., 2020). For example, Corona Corp experienced, according to the authors, a substantial deterioration in share price beyond expectations based on market-driven forces. In contrast, the pandemic-induced fall in stock prices has been milder for companies with stronger pre-2020 finances, less international supply chain and customer location exposure to COVID-19 and strong investment in corporate social responsibility activities (Ding et al., 2020).

Various studies have explored the COVID-19 effect on financial market volatility (Albulescu, 2020; Baker et al., 2020; Corbet, Larkin, et al., 2020; Onali, 2020). Zaremba et al. (2020), for example, have demonstrated that government social distancing interventions have unanimously increased stock market volatility in international markets. Our study is unique in that we focus on the context behind market trading volatility and sharp discontinuities in traded value. First, we explore the correlated dynamics of traded value in 28 countries in response to their country-specific COVID-19 variables such as population mobility, outbreak severity and established policy interventions. Next, we investigate the context of observed market discontinuities by associating the temporal sequence of events (e.g. WHO pandemic declaration, different stages of stay-at-home policy) to the identified structural breaks in traded value.

2 Background

Conventional literature on the study of financial markets is built on the fundamental assumption that financial markets are characterised by a Gaussian (normal) distribution and exhibit independent and random price fluctuations as per the random-walk hypothesis (RWH) or Brownian motion proposed by Bachelier (1900). Historical evidence of rare, yet reoccurring sharp market discontinuities such as financial market crashes and rapid price fluctuations suggest otherwise. Mandelbrot (1963) strongly rejected the normal distribution model for financial markets instead suggesting that they exhibit fundamentally different properties. These properties include fat-tailed distributions (Gopikrishnan et al., 2001), long-range dependencies (Barkoulas & Baum, 1996; Greene & Fielitz, 1977), volatility persistence (Charles & Darné, 2014; Constantin, 2005), fractals and multifractals (Calvet & Fisher, 2002), chaos (Çağlar, 2018; Savit, 1988) and complexity (Jacobs & Levy, 1989; Kauê Dal'maso Peron et al., 2012). These properties can more accurately capture the dynamic properties of these so-called market anomalies and provide a rational explanation for such phenomena rather than writing them down to irrational deviations from the norm resulting from speculation, mass greed or other unpleasant factors, as suggested in the conventional theories of finance and economics (Mandelbrot & Hudson, 2004).

Following such a significant global impact, literature on the economic effects of COVID-19 has grown rapidly. Akhtaruzzaman et al. (2020) find that financial firms have played a critical role in financial contagion transmission during COVID-19 and shown that the transmission of financial contagion has followed a similar pattern to that of the virus, with Chinese and Japanese financial and non-financial firms acting as net transmitters of shocks to G7 countries. Huber et al. (2020) explore the effects of the COVID-19 market shock on financial professionals' risk-taking behaviour and found that higher levels of risk aversion have resulted, potentially increasing the further downside pressure on prices and thus, contributing to a more severe crisis and slower recovery. The role and effectiveness of safe haven assets have also been explored in gold, forex currencies, commodities and cryptocurrencies, with gold remaining a strong candidate as a safe haven (Ji et al., 2020). Bitcoin appears to have failed the test during the era of COVID-19 (Conlon & McGee, 2020) with suggestions that this asset may even amplify contagion effects (Corbet, Larkin, et al., 2020).

Various studies have explored the COVID-19 effect on financial market volatility (Albulescu, 2020; Baker et al., 2020; Corbet, Larkin, et al., 2020; Onali, 2020; Zaremba et al., 2020). The main take away is that market volality has increased and is influenced by both pandemic- and policy-induced factors. The authors are aware of only one paper on market volatility in response to COVID-19 which reports the Hurst exponent, a measure of long-range dependence/volatility persistence (Aslam et al., 2020). The Hurst exponent is a measure of bias in fractional brownian motion (Mandelbrot & Hudson, 2004) and can change over time particuarly in response to signficant market disruptions (Dajcman, 2012). The Hurst exponent (H) takes on a value between 0 and 1. When H = 0.5, H > 0.5 and H < 0.5 indicate brownian motion, peristent and anti-persistent behaviour, respectively. In other words, its value determines the degree to which a financial market displays memory and depedency of past values on future values. For example, when H > 0.5 (< 0.5) negative movements are generally followed by negative (positive) movements. Christodoulou-Volos and Siokis (2006) propose that long-range dependency, characterised by the Hurst exponent, can be used as a proxy for stock market inefficiency as it provides an increased level of predictability and hence, opportunity for traders to capitalise on observed market behaviours.

3 Materials and Methods

3.1 Data Description

3.1.1 Mobility

We incorporated country and regional level mobility measures from the COVID-19 Community Mobility Reports (Google LLC, 2020) (see also Chan et al. 2020 for how this index was constructed). Google provided access to this data during the COVID-19 pandemic so that researchers were able to measure compliance efficacy to various social distancing and stay-at-home measures that were implemented to reduce the spread of infection. Google calculates mobility by observing the percentage change in total visitors to the following classifications: Retail and Recreation, Grocery and Pharmacy, Parks, Transit Stations, Workplaces, and finally the length of stay at Residential places within the geographical location, from 15 February to the current day (last report created on 21 July 2020). The final calculation for mobility is measured as the percentage change in length of stay from the median value (of the corresponding day and location) taken between 3 January and 6 February. For the purpose of this study, we only observed mobility change measures on the Residential category.

3.1.2 Oxford Covid-19 Government Response Tracker (OxCGRT)

The record for each country's COVID-19 policy interventions are obtained from the Oxford Covid-19 Government Response Tracker (OxCGRT) database (Hale et al., 2020). The database records the level of strictness on various government policy responses such as school closures, workplace closures, cancellation of public events, closure of public transport, public information campaigns, restrictions on travel and international travel controls, from 1 Jan 2020 to present (continual updating). Each of these are categorised by severity on a scale of 0 to 3 with the exception of public information campaigns score on a scale of 0 to 2. The mild response (e.g. no intervention) scores a 0 and a higher number represents a stricter government response. In our analyses, we consider both the time and severity of the government policy implemented. Some countries (e.g., Taiwan) have not implemented any government policy or control measures and others do not proceed in a linear fashion from mild to strict.

3.1.3 Market Indices

All daily value-traded data was sourced from Bloomberg from 24 May 2019 to 16 June 2020 for 28 countries across Europe, Asia-Pacific, and the Americas. We use only the period from 1 January 2020 to 16 June 2020 in our analyses. The list of countries, stock market indexes and number of observations are presented in Table 1 below. There is a total of 5939 daily value-traded observations. The observations are clustered by stay-at-home policy strictness (C1, C2, C3, with C3 as strictest policy) based on OxCGRT and a binary value (0,1) corresponding to pre/post-policy timing, respectively. C1 has a total of 2631 observations across 22 countries with a 54% split between pre- and post-policy observations. C2 has a total of 2632 observations across 22 countries with a 49% split between pre- and post-policy observations. C3 has a total of 676 observations across 5 countries with a 36% split between pre- and post-policy observations.

Table 1: List of countries and corresponding stock index.

No.	Country	Index Shorthand	Observations (daily)		
			C1	**C2**	**C3**
1	Australia	ASX	115	115	0
2	Austria	ATX	0	115	0
3	Belgium	BEL	0	107	0
4	Brazil	IBOVESPA	115	115	0
5	Canada	TSX	118	0	0
6	China	SSE / SZSE *	220	0	220
7	France	CAC	117	117	0
8	Germany	CDAX	117	117	0
9	Great Britain	FTSE	115	115	0
10	Greece	ASE	111	111	0
11	Hong Kong	HangSeng	113	0	0
12	India	BSE	115	115	115
13	Indonesia	IDX	112	0	0
14	Italy	ITLMS	118	118	118
15	Japan	NIKKEI	111	0	0
16	Korea	KOSPI	115	115	0
17	Malaysia	BURSA	113	0	0
18	Mexico	SPBMVIPC	0	116	0
19	New Zealand	NZX	112	112	0
20	Philippines	PSEI	111	111	111
21	Poland	WIG	115	115	0
22	Russia	MOEX	112	112	0
23	Singapore	SGX	115	115	0
24	Spain	IBEX	118	118	0
25	Switzerland	SMW	115	115	0
26	Thailand	SET	116	0	0
27	United States	NASDAQ / NYSE *	0	230	0
28	South Africa	JALSH	116	116	0
	Total	**5939**	2631	2632	676

Notes: C1, C2, C3 refer to the strictness of the stay-at-home policy with C3 as the strictest level of stay-at-home policy. * Cumulative Sum of Both Markets. C1 - recommend not leaving house; C2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips; and, C3 - require not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc).

Exchange/Index value-traded is equal to the number of shares traded multiplied by price, summed across all securities included in the exchange/index. Value-traded was chosen over volume as it gives a better indication of the size of trades taking place; volume (number of shares traded) is a somewhat arbitrary figure when aggregating across securities. Value-traded was sourced at the entire exchange level where possible, in order to capture as much of a country's trading activities as possible. Where unavailable, the value-traded of a composite index for a given country was used as a proxy for the entire exchange.

3.2 Methodology

The analysis of the daily stock market value-traded data is divided into 5 stages and described below.

3.2.1 Stage 1 – Correlation

The correlation between traded value, coronavirus case statistics (number of confirmed and deaths) and population mobility is calculated using a 30-day moving average window. For each focal date, values of the variable pair from 15 days before and after (30 days inclusive) are used and the corresponding correlation is plotted. Correlations that are statistically significant (at least 10%) are shown with a marker. Relative (percentage) differences are found by taking the first difference of the log time series (daily change) and repeating the above.

3.2.2 Stage 2 – Structural Breaks

To calculate the structural breaks in traded value, each log time series is regressed to a linear time trend and a Wald test for a structural break with an unknown break date (vertical blue line) is performed. The test is then repeated with the stay at home policy dates for each country on the corresponding time series. For countries with multiple policy stages, multiple breaks are tested as well as the individual breaks. For example, for the United Kingdom (GBR), first a Wald test of both dates (after regression of the log time series against the trend line) is performed, then another two Wald tests are performed for each date individually.

3.2.3 Stage 3 – Daily Log Return

The daily log return is defined as:

$$r_i(t) = \ln v_i(t) - \ln v_i(t - \Delta t) \tag{1}$$

where the closing value-traded of the index i is represented by $v_i(t)$ and the time interval is Δt. Converting the daily value-traded data to log returns normalises the market data so that all data are in a comparable metric despite originating from different time series data. For estimation of the daily log return we used the R package with a lag of 1 time period (i.e., 1 day).[1]

3.2.4 Stage 4 – Seasonal and Trend Decomposition using Loess (STL)

Seasonal and Trend Decomposition using Loess (STL) method is employed to decompose the time series value-traded log return data, as proposed by Cleveland et al. (1990). This operation extracts the seasonal variation (S_i), deterministic trend (T_i), and stochastic remainder (R_i) from the time series log return data where:

$$r_i(t) = T_i + S_i + R_i \tag{2}$$

For STL decomposition, we used the R package[2]. The span (in lags) of the Loess window for seasonal extraction is set to 7, which is the number of trading prices in one week and is the minimum value (Cleveland et al., 1990).

Fig. **1** shows the STL Decomposition of NYSE daily value-traded data (for C2 policy strictness) split into pre-policy (left) and post-policy (right) periods. The raw data (top), seasonal variation (second from top), deterministic trend (second from bottom) and stochastic remainder (bottom) are shown for each policy time period.

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[1] The details of the 'diff' equation are available at https://www.rdocumentation.org/ packages/ base/versions/3.6.2/topics/diff.
[2] For details on the STL equation, see https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/stl.

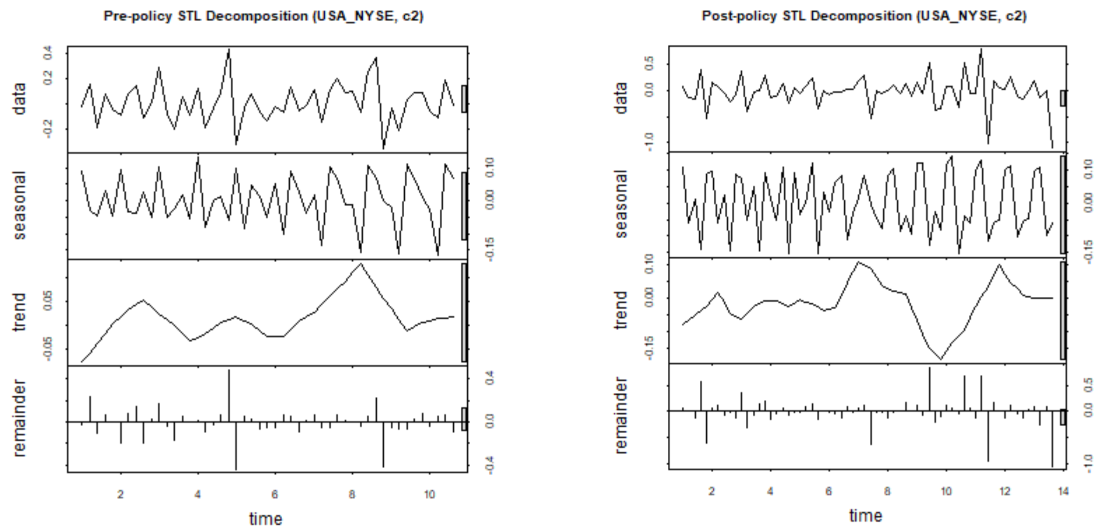


Fig. 1: STL Decomposition for NYSE, Pre (Left) and Post (Right) Policy.

3.2.5 Stage 5 – Multifractal Detrended Fluctuation Analysis (MFDFA)

In situations where the Hurst exponent can change over time (Dajcman, 2012), multifractal analysis must be applied for a full description of scaling behaviour. Multifractal detrended fluctuation analysis (MFDFA) is a method used for the multifractal characterisation of non-stationary time series information (Kantelhardt et al., 2002). Employing this method, we can infer the long-range dependency of the time series information in the value-traded dataset. This study employs the procedure described by Açikgöz & Günay (2020) to compute the multifractality of the data and uses the MFDFA R package.[3] The MFDFA analysis is applied to the stochastic remainder (R_i) of the value-traded log return data.

Fig. **2** shows the Generalised Hurst Exponent (top) and Mass Exponent (bottom) for NYSE daily value-traded data (for C2 policy strictness) for values of q ranging from -10 to 10. The pre-policy and post-policy estimates are represented as black and red points, respectively. As can be seen in Fig. **2**, there is slightly less multifractal content following the policy establishment as indicated by the smaller range between the maximum and minimum values of

[3] See https://www.rdocumentation.org/packages/MFDFA/versions/ 1.1/topics/MFDFA).

the Generalised Hurst Exponent. This indicates market stabilisation perhaps due to the government intervention. Similar figures are provided in the Supplementary Materials for all of the market indices as they respond to policies of C1, C2 and C3 strictness where available as listed in Table 1.

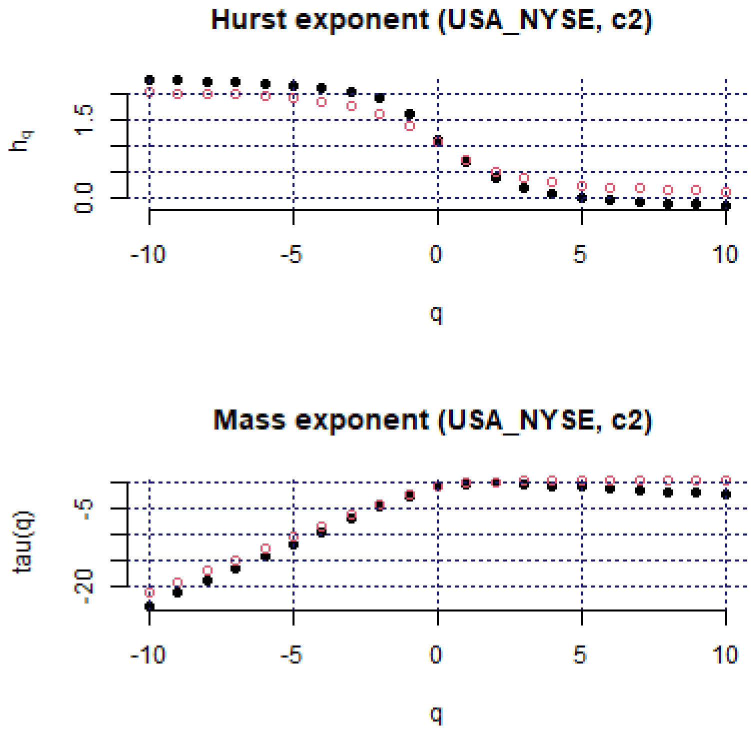


Fig. 2: Estimates of Generalised Hurst Exponent, h(q), and Mass Exponent, tau(q), for NYSE

We calculate the range of the Generalised Hurst Exponent, the Hurst Exponent (when $q = 2$) and the Market Deficiency Measure (MDM) for both the pre-policy and post-policy periods. The variability of the generalised Hurst exponent indicates the degree of multifractality of the time series data where greater variability indicates richer multifractality. The value of the Hurst exponent indicates one of three: persistence if $h(2) > 0.5$; anti-persistence if $h(2) < 0.5$; and random-walk behaviour if $h(2) = 0.5$. Finally, MDM indicates market efficiency where an efficient market has an MDM value which is close to zero. A large MDM value indicates an inefficient market.

The value of the MDM estimate is defined as:

$$MDM = \frac{1}{2}(|H(-10) - 0.5|) + (|H(10) - 0.5|) \tag{3}$$

The difference between the variability of generalised Hurst exponent, the Hurst exponent and the MDM values for the pre-policy and post-policy periods is also calculated by subtracting the pre-policy values from the post-policy values.

4 Results

Fig. **3** displays the daily traded value (in logs) of the New York Stock Exchange in conjunction with various COVID-19 statistics, including confirmed deaths, and infections (also in logs) through the dates beginning 1 January 2020 and ending near the end of June 2020. Visually, we observe a somewhat positively trending relationship in traded value as the number of confirmed cases (particularly in the United States) increases. As the number of confirmed cases start to level out (around mid-March), the traded value trend direction changes to negative. In addition to this, we also observe that the variability of the traded value appears to increase substantially after this point in time, hinting at delayed increase in market volatility in response to the COVID-19 pandemic.

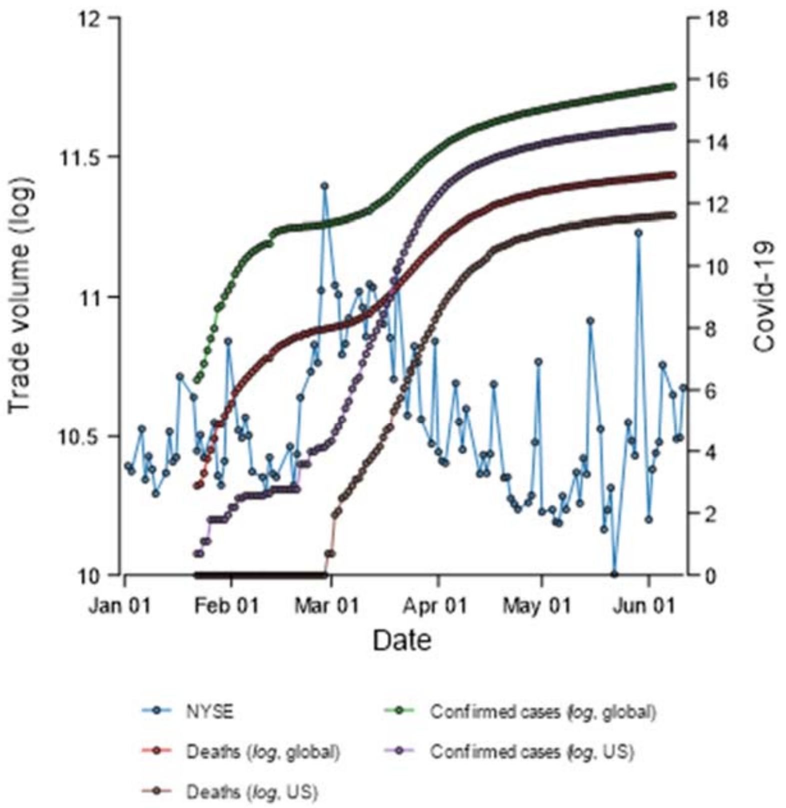


Fig. 3: Daily traded value (in logs) of the New York Stock Exchange (NYSE) against various COVID-19 statistics including confirmed cases and deaths, from 1 January 2020 to mid-June 2020.

Fig. **4** plots the correlation between daily log traded value with daily log of COVID-19 statistics (e.g., deaths, confirmed cases, etc.). We show this through 28 different countries and their respective market index. Also marked on each of the graphs (if applicable), are sets of vertical lines that indicates the date where a stay-at-home policy was introduced in that respective country. We break up the various stay-at-home policy measures into three categories of varying strictness. The green line represents the recommendation by health experts to not leave the house (the least strict policy measure). Yellow represents a policy which requires citizens to stay home with some exceptions that include exercise, grocery shopping and other "essentials," (mid-level strictness). Lastly, orange represents very strict stay-at-home measures, where people are required by law to stay home, with very minimal exceptions, i.e. they may leave the house once per week and only one person of the household may leave at any one time. Markers on each graph represent a significant correlation at the 10% level. Correlation significance seem to predominantly lie at points where correlations are greater than 0.4 and less than -0.4. We also show similar correlation graphs, using differenced COVID-19 log variables with log of traded value and then again with differenced log COVID-19 variables and differenced log traded value, in the Supplementary Materials.

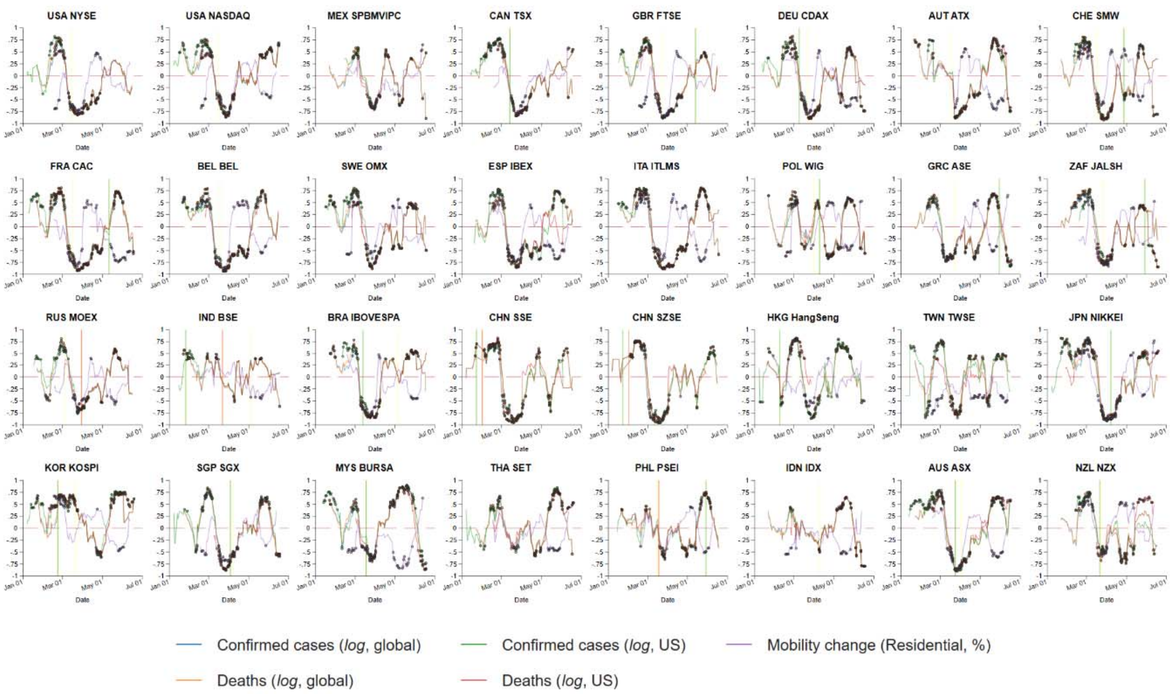


Fig. 4: Log trade volume with daily log COVID-19 case statistics. Markers indicate the correlation is statistically significant below 10%.

The correlation plots in Fig. **4** for the United States tell the same story as in Fig. **3**. Namely, there is a sharp increase in traded value between February and March, which then subsides through April and May while cases and deaths continue to rise, before traded value once again starts to increase through to June. Evidently, most other countries follow a similar pattern, likely due to the substantial correlation between global stock markets. One clear exception is China, which experiences the initial increase in trading volume earlier in January, likely due to experiencing their local outbreak before other countries. Traded value in India, Philippines, and Indonesia display noticeably subdued reactions to United States and global cases. South Korea appears to have high trading activity extended through to April, with the subsequent reduction also subdued compared to others.

Next, we focus on detected structural breaks in traded value data. Figure 5 displays our entire sample of countries' traded value through time, with the vertical blue line indicating a detected unknown break in the time series based on significant (p-value < 0.01) supremum Wald tests. For clarification Table 2, confirms at what dates this occurs. Again, countries that employed stay-at-home measures are also shown on their respective graphs by either green, yellow, or orange vertical lines (depending on their policy strictness) at the point in time the policy was implemented. For half of the countries we analyse (14 out of the 28 countries), detected unknown breaks occur around late February 2020 (between 21 February and 27 February), approximately 2-3 weeks before the WHO declared COVID-19 a pandemic. Interestingly, when observing China's two indices, the structural break for SSE and SZSE occurs on 27 December 2019 and 4 February 2020, respectively indicating a somewhat early response in comparison to the rest of the global markets.

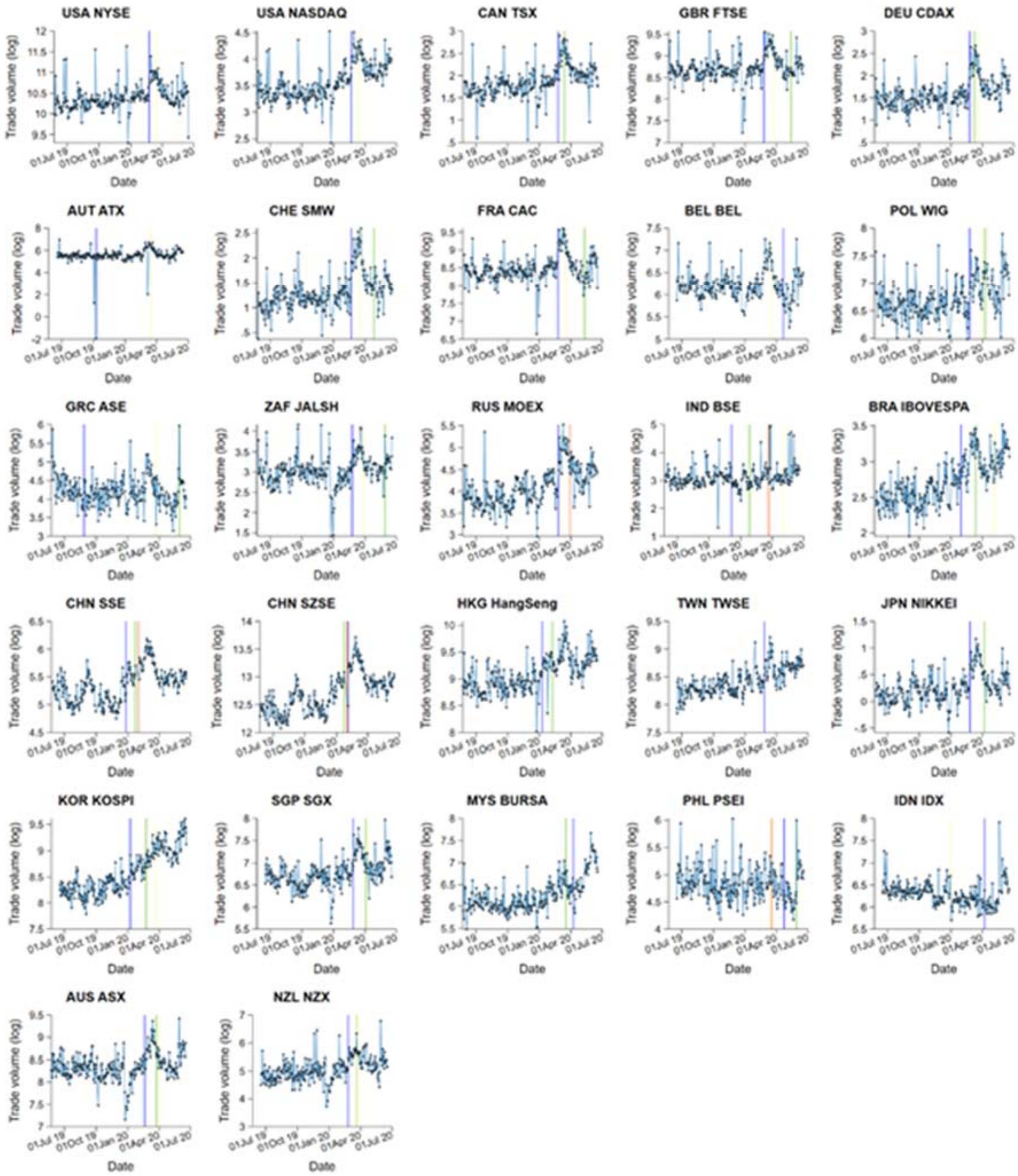


Figure 5: Correlation between daily log traded value with daily log of COVID-19 statistics (deaths, confirmed cases, etc.) for all 28 countries and their respective market index.

Table 2: Date of identified structural breaks for all of the 28 countries and their respective market index

Country	Market Index	Break date	p-val
USA	NYSE	24-Feb-20	<0.001
USA	NASDAQ	21-Feb-20	<0.001
CAN	TSX	24-Feb-20	<0.001
GBR	FTSE	24-Feb-20	<0.001
DEU	CDAX	24-Feb-20	<0.001
AUT	ATX	9-Oct-19	0.003
CHE	SMW	21-Feb-20	<0.001
FRA	CAC	24-Feb-20	<0.001
BEL	BEL	20-Apr-20	<0.001
POL	WIG	24-Feb-20	<0.001
GRC	ASE	27-Aug-19	<0.001
ZAF	JALSH	24-Feb-20	<0.001
RUS	MOEX	25-Feb-20	<0.001
IND	BSE	5-Dec-19	0.0006
BRA	IBOVESPA	30-Jan-20	<0.001
CHN	SSE	27-Dec-19	<0.001
CHN	SZSE	4-Feb-20	<0.001
HKG	Hang Seng	9-Jan-20	<0.001
TWN	TWSE	26-Feb-20	<0.001
JPN	NIKKEI	25-Feb-20	<0.001
KOR	KOSPI	8-Jan-20	<0.001
SGP	SGX	27-Feb-20	<0.001
MYS	BURSA	9-Apr-20	<0.001
PHL	PSEI	23-Apr-20	0.0006
IDN	IDX	8-Apr-20	<0.001
AUS	ASX	19-Feb-20	<0.001

Note: Statistical significance (p-val) in the right-most column.

The tests for structural breaks in traded value are consistent with the previous findings. Namely, the vast majority of markets experience a statistically significant structural break in trading activity on the 24th of February, which coincides with the peak of trading activity seen in the early graphs. Interestingly, China had an earlier break on the 4th of February detected in the Shenzhen Composite.

Next, we statistically test for known structural breaks at the point where stay-at-home policies are implemented. Table 3 displays the Chi-square value based on Wald tests at each stay-at-home policy stage to test whether a structural break occurs at this point. Countries that implement more than one stay-at-home policy are tested for structural breaks at each stage individually (individual break column) and collectively (break/s) if that particular country adopted multiple stay-at-home measures during COVID-19. For some countries, changes in stay-at-home measures were modified too quickly and thus prevented us from implementing structural break analysis due to a limited number of observations. From Table 3, we observe significant structural breaks for 15 of the 28 countries at each policy stage (i.e., 53.57%). Namely, the countries and severity of significant policy level are given: United States (NYSE)(C2), Canada (C1), Germany (C1), Switzerland (C1 and C2), France (C1), Spain (C1), Italy (C1, C2 and C3), Belgium (C2), Russia (C2), Hong Kong (C1), Japan (C1), Korea (C1 and C2), Malaysia (C1), Philippines (C1), and Indonesia (C2).

Table 3: Testing for known structural breaks at the implementation of stay-at-home policies (C1, C2, C3) for all 28 countries and their respective market index.

Country	**Policy stage**	**Date**	**Break(s)**	**Individual break**	**SD test (one-tailed)**
USA (NYSE)	C2	15-Mar	χ^2=22.54; p<0.001		+ve, p=0.689
USA (NASDAQ)			χ^2=0.35; p=0.841		+ve, p=0.725
MEX	C2	30-Mar	χ^2=0.125; p=0.939		-ve, p=0.073
CAN	C1	14-mar	χ^2=22.47; p<0.001		-ve, p=0.222
GBR	C1	13-May	χ^2= 14.57; p=0.006	χ^2=2.339; p=0.310	+ve, p=0.804
GBR	C2	23-Mar		χ^2=5.536; p=0.063	-ve, p=0.409
DEU	C1	09-mar	χ^2=61.13; p<0.001	χ^2=30.21; p<0.001	-ve, p=0.142
DEU	C2	21-mar		χ^2=2.36; p=0.307	+ve, p=0.689
AUT	C2	16-Mar	χ^2=0.74; p=.692		-ve, p<.001
CHE	C1	27-apr	χ^2=47.25; p<0.001	χ^2=18.46; p<0.001	+ve, p=0.985
CHE	C2	17-mar		χ^2=26.32; p<0.001	+ve, p=0.950
FRA	C1	11-May	χ^2=43.41; p<0.001	χ^2=9.96; p=0.007	+ve, p=0.768
FRA	C2	17-Mar		χ^2=11.21; p=0.004	+ve, p=0.608
ESP	C1	27-May	χ^2=35.33; p<0.001	χ^2=7.15; p=0.028	+ve, p=0.590
ESP	C2	14-Mar		χ^2=3.92; p=0.141	+ve, p=0.859
ITA	C1	04-May	Break1 and 2: χ^2=220.88; p<0.001	χ^2=40.33; p<0.001	+ve, p=0.865
ITA	C2	23-Feb	Break1 and 3: χ^2=106.92; p<0.001	χ^2=53.84; p<0.001	-ve, p=0.457
ITA	C3	20-Mar		χ^2=47.69; p<0.001	+ve, p=0.789
BEL	C2	18-Mar	χ^2=16.18; p<0.001		+ve, p=0.547
POL	C1	9-Apr	χ^2=12.31; p=0.015	χ^2=4.68; p=0.096	-ve, p=0.157
POL	C2	31-Mar		χ^2=7.50; p=0.024	-ve, p=0.1
GRC	C1	30-May	χ^2=32.74; p<0.001	χ^2=21.2; p<0.001	+ve, p=0.793
GRC	C2	23-Mar		χ^2=8.63; p=0.013	+ve, p=0.785
ZAF	C1	29-may	χ^2=6.80; p=0.147	χ^2=4.464; p=0.107	+ve, p=0.849
ZAF	C2	26-mar		χ^2=0.496; p=0.781	-ve, p=0.112
RUS	C2	5-Mar	χ^2=67.92; p<0.001	χ^2=47.75; p<0.001	-ve, p=0.021
RUS	C3	30-Mar		χ^2=3.38; p=0.184	+ve, p=0.113
IND	C1	26-jan	χ^2=20.81; p=0.002	χ^2=9.77; p=0.008	+ve, p=0.514
IND	C2	04-may		χ^2=8.44; p=0.015	+ve, p=0.999
IND	C3	22-mar		χ^2=6.38; p=0.041	+ve, p=0.999
BRA	C1	13-mar	χ^2=16.89; p=0.002	χ^2=0.203; p=0.904	+ve, p=0.644
BRA	C2	05-may		χ^2=4.436; p=0.109	-ve, p=0.133

CHN (SSE)*	C1	23-Jan		χ^2=145.39; p<0.001	+ve, p=0.999
CHN (SSE)	C3	1-Feb	Insufficient	χ^2=142.24; p<0.001	+ve, p=0.999
CHN (SZSE)*	C1	23-Jan	observations	χ^2=127.01; p<0.001	ve, p=0.435
CHN (SZSE)	C3	1-Feb		χ^2=121.60; p<0.001	+ve, p=0.552
HKG	C1	8-Feb	χ^2=21.5; p<0.001		-ve, p<.001
JPN	C1	07-apr	χ^2=14.41; p<0.001		-ve, p=0.208
KOR	C1	23-Feb	χ^2=66.21; p<0.001	χ^2=65.09; p<0.001	-ve, p=0.279
KOR	C2	21-Mar		χ^2=29.97; p<0.001	-ve, p=0.200
SGP*	C1	3-Apr	insufficient	χ^2=7.31; p=0.026	+ve, p=0.675
SGP	C2	8-Apr	observations	χ^2=10.90; p=0.004	+ve, p=0.696
MYS	C1	18-Mar	χ^2=88.43; p<0.001		-ve, p=0.107
THA	C1	21-Mar			
PHL*	C1	29-May	Break1 and 2: χ^2=48.16; p<0.001	χ^2=33.11; p<0.001	+ve, p=0.976
PHL	C2	15-Mar	Break1 and 3: χ^2=48.25; p<0.001	χ^2=2.50; p=0.29	-ve, p=0.470
PHL	C3	18-Mar		χ^2=2.73; p=0.26	+ve, p=0.638
IDN	C2	10-Apr	χ^2=78.48; p<0.001		-ve, p=<0.001
AUS	C1	24-Mar	χ^2=9.89; p=0.042	χ^2=1.98; p=0.372	-ve, p=0.05
AUS	C2	2-Apr		χ^2=7.62; p=0.022	-ve, p<.001
NZL*	C1	21-Mar	insufficient	χ^2=9.98; p=0.007	+ve, p=0.997
NZL	C2	23-Mar	observations	χ^2=6.50; p=0.039	+ve, p=0.524

Notes: C1 - recommend not leaving house; C2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips; and, C3 - require not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc).
*insufficient observations between policy dates to test for structural breaks
^Taiwan and Sweden did not impose any stay at home measures.

Fig. **6**, Fig. **7** and Fig. **8** show for both the pre-policy and post-policy periods, the generalised Hurst exponents for all 28 countries and their corresponding market index at policy restrictions of C1, C2 and C3, respectively. The black points represent the pre-policy periods while the red points represent the post-policy periods. As it can be seen there is a high degree of variability in market volatility across each of the 28 countries and their market indices. In some cases, policy decisions appear to increase multifractality and hence, the efficiency of a market. In other cases, establishment of stay-at-home policies appear to increase market volatility.

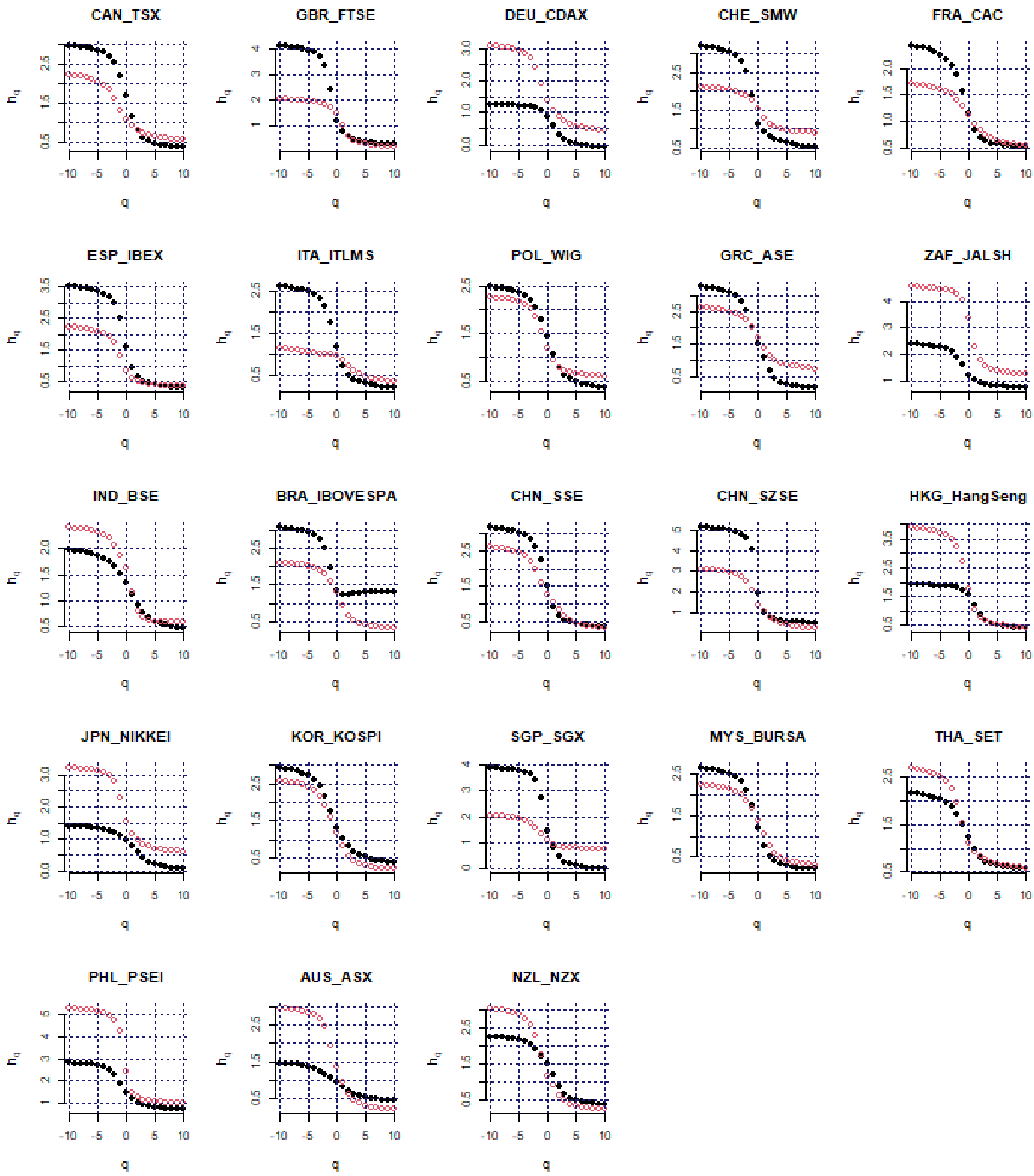


Fig. 6: Generalised Hurst exponent for each market index, from q = -10 to 10, for pre- (black) and post-(red) level 1 (C1) stay-at-home policy recommendation.

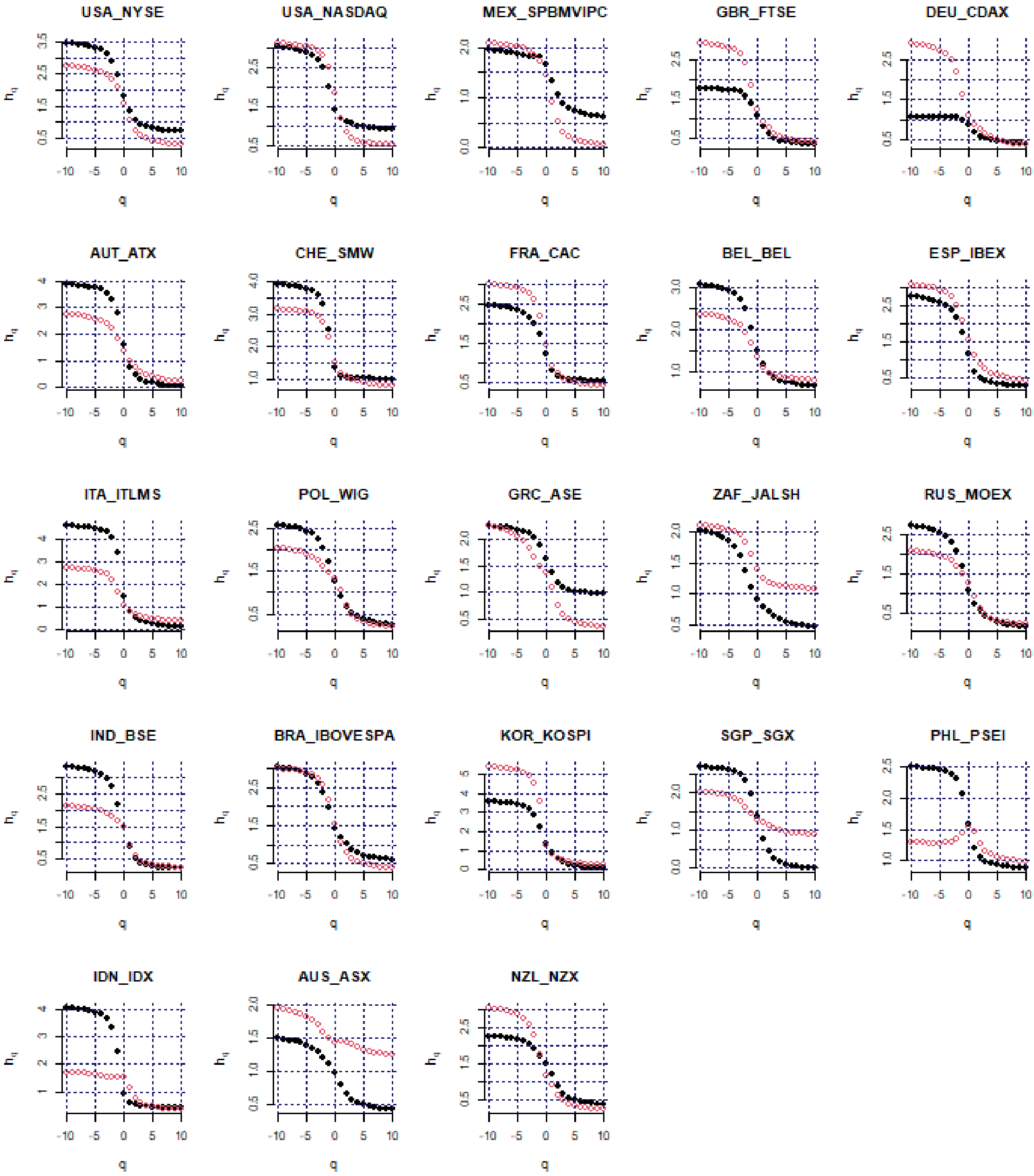


Fig. 7: Generalised Hurst exponent for each market index, from q = -10 to 10, for pre- (black) and post-(red) level 2 (C2) stay-at-home policy recommendation.

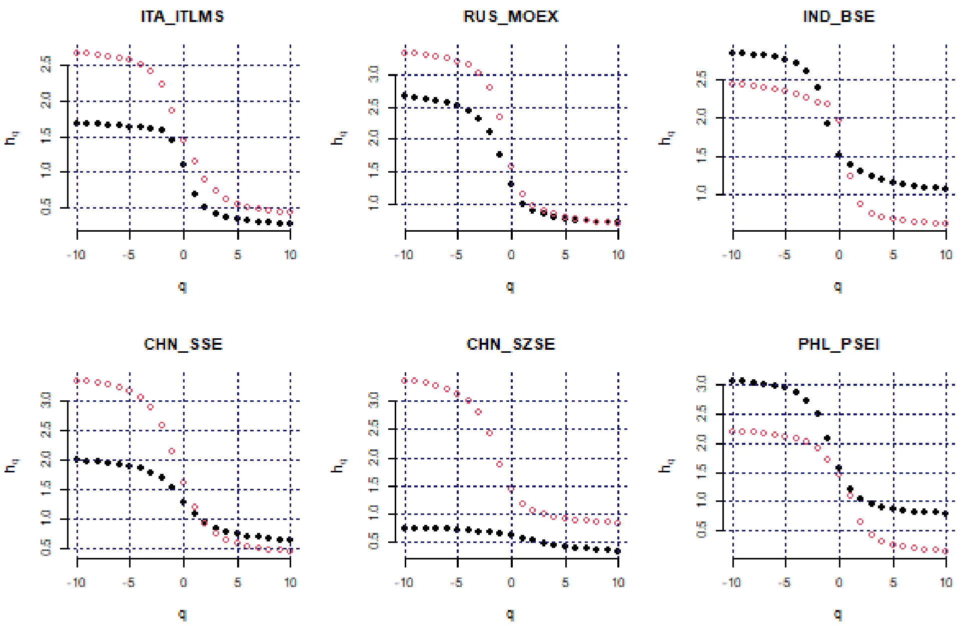


Fig. 8: Generalised Hurst exponent for each market index, from q = -10 to 10, for pre- (black) and post-(red) level 3 (C3) stay-at-home policy recommendation.

The MFDFA turns into a DFA at $q = 2$ and so, the generalised Hurst exponent becomes identical to the standard Hurst exponent which describes the fractal characteristics of the time series value-traded data (Açikgöz & Günay, 2020). Table 4 to 6 display the salient measures of market turbulence for policy strictness of C1, C2, and C3, respectively. The measures include the range of the generalised Hurst exponent, the estimated Hurst exponent (when $q = 2$), and the Market Deficiency Measurements (MDM), for both the pre-policy and post-policy periods. As it can be seen, the estimated Hurst exponent (when $q = 2$) varies greatly across each country. Interestingly, the post-policy values are not always higher than the pre-policy values meaning that sometimes, there is less multifractal content following a policy establishment. This indicates market stabilisation perhaps due to the government intervention. The country with the greatest MDM value (indicating highest market inefficiency) is given in bolded red text. In all but the C3 policy strictness, the most inefficient market does not remain the same between the pre-policy and post-policy period. This indicates that, at least for the most volatile markets in the pre-policy stage, a stay-at-home policy is effective in stabilising the market. This insight must be approached with caution. The MDM values for the C1 policy restriction reduced the MDM value for 15 of the 22 markets (i.e., 68.18% of the time). The MDM values for the C2 policy restriction reduced the MDM from pre- to post-policy periods for 14 of the 22 markets (i.e., 63.63% of the time). The MDM values for the C3 policy restriction reduced MDM from pre- to post-policy periods for 1 of the 5 markets (i.e., 20% of the time). From this, the majority of stay-at-home policies established appear to have been successful in the least, at stablishing financial markets (i.e., 61.22% of the time).

Table 4: Market turbulence measures including Generalised Hurst exponent range, Hurst exponent estimate h(2) and market deficiency measurements (MDM) for pre- and post- level 1 stay-at-home policy recommendation.

Country	**Δh pre-c1**	**Δh post-c1**	**DΔh c1**	**h(2) pre-c1**	**h(2) post-c1**	**MDM pre-c1**	**MDM post-c1**
AUS	4.0169	2.9093	-1.1076	0.4144	0.6124	**1.9161**	1.377
AUT							
BEL							
BRA	1.4269	1.879	0.4521	0.5772	0.5658	0.63335	0.83505
CAN	2.3451	1.2688	-1.0763	0.6056	0.6063	1.0625	0.533
CHE	3.6024	4.1079	0.5055	0.5003	0.5352	1.66825	**1.93735**
CHN*	2.2058	2.9535	0.7477	0.3401	0.5202	1.00065	1.40185
DEU	3.8149	1.4878	-2.3271	0.4219	0.3976	1.8045	0.63735
ESP	2.2515	1.6976	-0.5539	0.3644	0.0987	1.0343	0.7583
FRA	0.9419	1.4251	0.4832	0.482	0.5444	0.4122	0.59305
GBR	2.5293	1.3095	-1.2198	0.3203	0.2927	1.1458	0.5819
GRC	2.7952	0.7713	-2.0239	0.5149	0.8875	1.2531	0.5804
HKG	2.8819	3.0253	0.1434	0.7228	0.3576	1.3215	1.395
IDN							
IND	4.0353	2.4559	-1.5794	0.3646	0.3991	1.89945	1.07025
ITA	3.3455	1.6372	-1.7083	0.3813	0.4533	1.51185	0.69025
JPN	2.7525	0.9378	-1.8147	0.4537	0.7666	1.22595	0.6108
KOR	1.4429	2.607	1.1641	0.7645	0.4755	0.6337	1.184
MEX							
MYS	1.7032	1.3594	-0.3438	0.5408	0.5182	0.74755	0.6068
NZL	2.3061	1.5904	-0.7157	0.5338	0.4516	1.03175	0.64385
PHL	2.6753	1.5037	-1.1716	0.4573	0.5012	1.2177	0.6693
POL	2.7068	0.709	-1.9978	0.4477	0.5998	1.21145	0.2882
RUS							
SGP	4.1095	3.6012	-0.5083	0.3266	0.4098	1.903	1.65255
THA	1.8283	2.4459	0.6176	0.3814	0.4785	0.7822	1.1247
USA*							

ZAF	2.4087	0.6993	-1.7094	0.4763	0.5224	1.06655	0.2583

* SZSE and NYSE used.

Table 5: Market turbulence measures including Generalised Hurst exponent range, Hurst exponent estimate h(2) and market deficiency measurements (MDM) for pre- and post- level 2 stay-at-home policy recommendation.

Country	**Δh pre-c2**	**Δh post-c2**	**DΔh c2**	**h(2) pre-c2**	**h(2) post-c2**	**MDM pre-c2**	**MDM post-c2**
AUS	3.2377	2.2698	-0.9679	0.34	0.5105	1.51255	1.0451
AUT	2.9772	1.7676	-1.2096	0.0088	0.4079	1.3401	0.78925
BEL	2.0411	2.6361	0.595	0.6674	0.5268	0.8834	1.1797
BRA	3.3571	2.2016	-1.1555	0.4319	0.3223	1.44855	0.99035
CAN							
CHE	1.9044	2.7228	0.8184	0.5755	0.5459	0.85735	1.24315
CHN*							
DEU	1.845	0.7957	-1.0493	0.4733	0.3496	0.85755	0.2878
ESP	2.0775	1.5814	-0.4961	0.2946	0.5651	0.93895	0.73035
FRA	1.0448	1.8527	0.8079	0.4389	0.4195	0.4424	0.78205
GBR	2.0057	1.5639	-0.4418	0.4536	0.3908	0.91035	0.66475
GRC	1.2149	1.4762	0.2613	0.5787	0.4467	0.5476	0.6331
HKG							
IDN	1.1898	1.4703	0.2805	0.4844	0.5812	0.47425	0.6472
IND	3.1909	1.8782	-1.3127	0.3223	0.1729	1.46715	0.8098
ITA	2.459	1.6573	-0.8017	0.3689	0.4318	1.11295	0.70205
JPN							
KOR	2.0704	1.6463	-0.4241	0.5017	0.3347	0.876	0.70925
MEX	2.761	1.9099	-0.8511	0.5046	0.3186	1.2823	0.8678
MYS							
NZL	2.3061	1.5904	-0.7157	0.5338	0.4516	1.03175	0.64385
PHL	3.6006	3.6253	0.0247	0.6019	0.5871	1.70325	1.6967
POL	3.2403	4.4111	1.1708	0.4485	0.5512	1.4568	**2.07245**
RUS	0.9156	2.0357	1.1201	0.3064	0.8047	0.3922	0.88545
SGP	4.1158	1.7406	-2.3752	0.3443	0.3767	**1.90325**	0.7698
THA							
USA*	2.387	1.8917	-0.4953	0.3702	0.515	1.0825	0.8311
ZAF	2.4081	3.8609	1.4528	0.3638	0.5839	1.0433	1.79295

* SZSE and NYSE used.

Table 6: Market turbulence measures including Generalised Hurst exponent range, Hurst exponent estimate h(2) and market deficiency measurements (MDM) for pre- and post- level 3 stay-at-home policy recommendation.

Country	**Δh pre-c3**	**Δh post-c3**	**DΔh c3**	**h(2) pre-c3**	**h(2) post-c3**	**MDM pre-c3**	**MDM post-c3**
AUS							
AUT							
BEL							
BRA							
CAN							
CHE							
CHN*	1.7178	2.8185	1.1007	0.3665	0.6715	0.7491	1.2352
DEU							
ESP							
FRA							
GBR							
GRC							
HKG							
IDN							
IND	2.2191	2.7046	0.4855	0.5742	0.4106	1.01065	1.2082
ITA	2.9919	2.1533	-0.8386	0.4031	0.363	1.3305	0.9367
JPN							
KOR							
MEX							
MYS							
NZL							
PHL	3.694	4.5356	0.8416	0.6043	0.3313	**1.75035**	**2.13265**
POL							
RUS	1.1306	1.4463	0.3157	0.5987	0.5737	0.54305	0.62335
SGP							
THA							
USA*							
ZAF							

* SZSE and NYSE used.

5 Conclusions

In this study, we explore the observed market trading volatility and structural breaks present in financial market activity in response to various stages of a country establishing a stay-at-home policy. The financial market indices of 28 countries have been shown to be correlated with country-specific COVID-19 variables such as population mobility, outbreak severity and established policy interventions. In particular, markets tend to have reacted sharply (i.e., a substantial increase in traded value) in the early stages of COVID-19 global transmission

(February/March) and then become more volatile in the following months. We have also shown that that structural breaks tend to have occurred during the initial stages of COVID-19 global transmission and that in more than half of the observed cases, the establishment of a stay-at-home policy appear to have elicited a strong response but also somewhat stablished that country's market, as indicated by the tests for structural breaks and calculated MDM values.

The implication of these results is important to understand for policy makers and financial professionals alike. For investors, the evidence of long-range dependency might indicate an increased level of predictability in an otherwise unpredictable and volatile market. For policy makers, controls and measures can be established and their efficacy in stabilising economic markets empirically determined by employing methods of multifractal analysis such as those used in this paper.

References

Açikgöz, Ö., & Günay, A. (2020). The early impact of the Covid-19 pandemic on the global and Turkish economy. *Turkish journal of medical sciences, 50*(SI-1), 520. https://doi.org/10.3906/sag-2004-6

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2020, 2020/05/23/). Financial contagion during COVID–19 crisis. *Finance Research Letters*, 101604. https://doi.org/https://doi.org/10.1016/j.frl.2020.101604

Albulescu, C. (2020). *Coronavirus and financial volatility: 40 days of fasting and fear*.

Aslam, F., Ferreira, P., & Mothi, W. (2020, 05/01). Evidence of Intraday Multifractality in European Stock Markets during the recent Coronavirus (COVID-19) Outbreak. *International Journal of Financial Studies, 8*, 31. https://doi.org/10.3390/ijfs8020031

Bachelier, L. (1900). *Theory of Speculation in the Random Character of Stock Market Prices* MIT]. Cambridge.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., & Viratyosin, T. (2020). The Unprecedented Stock Market Impact of COVID-19. *National Bureau of Economic Research Working Paper Series, No. 26945*. https://doi.org/10.3386/w26945

Barkoulas, J. T., & Baum, C. F. (1996). Long-term dependence in stock returns. *Economics Letters, 53*(3), 253-259. https://doi.org/10.1016/S0165-1765(96)00935-4

Çağlar, S. (2018). APPLICATIONS OF THEORIES OF COMPLEXITY AND CHAOS TO GOLD PRICES. *Kafkas University. Faculty of Economics and Administrative Sciences. Journal, 9*(17), 181-190. https://doi.org/10.9775/kauiibfd.2018.008

Calvet, L., & Fisher, A. (2002). Multifractality in Asset Returns: Theory and Evidence. *Review of Economics and Statistics, 84*(3), 381-406. https://doi.org/10.1162/003465302320259420

Charles, A., & Darné, O. (2014). Volatility persistence in crude oil markets. *Energy Policy, 65*(C), 729-742. https://doi.org/10.1016/j.enpol.2013.10.042

Cleveland, R., Cleveland, W., & Terpenning, I. (1990). STL: A Seasonal-Trend Decomposition Procedure Based on Loess. *Journal of Official Statistics, 6*(1), 3.

Conlon, T., & McGee, R. (2020, 2020/07/01/). Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. *Finance Research Letters, 35*, 101607. https://doi.org/https://doi.org/10.1016/j.frl.2020.101607

Constantin, M. (2005). Volatility, Persistence, and Survival in Financial Markets. *arXiv.org, 72*(5 Pt 1). https://doi.org/10.1103/PhysRevE.72.051106

Corbet, S., Hu, Y., Lucey, B., & Oxley, L. (2020, 01/01). Aye Corona! The Contagion Effects of Being Named Corona during the COVID-19 Pandemic. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3561866

Corbet, S., Larkin, C., & Lucey, B. (2020, 2020/07/01/). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters, 35*, 101554. https://doi.org/https://doi.org/10.1016/j.frl.2020.101554

Ding, W., Levine, R., Lin, C., & Xie, W. (2020). Corporate Immunity to the COVID-19 Pandemic. *National Bureau of Economic Research Working Paper Series, No. 27055*. https://doi.org/10.3386/w27055

Filimonov, V., & Sornette, D. (2012). Quantifying reflexivity in financial markets: towards a prediction of flash crashes. *arXiv.org, 85*(5 Pt 2). https://doi.org/10.1103/PhysRevE.85.056108

Goodell, J. W. (2020, 2020/07/01/). COVID-19 and finance: Agendas for future research. *Finance Research Letters, 35*, 101512. https://doi.org/https://doi.org/10.1016/j.frl.2020.101512

Gopikrishnan, P., Plerou, V., Gabaix, X., Amaral, L. A. N., & Stanley, H. E. (2001). Price fluctuations and market activity. *Physica A: Statistical Mechanics and its Applications, 299*(1-2), 137-143. https://doi.org/10.1016/S0378-4371(01)00288-6

Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. *Journal of Financial Economics, 4*(3), 339-349. https://doi.org/10.1016/0304-405X(77)90006-X

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance, 27*. https://doi.org/10.1016/j.jbef.2020.100343

Huber, C., Huber, J., & Kirchler, M. (2020). *Market shocks and professionals' investment behavior – Evidence from the COVID-19 crash*. https://doi.org/10.31219/osf.io/fgxpb

Jacobs, B., & Levy, K. (1989). The Complexity Of The Stock Market. *Journal of Portfolio Management, 16*(1), 19. https://doi.org/10.3905/jpm.1989.409244

Ji, Q., Zhang, D., & Zhao, Y. (2020, 2020/10/01/). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis, 71*, 101526. https://doi.org/https://doi.org/10.1016/j.irfa.2020.101526

Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A: Statistical Mechanics and its Applications, 316*(1-4), 87-114. https://doi.org/10.1016/S0378-4371(02)01383-3

Kauê Dal'maso Peron, T., Da Fontoura Costa, L., & Rodrigues, F. A. (2012). The structure and resilience of financial market networks. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 22*(1). https://doi.org/10.1063/1.3683467

Kuhlmann, M. (2014). Explaining Financial Markets in Terms of Complex Systems. *Philosophy of Science, 81*(5), 1117-1130. https://doi.org/10.1086/677699

Mandelbrot, B. (1963). THE VARIATION OF CERTAIN SPECULATIVE PRICES. *The Journal of Business (pre-1986), 36*(4), 394. https://doi.org/10.1086/294632

Mandelbrot, B. B., & Hudson, R. L. (2004). *The (Mis)Behavior of Markets : A Fractal View of Risk, Ruin, and Reward*. Basic Books.

Onali, E. (2020). *Covid-19 and stock market volatility*.

Savit, R. (1988). When random is not random: An introduction to chaos in market prices. *Journal of Futures Markets, 8*(3), 271-290. https://doi.org/10.1002/fut.3990080303

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis, 70*. https://doi.org/10.1016/j.irfa.2020.101496

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020, 2020/07/01/). Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. *Finance Research Letters, 35*, 101597. https://doi.org/https://doi.org/10.1016/j.frl.2020.101597

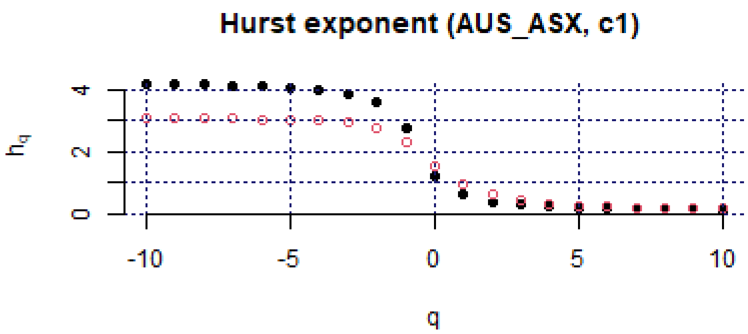
Zhang, D., Hu, M., & Ji, Q. (2020, 2020/04/16/). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 101528. https://doi.org/https://doi.org/10.1016/j.frl.2020.101528

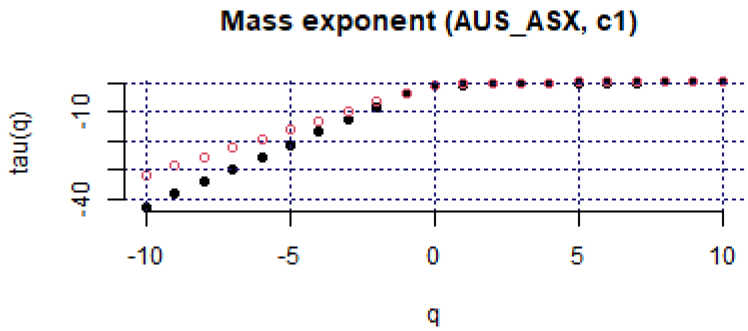
Declarations

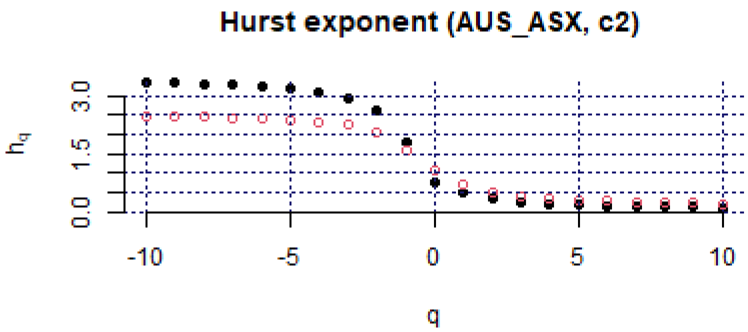
Ethics approval and consent to participate	Not Applicable.
Consent for publication	Not Applicable.
Availability of data and materials	Data and materials used in the study are available on request to the corresponding author of this paper.
Competing interests	There is no competing interest to declare.
Funding	There is no funding support for the study.
Author Contributions	SJB, HFC and BT designed the research; RC extracted the data; SJB, HFC and BT analysed the data. SJB, MB and RC drafted the paper. BT and HFC revised the manuscript and provided substantial inputs. All authors read and approved the final manuscript.
Acknowledgements	Not applicable.

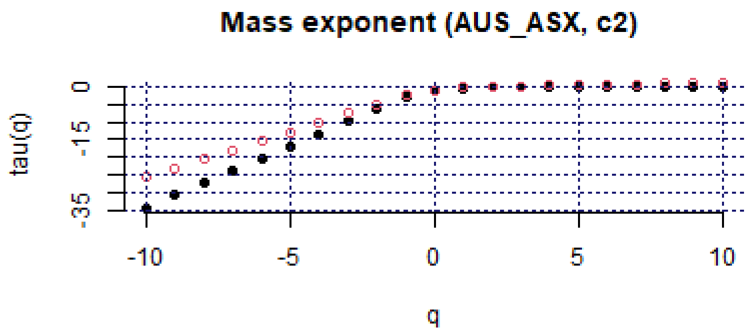
Supplementary Material

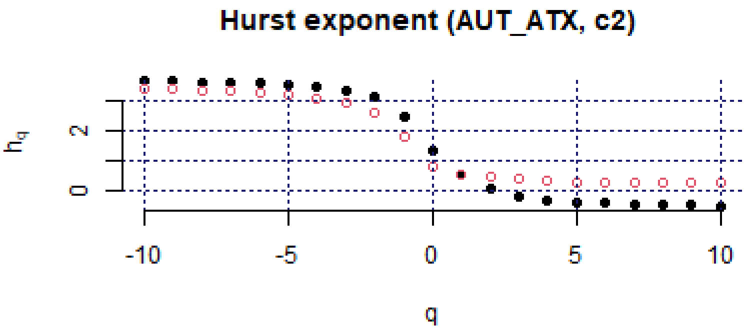
Section 1: Generalised Hurst Exponents and Mass Exponents

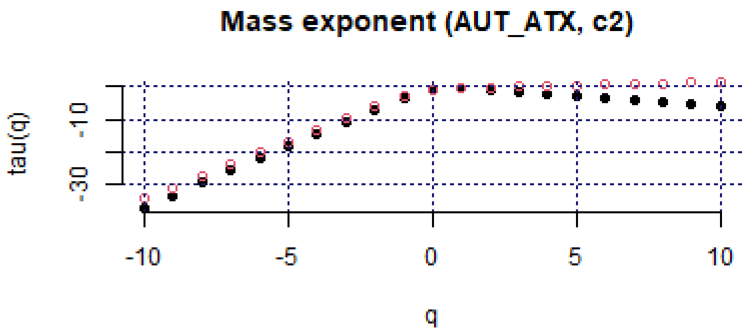


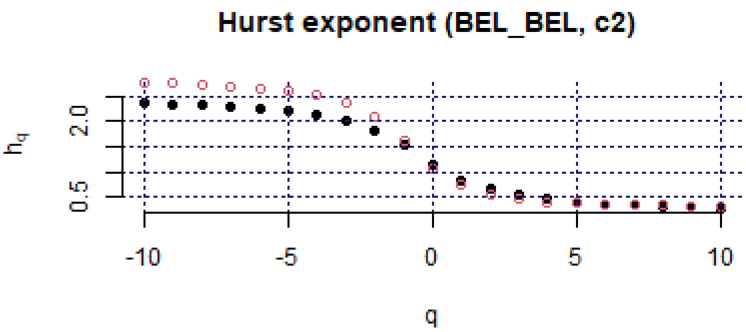


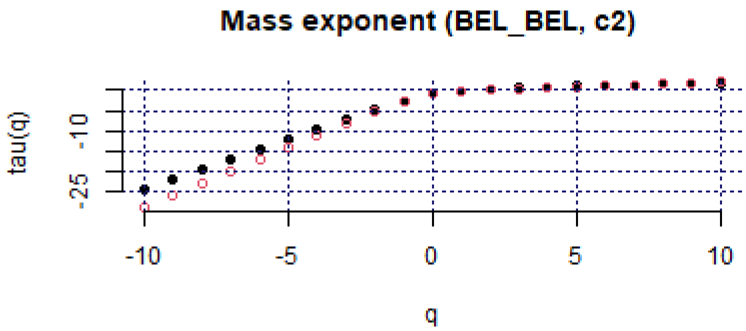


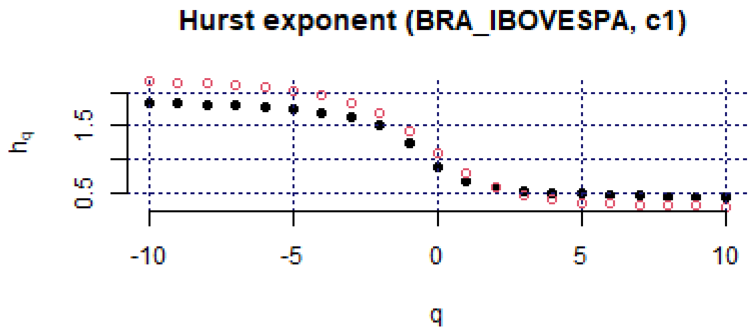


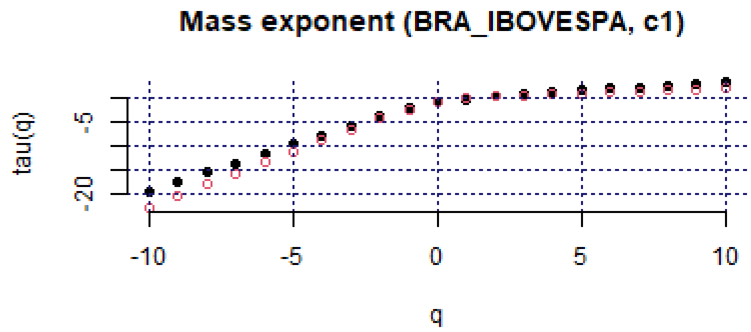

Hurst exponent (AUT_ATX, c2)
h_q
0
2
-10
-5
0
5
10
q

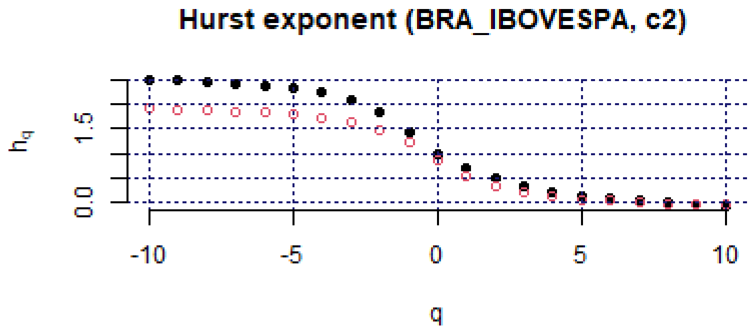

Mass exponent (AUT_ATX, c2)
tau(q)
-30
-10
-10
-5
0
5
10
q

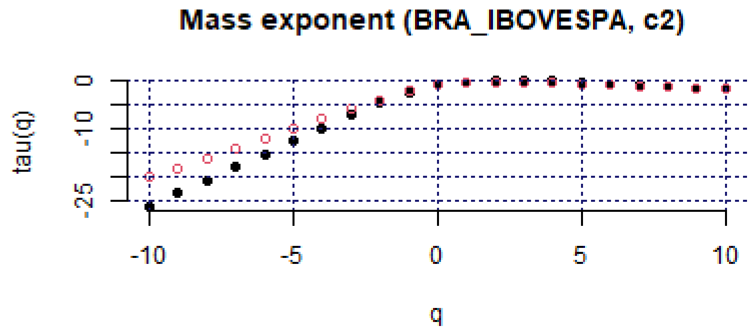

Hurst exponent (BEL_BEL, c2)
h_q
0.5
2.0
-10
-5
0
5
10
q

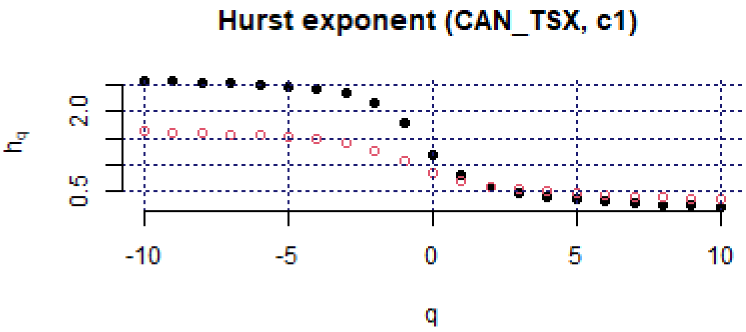

Mass exponent (BEL_BEL, c2)
tau(q)
-25
-10
-10
-5
0
5
10
q

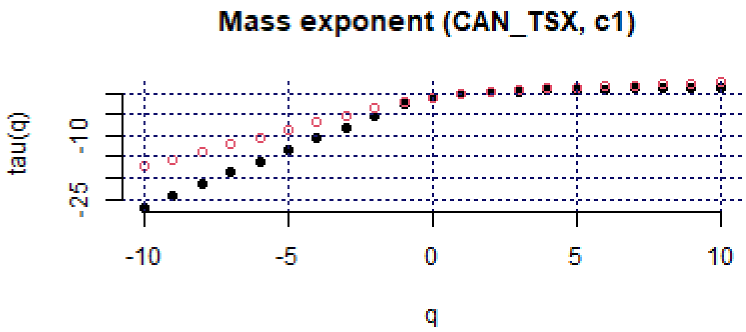

Hurst exponent (BRA_IBOVESPA, c1)
h_q
0.5
1.5
-10
-5
0
5
10
q

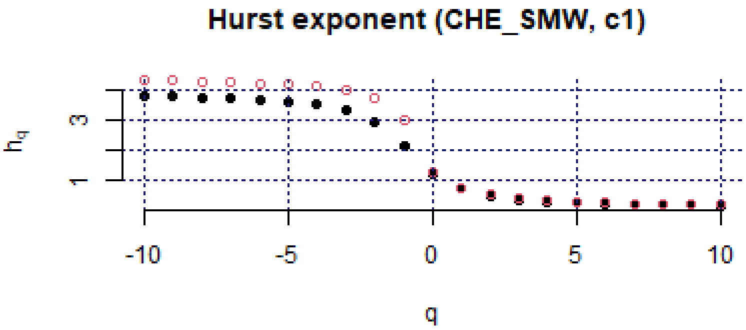

Mass exponent (BRA_IBOVESPA, c1)
tau(q)
-20
-5
-10
-5
0
5
10
q

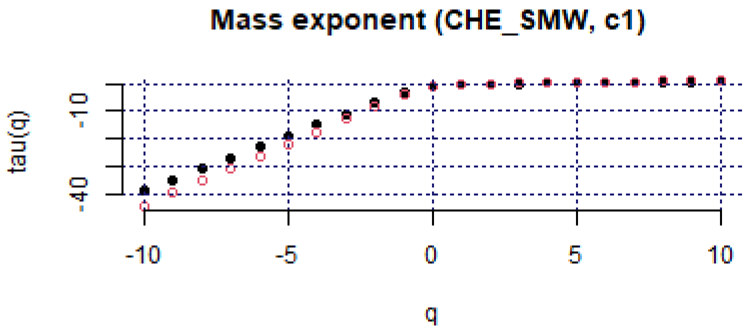

Hurst exponent (BRA_IBOVESPA, c2)
h_q
0.0
1.5
-10
-5
0
5
10
q

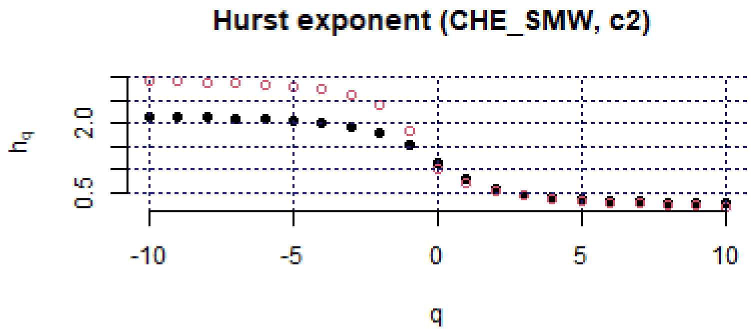

Mass exponent (BRA_IBOVESPA, c2)
tau(q)
-25
-10
0
-10
-5
0
5
10
q

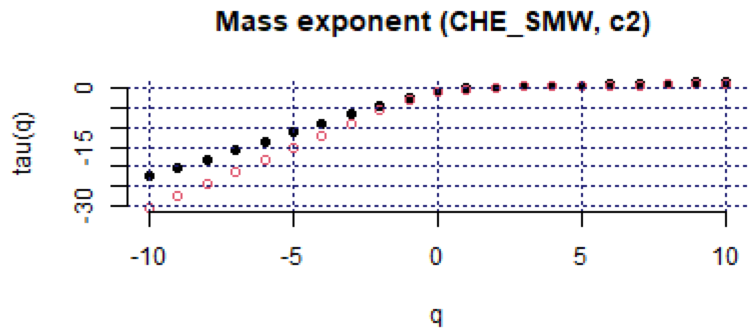

Hurst exponent (CAN_TSX, c1)
h_q
0.5
2.0
-10
-5
0
5
10
q

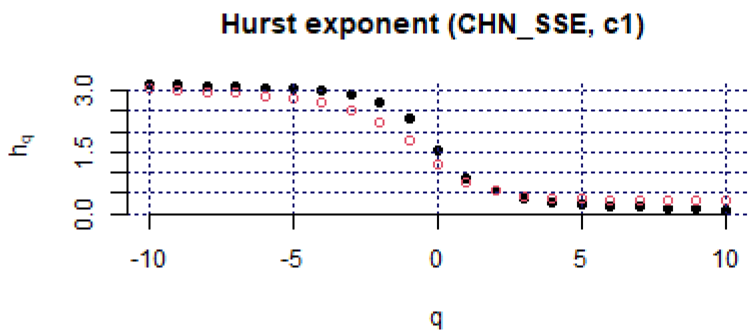

Mass exponent (CAN_TSX, c1)
tau(q)
-25
-10
-10
-5
0
5
10
q

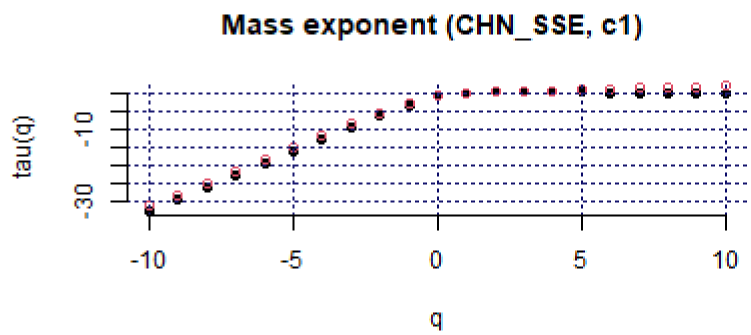

Hurst exponent (CHE_SMW, c1)
h_q
1
3
-10
-5
0
5
10
q

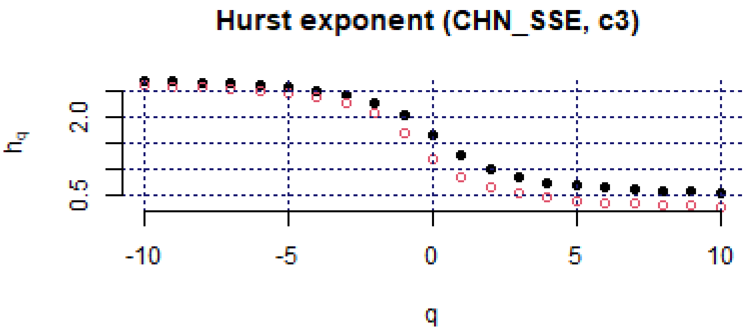

Mass exponent (CHE_SMW, c1)
tau(q)
-40
-10
-10
-5
0
5
10
q

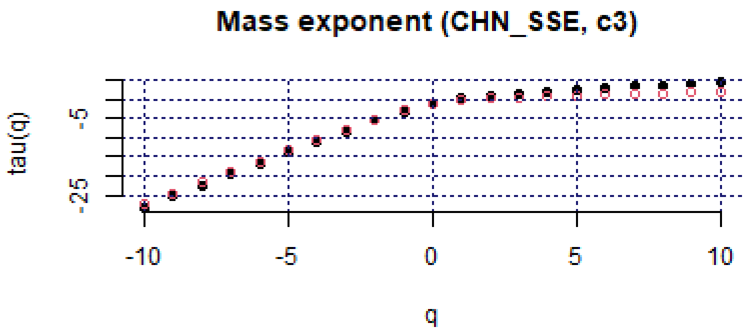

Hurst exponent (CHE_SMW, c2)
h_q
0.5
2.0
-10
-5
0
5
10
q

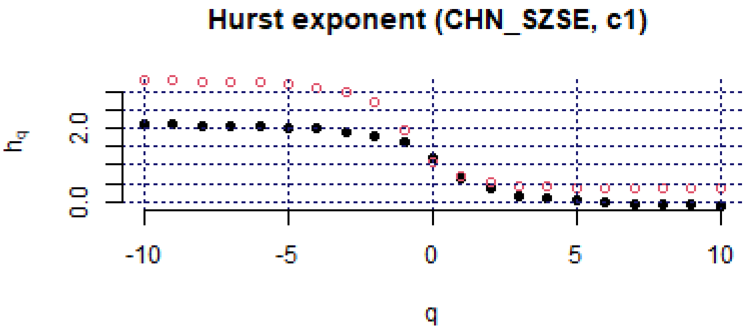

Mass exponent (CHE_SMW, c2)
tau(q)
-30
-15
0
-10
-5
0
5
10
q

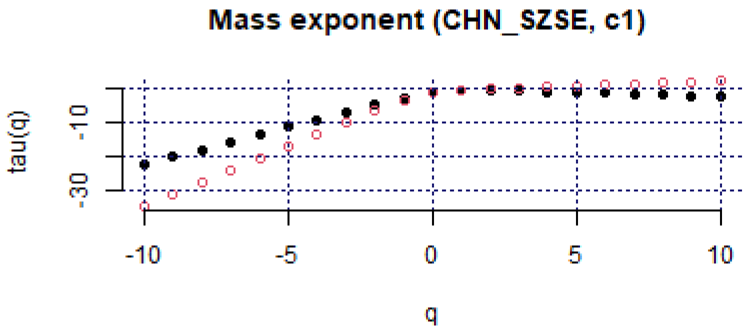

Hurst exponent (CHN_SSE, c1)
h_q
0.0
1.5
3.0
-10
-5
0
5
10
q

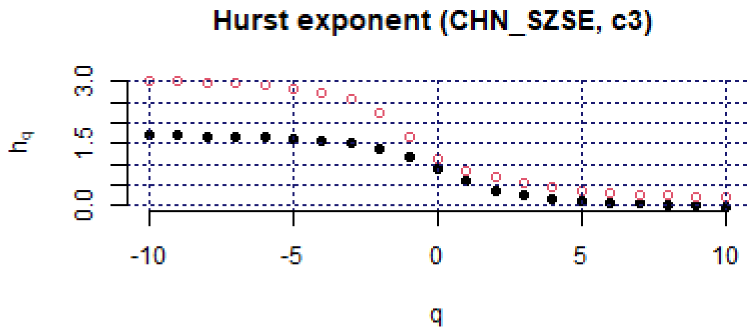

Mass exponent (CHN_SSE, c1)
tau(q)
-30
-10
-10
-5
0
5
10
q

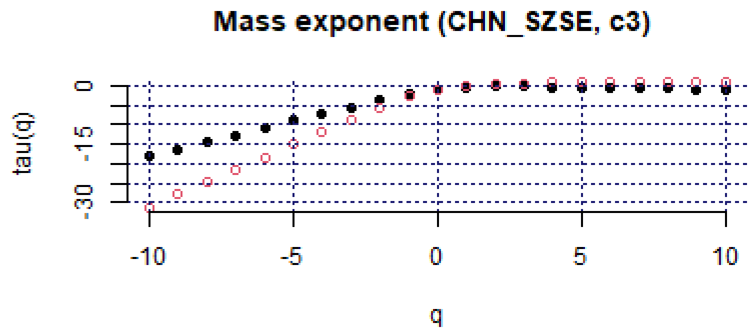

Hurst exponent (CHN_SSE, c3)
h_q
0.5
2.0
-10
-5
0
5
10
q

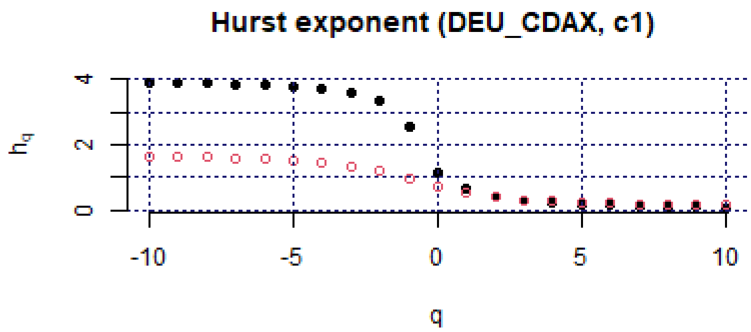

Mass exponent (CHN_SSE, c3)
tau(q)
-25
-5
-10
-5
0
5
10
q

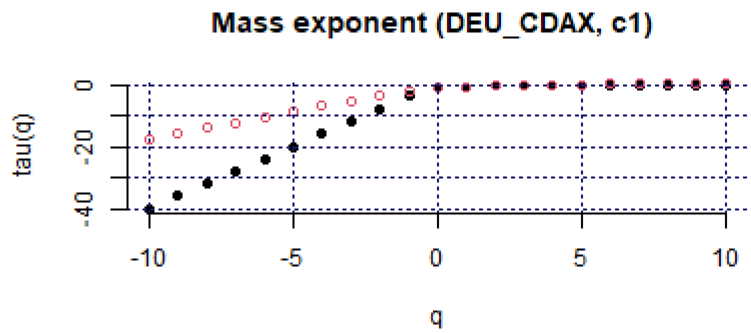

Hurst exponent (CHN_SZSE, c1)
h_q
0.0
2.0
-10
-5
0
5
10
q

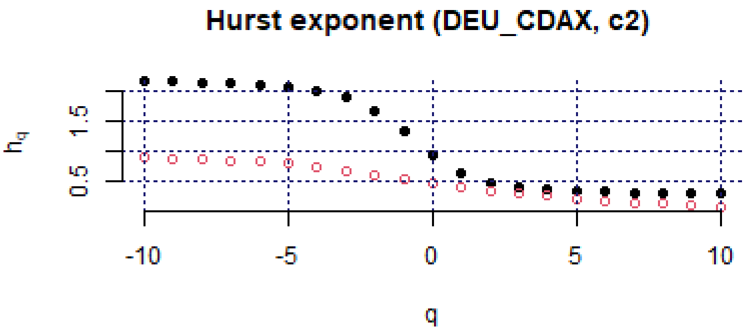

Mass exponent (CHN_SZSE, c1)
tau(q)
-30
-10
-10
-5
0
5
10
q

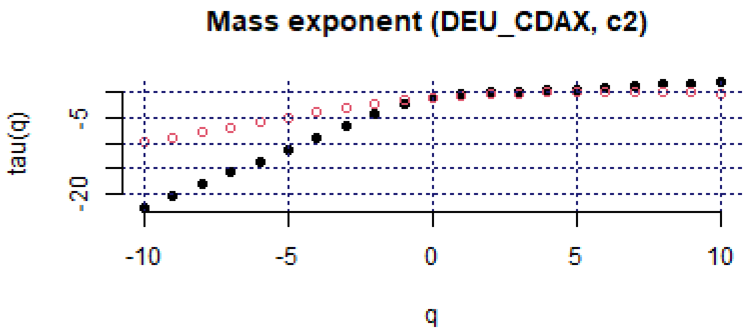

Hurst exponent (CHN_SZSE, c3)
h_q
0.0
1.5
3.0
-10
-5
0
5
10
q

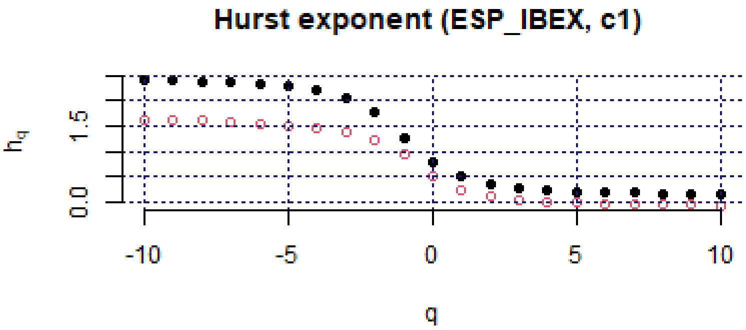

Mass exponent (CHN_SZSE, c3)
tau(q)
-30
-15
0
-10
-5
0
5
10
q

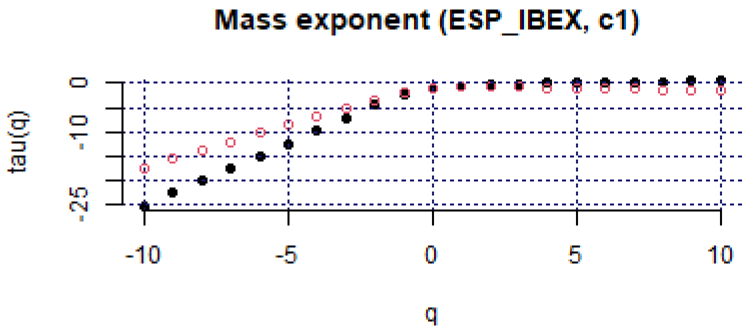

Hurst exponent (DEU_CDAX, c1)
h_q
0
2
4
-10
-5
0
5
10
q

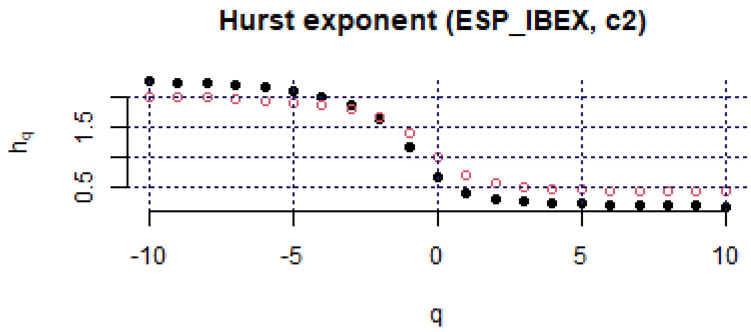

Mass exponent (DEU_CDAX, c1)
tau(q)
-40
-20
0
-10
-5
0
5
10
q

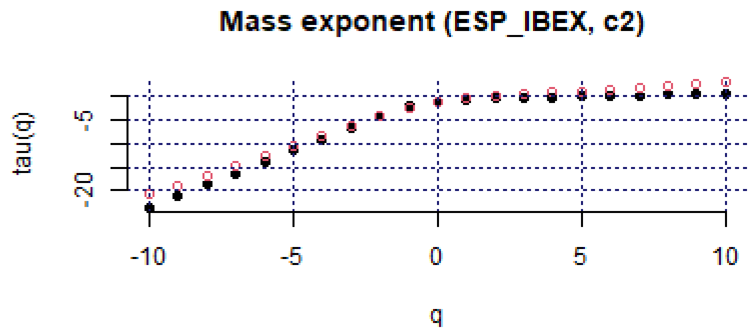

Hurst exponent (DEU_CDAX, c2)
h_q
0.5
1.5
-10
-5
0
5
10
q

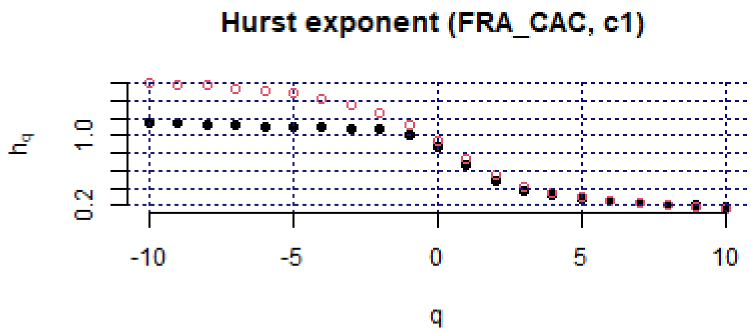

Mass exponent (DEU_CDAX, c2)
tau(q)
-20
-5
-10
-5
0
5
10
q

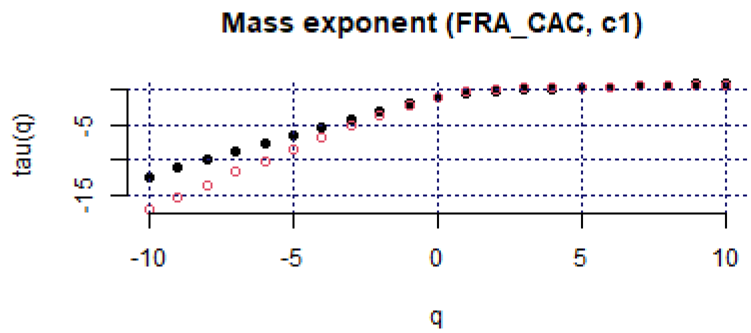

Hurst exponent (ESP_IBEX, c1)
h_q
0.0
1.5
-10
-5
0
5
10
q

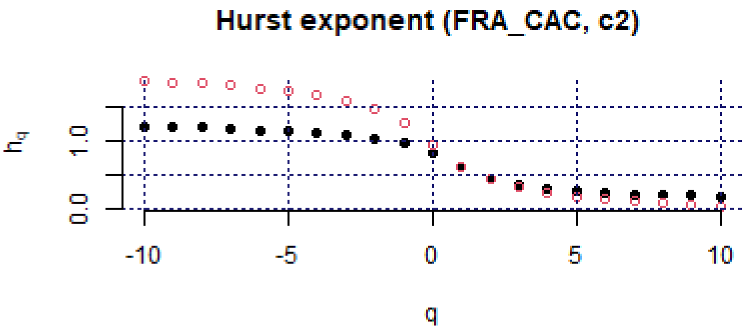

Mass exponent (ESP_IBEX, c1)
tau(q)
-25
-10
0
-10
-5
0
5
10
q

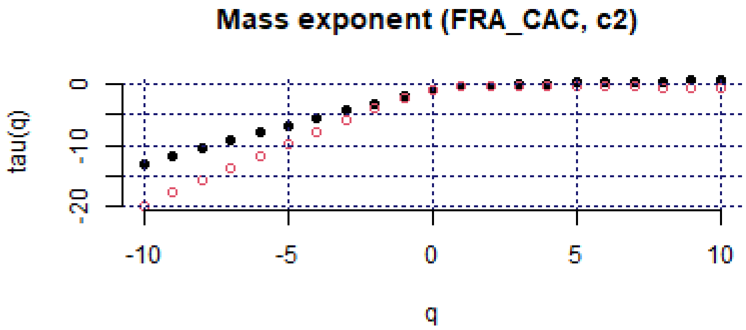

Hurst exponent (ESP_IBEX, c2)
h_q
0.5
1.5
-10
-5
0
5
10
q

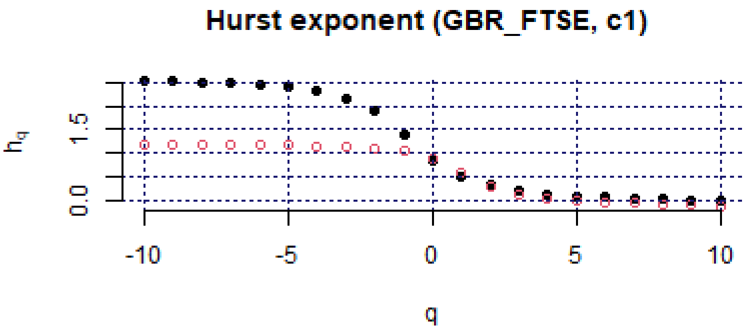

Mass exponent (ESP_IBEX, c2)
tau(q)
-20
-5
-10
-5
0
5
10
q

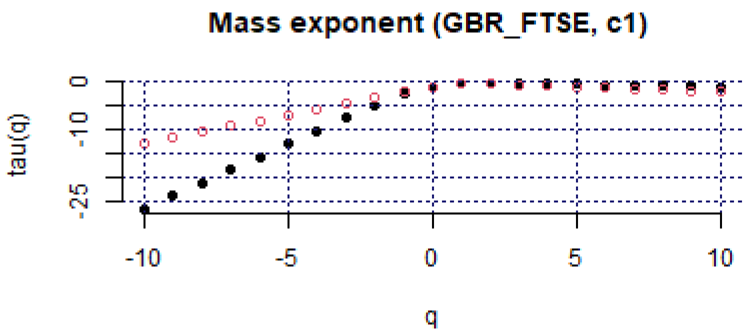

Hurst exponent (FRA_CAC, c1)
h_q
0.2
1.0
-10
-5
0
5
10
q

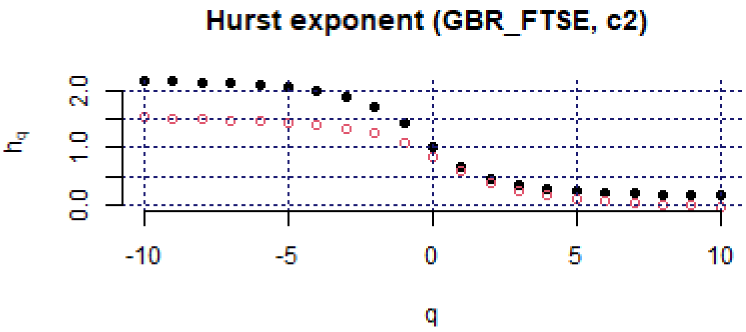

Mass exponent (FRA_CAC, c1)
tau(q)
-15
-5
-10
-5
0
5
10
q


Hurst exponent (FRA_CAC, c2)
h_q
0.0
1.0
-10
-5
0
5
10
q

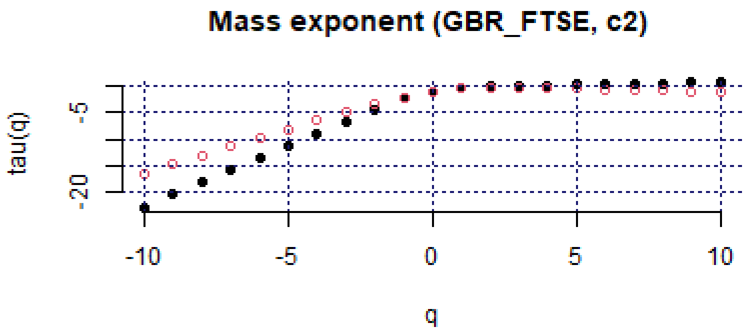

Mass exponent (FRA_CAC, c2)
tau(q)
0
-10
-20
-10
-5
0
5
10
q


Hurst exponent (GBR_FTSE, c1)
h_q
0.0
1.5
-10
-5
0
5
10
q

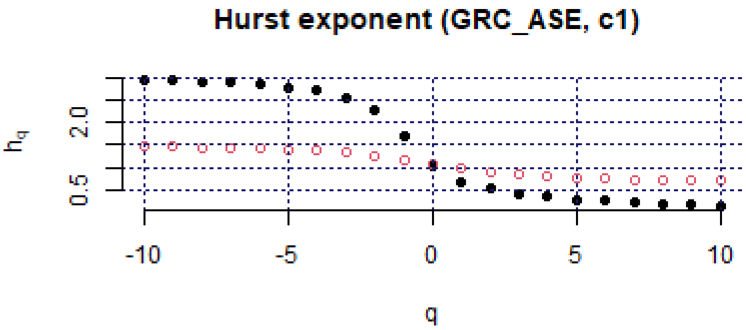

Mass exponent (GBR_FTSE, c1)
tau(q)
0
-10
-25
-10
-5
0
5
10
q



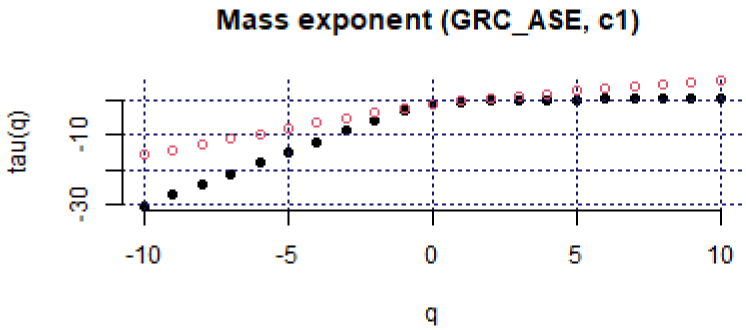
Hurst exponent (GBR_FTSE, c2)
h_q
0.0
1.0
2.0
-10
-5
0
5
10
q



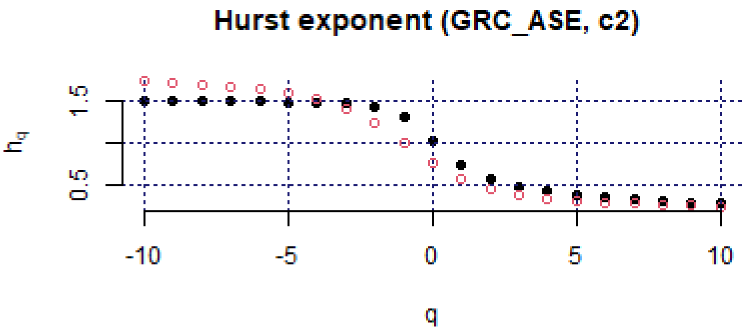
Mass exponent (GBR_FTSE, c2)
tau(q)
-20
-5
-10
-5
0
5
10
q

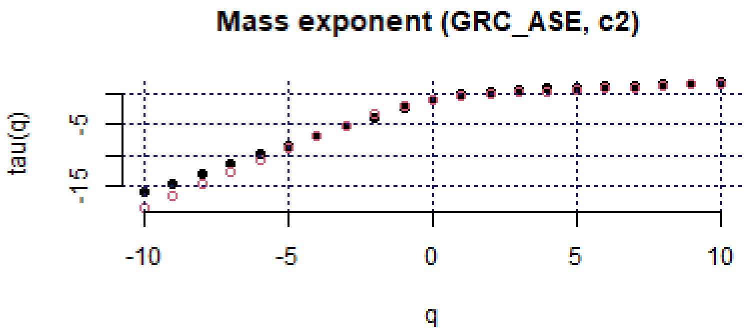


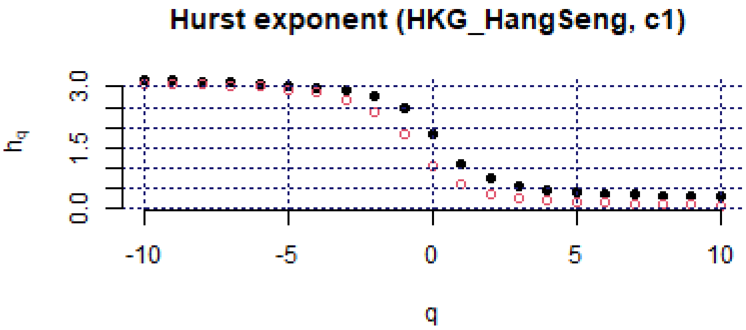
Hurst exponent (GRC_ASE, c1)
h_q
0.5
2.0
-10
-5
0
5
10
q

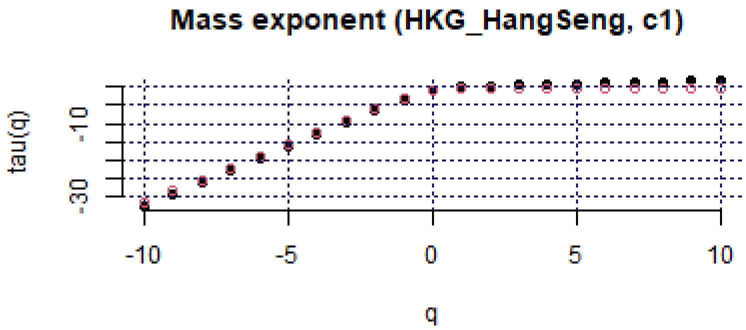


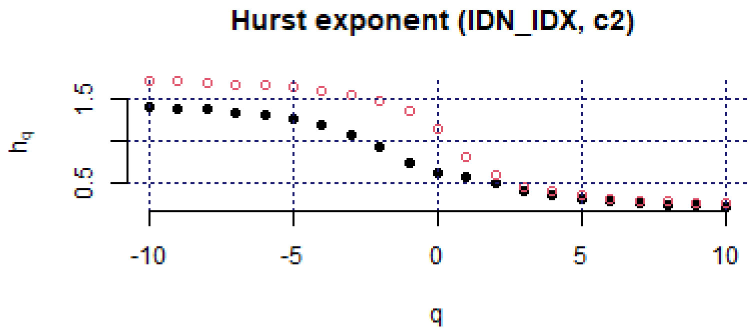
Mass exponent (GRC_ASE, c1)
tau(q)
-30
-10
-10
-5
0
5
10
q

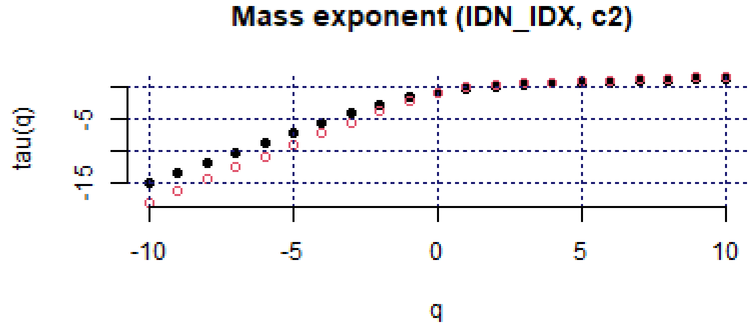

Hurst exponent (GRC_ASE, c2)
h_q
0.5
1.5
-10
-5
0
5
10
q

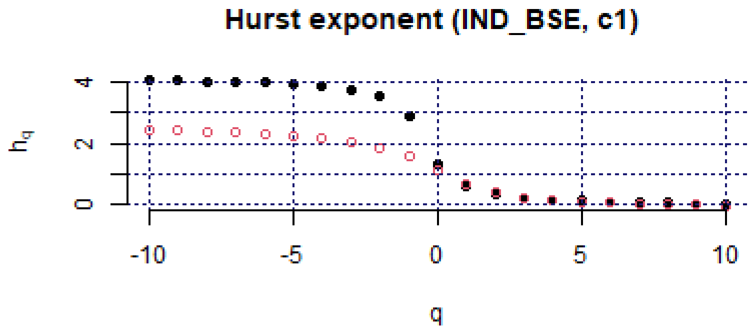

Mass exponent (GRC_ASE, c2)
tau(q)
-15
-5
-10
-5
0
5
10
q

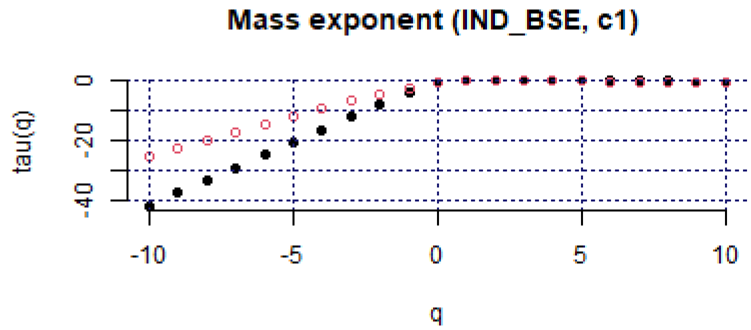

Hurst exponent (HKG_HangSeng, c1)
h_q
0.0
1.5
3.0
-10
-5
0
5
10
q

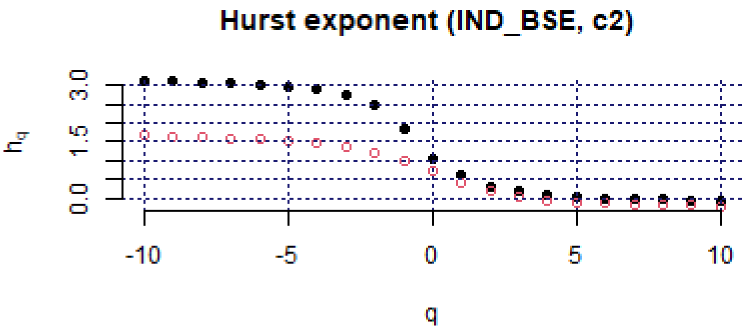

Mass exponent (HKG_HangSeng, c1)
tau(q)
-30
-10
-10
-5
0
5
10
q

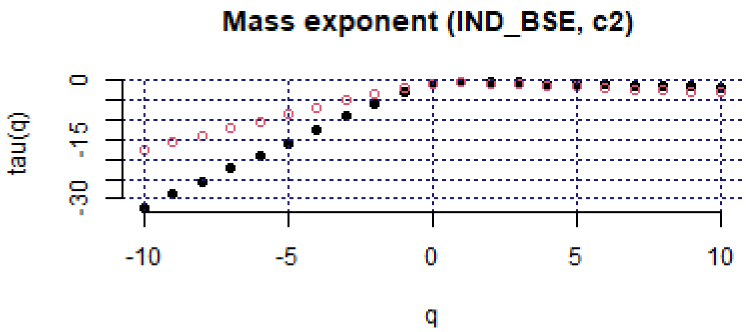

Hurst exponent (IDN_IDX, c2)
hq
0.5
1.5
-10
-5
0
5
10
q

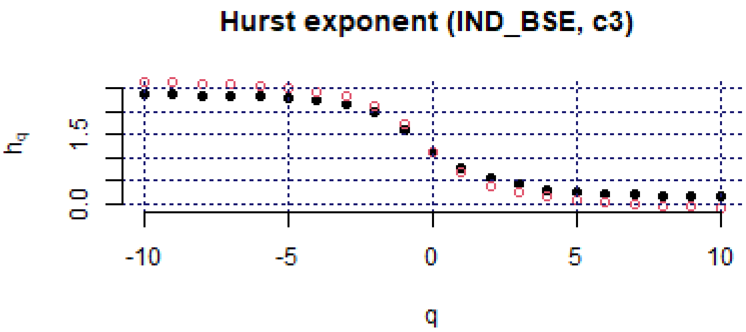

Mass exponent (IDN_IDX, c2)
tau(q)
-15
-5
-10
-5
0
5
10
q

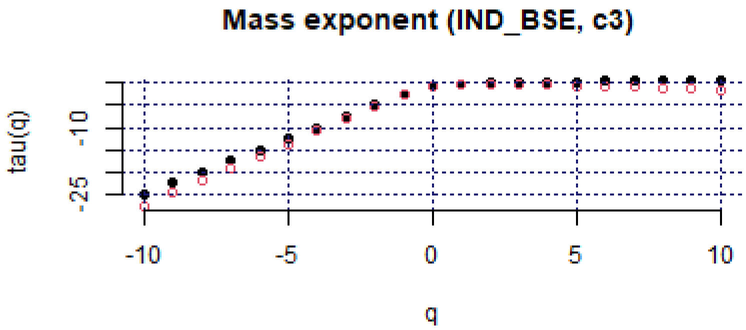

Hurst exponent (IND_BSE, c1)
hq
0
2
4
-10
-5
0
5
10
q

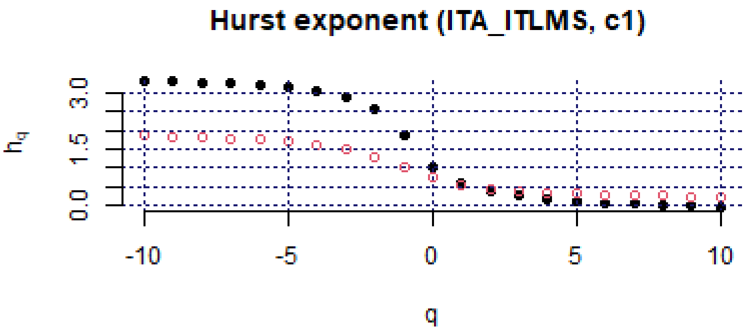

Mass exponent (IND_BSE, c1)
tau(q)
-40
-20
0
-10
-5
0
5
10
q

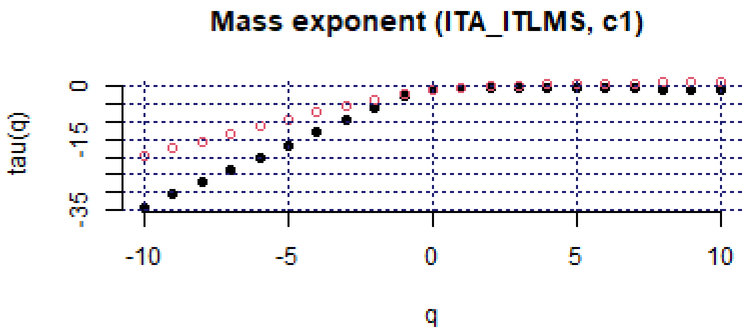

Hurst exponent (IND_BSE, c2)
h_q
3.0
1.5
0.0
-10
-5
0
5
10
q

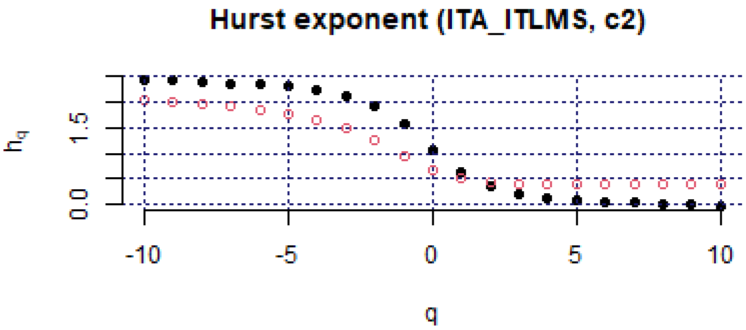

Mass exponent (IND_BSE, c2)
tau(q)
0
-15
-30
-10
-5
0
5
10
q

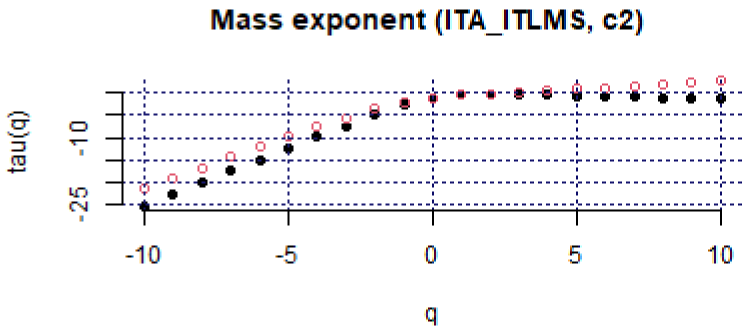

Hurst exponent (IND_BSE, c3)
h_q
1.5
0.0
-10
-5
0
5
10
q

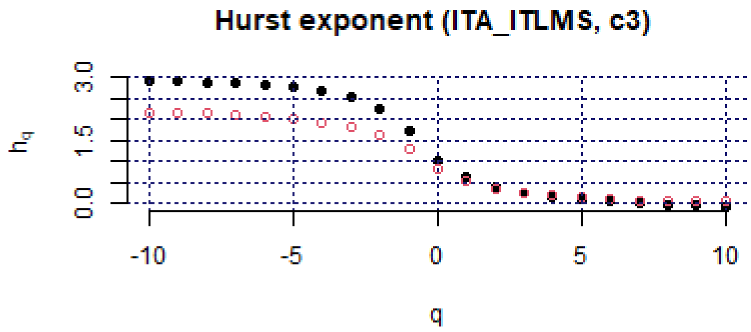

Mass exponent (IND_BSE, c3)
tau(q)
-10
-25
-10
-5
0
5
10
q

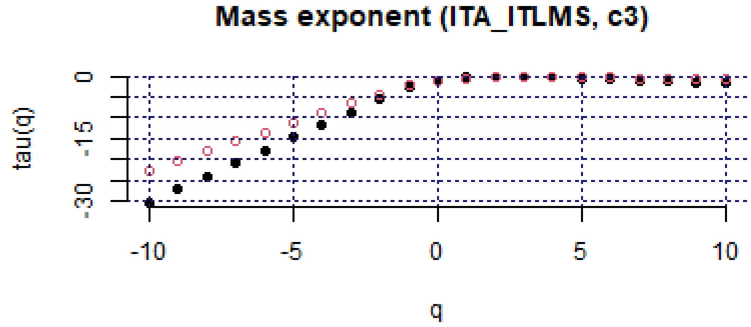

Hurst exponent (ITA_ITLMS, c1)
h_q
0.0
1.5
3.0
-10
-5
0
5
10
q

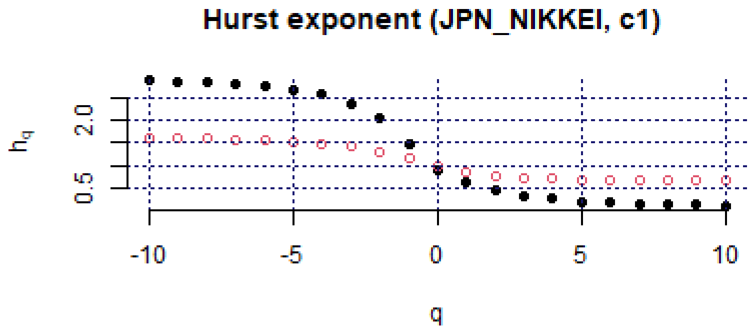

Mass exponent (ITA_ITLMS, c1)
tau(q)
-35
-15
0
-10
-5
0
5
10
q

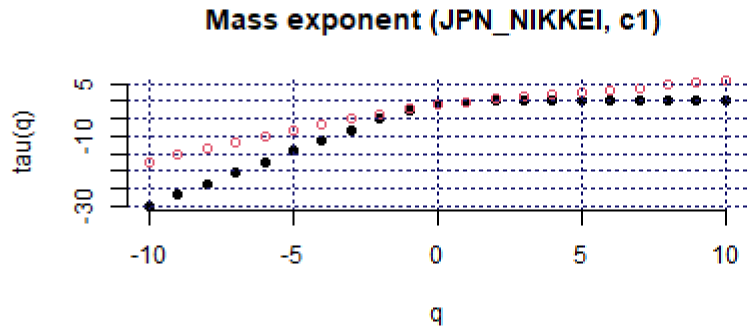

Hurst exponent (ITA_ITLMS, c2)
h_q
0.0
1.5
-10
-5
0
5
10
q

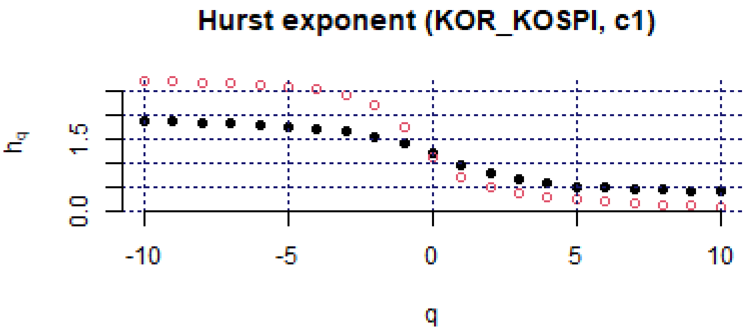

Mass exponent (ITA_ITLMS, c2)
tau(q)
-25
-10
-10
-5
0
5
10
q

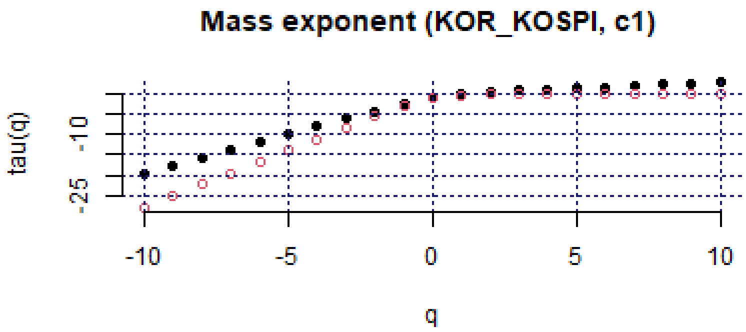

Hurst exponent (ITA_ITLMS, c3)
h_q
q

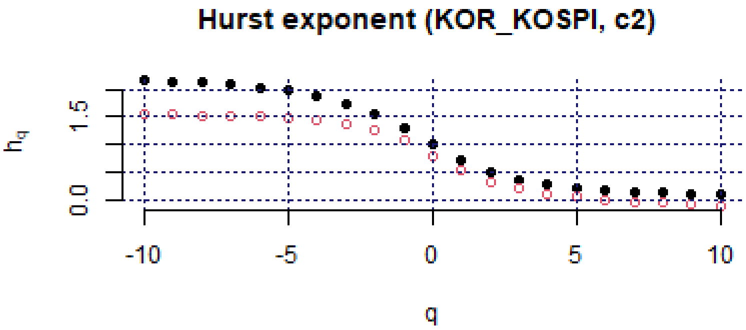

Mass exponent (ITA_ITLMS, c3)
tau(q)
q

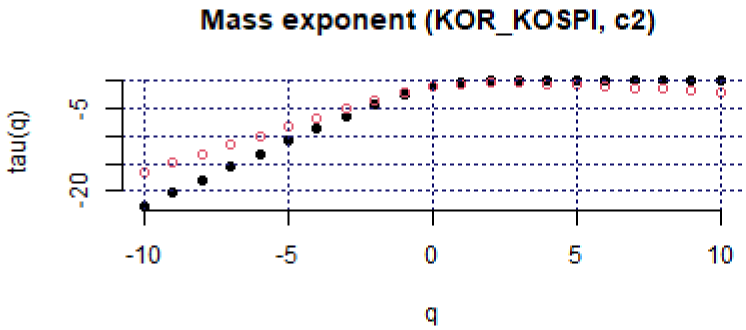

Hurst exponent (JPN_NIKKEI, c1)
h_q
q

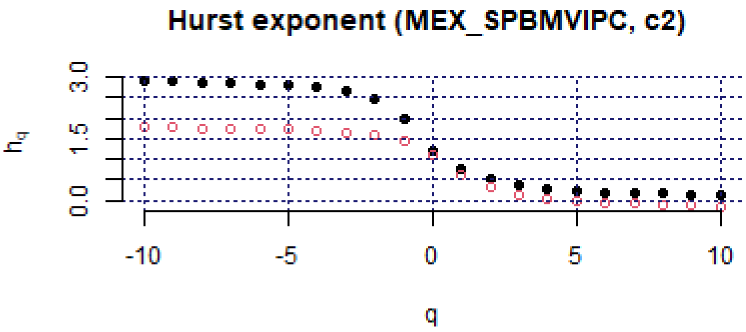

Mass exponent (JPN_NIKKEI, c1)
tau(q)
q

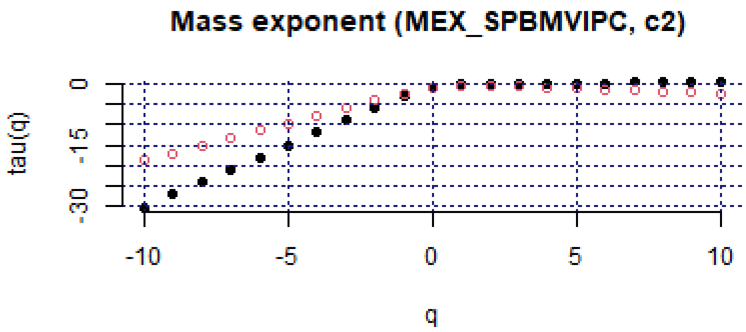

Hurst exponent (KOR_KOSPI, c1)
h_q
0.0
1.5
-10
-5
0
5
10
q

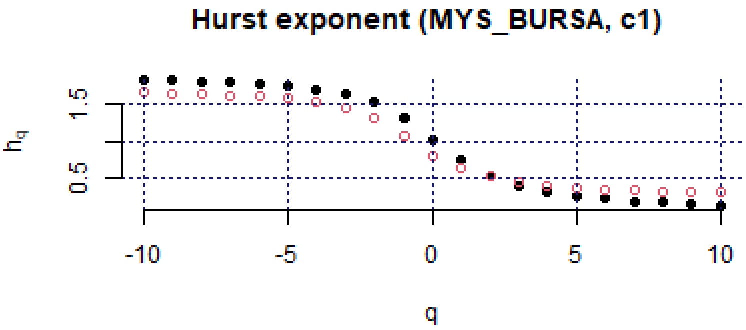

Mass exponent (KOR_KOSPI, c1)
tau(q)
-25
-10
-10
-5
0
5
10
q

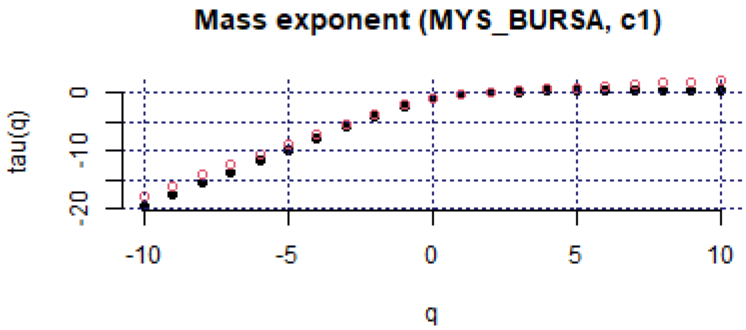

Hurst exponent (KOR_KOSPI, c2)
h_q
0.0
1.5
-10
-5
0
5
10
q

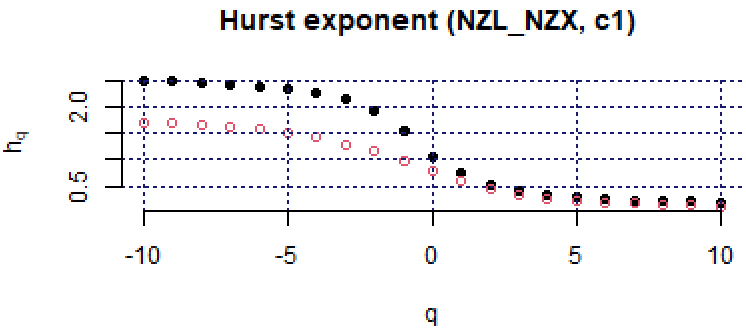

Mass exponent (KOR_KOSPI, c2)
tau(q)
-20
-5
-10
-5
0
5
10
q

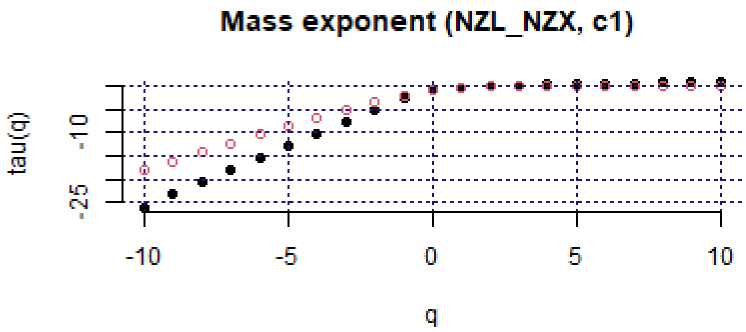

Hurst exponent (MEX_SPBMVIPC, c2)
h_q
0.0
1.5
3.0
-10
-5
0
5
10
q

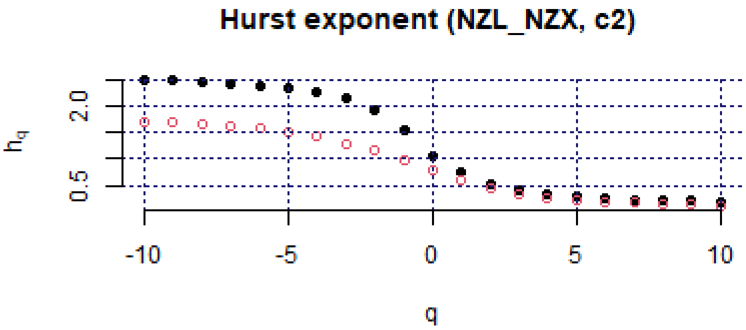

Mass exponent (MEX_SPBMVIPC, c2)
tau(q)
-30
-15
0
-10
-5
0
5
10
q

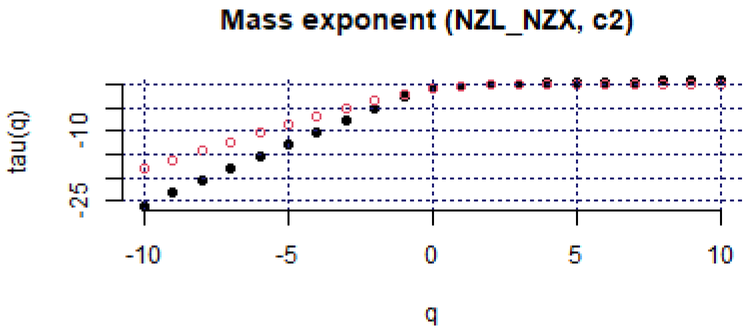

Hurst exponent (MYS_BURSA, c1)
h_q
0.5
1.5
-10
-5
0
5
10
q

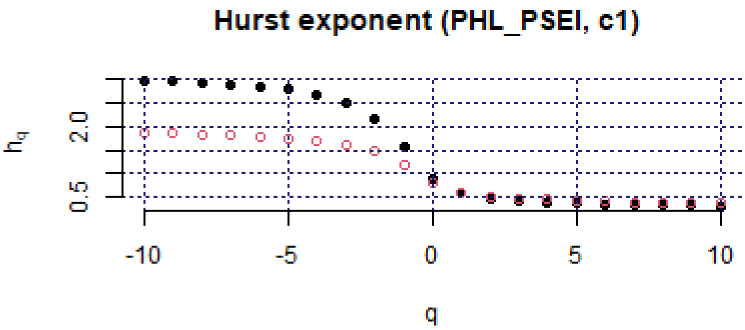

Mass exponent (MYS_BURSA, c1)
tau(q)
-20
-10
0
-10
-5
0
5
10
q

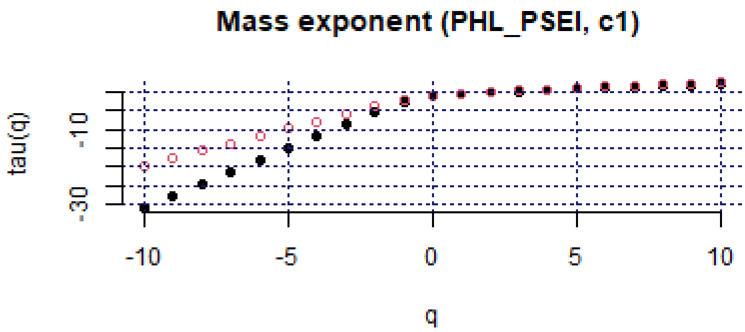

Hurst exponent (NZL_NZX, c1)
h_q
0.5
2.0
-10
-5
0
5
10
q

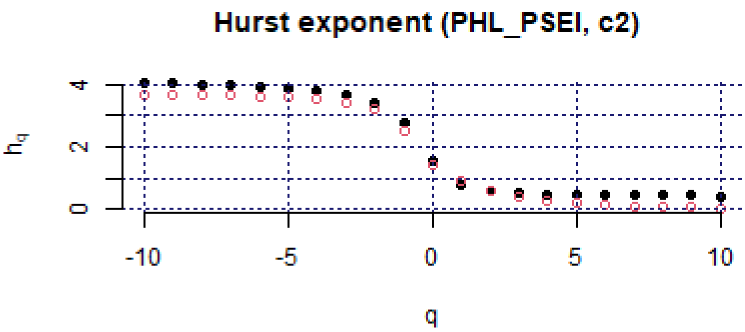

Mass exponent (NZL_NZX, c1)
tau(q)
-25
-10
-10
-5
0
5
10
q

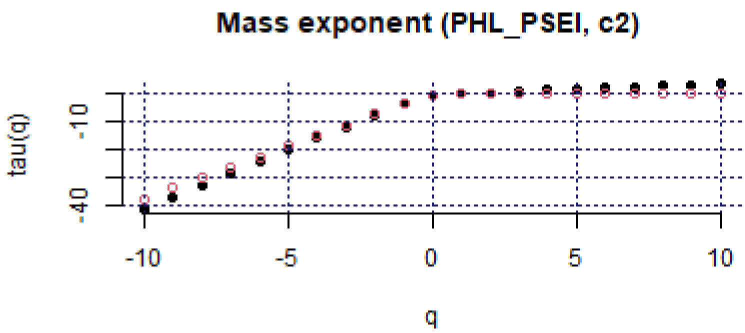

Hurst exponent (NZL_NZX, c2)
h_q
0.5
2.0
-10
-5
0
5
10
q


Mass exponent (NZL_NZX, c2)
tau(q)
-25
-10
-10
-5
0
5
10
q

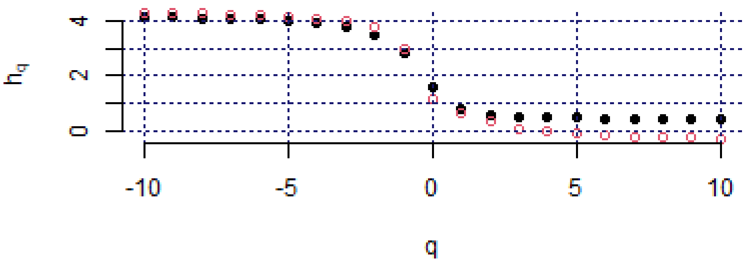

Hurst exponent (PHL_PSEI, c1)
h_q
0.5
2.0
-10
-5
0
5
10
q


Mass exponent (PHL_PSEI, c1)
tau(q)
-30
-10
-10
-5
0
5
10
q

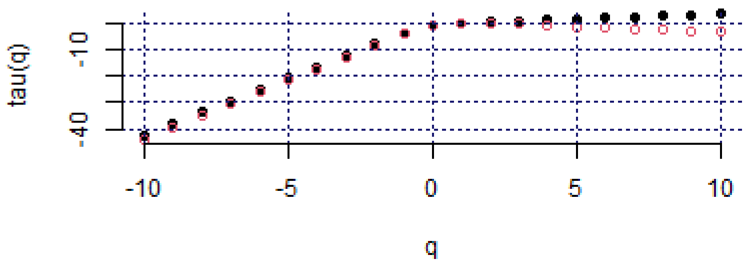

Hurst exponent (PHL_PSEI, c2)
h_q
0
2
4
-10
-5
0
5
10
q


Mass exponent (PHL_PSEI, c2)
tau(q)
-40
-10
-10
-5
0
5
10
q

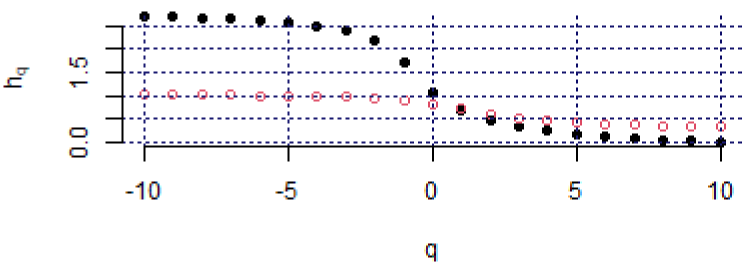
Hurst exponent (PHL_PSEI, c3)



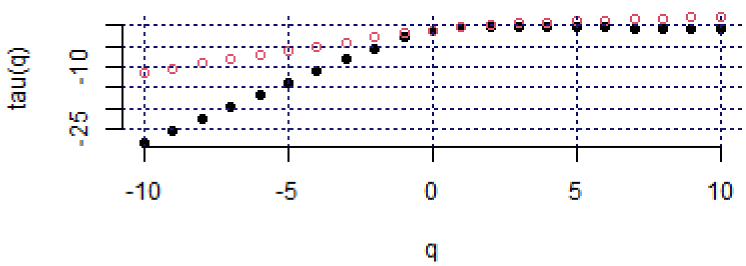
Mass exponent (PHL_PSEI, c3)

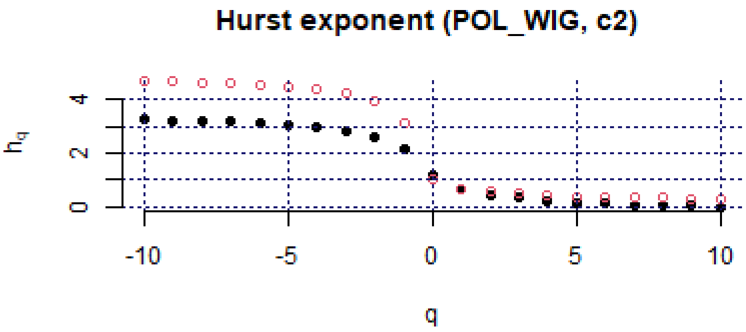


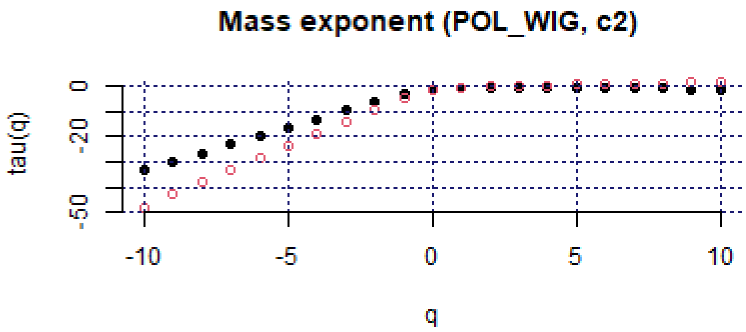
Hurst exponent (POL_WIG, c1)

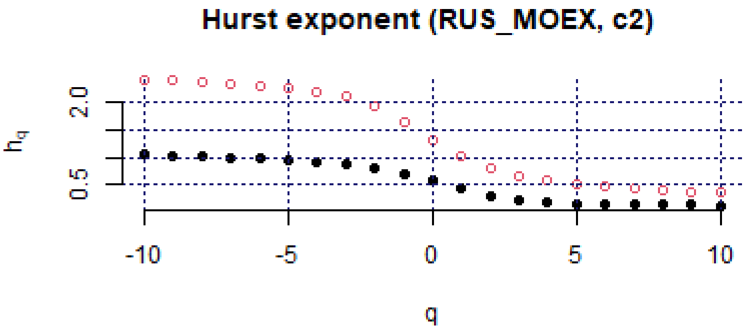


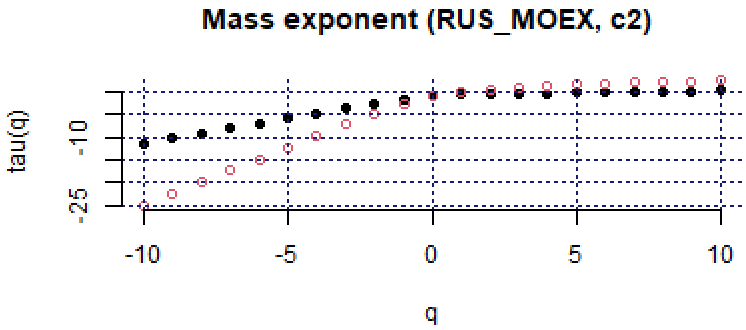
Mass exponent (POL_WIG, c1)

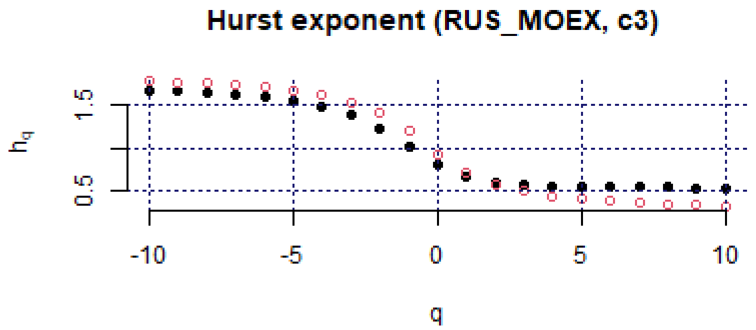


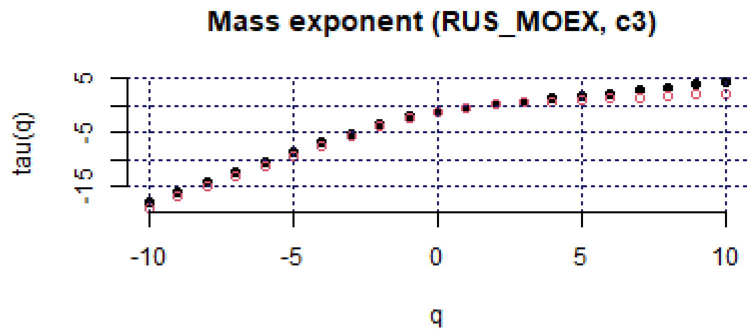

Hurst exponent (POL_WIG, c2)
hq
0
2
4
-10
-5
0
5
10
q

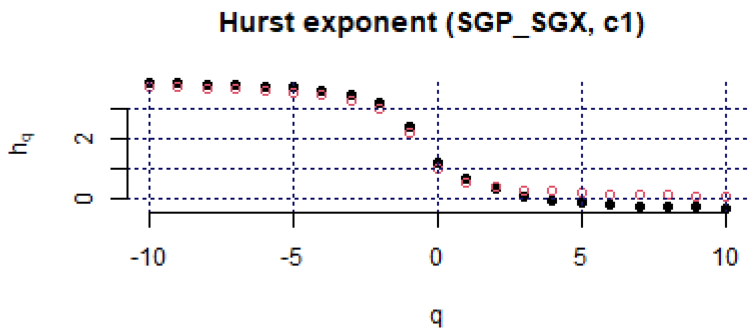

Mass exponent (POL_WIG, c2)
tau(q)
-50
-20
0
-10
-5
0
5
10
q

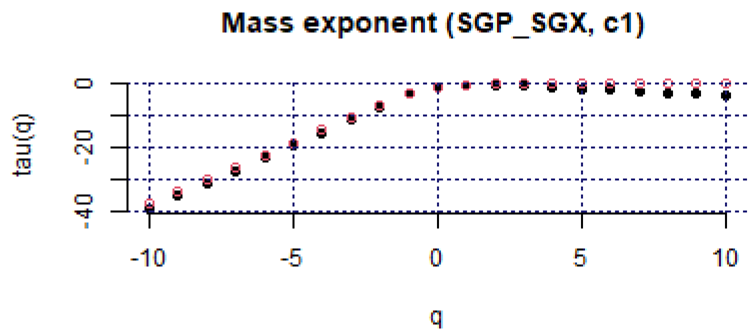

Hurst exponent (RUS_MOEX, c2)
hq
0.5
2.0
-10
-5
0
5
10
q

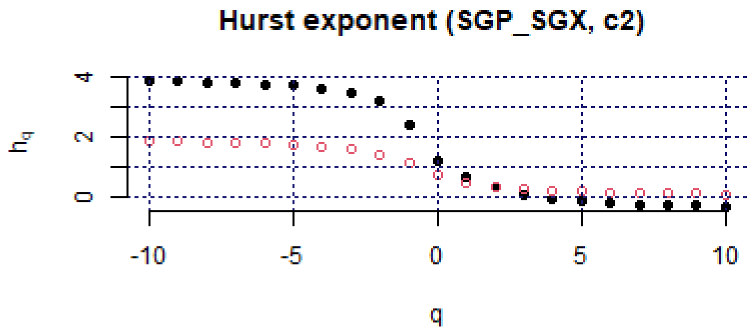

Mass exponent (RUS_MOEX, c2)
tau(q)
-25
-10
-10
-5
0
5
10
q

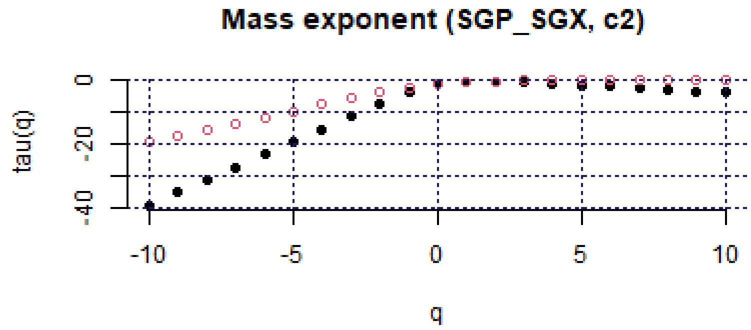

Hurst exponent (RUS_MOEX, c3)
h_q
0.5
1.5
-10
-5
0
5
10
q

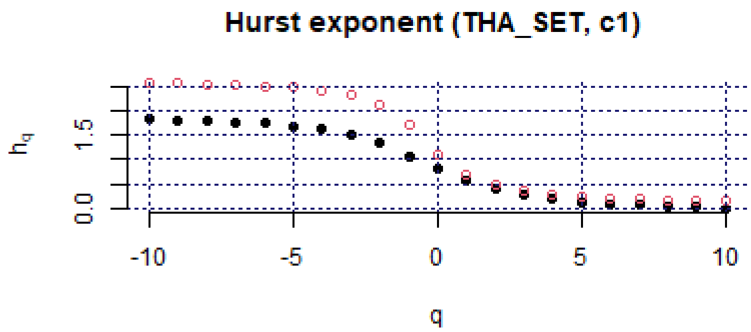

Mass exponent (RUS_MOEX, c3)
tau(q)
-15
-5
5
-10
-5
0
5
10
q

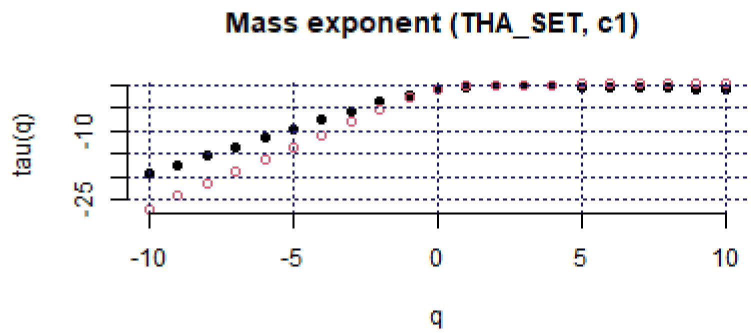

Hurst exponent (SGP_SGX, c1)
h_q
0
2
-10
-5
0
5
10
q

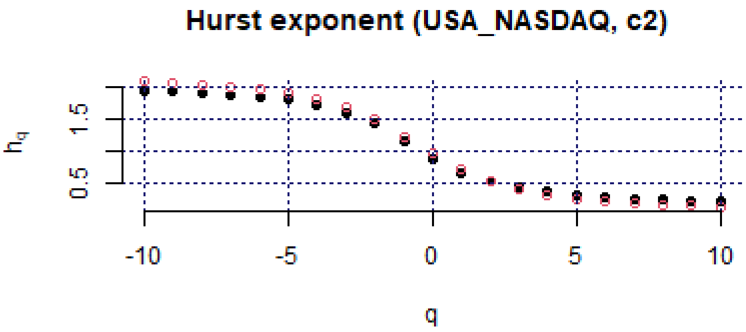

Mass exponent (SGP_SGX, c1)
tau(q)
-40
-20
0
-10
-5
0
5
10
q

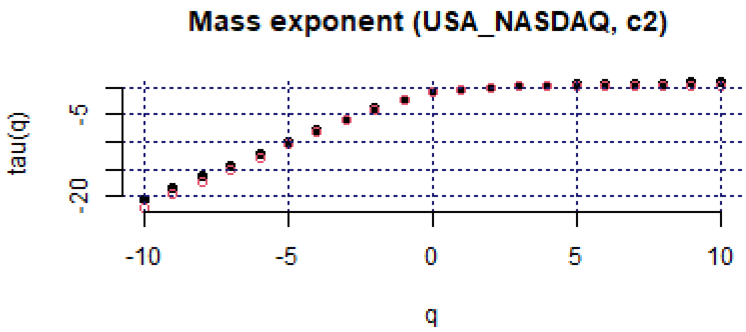

Hurst exponent (SGP_SGX, c2)
h_q
q
-10 -5 0 5 10
0 2 4

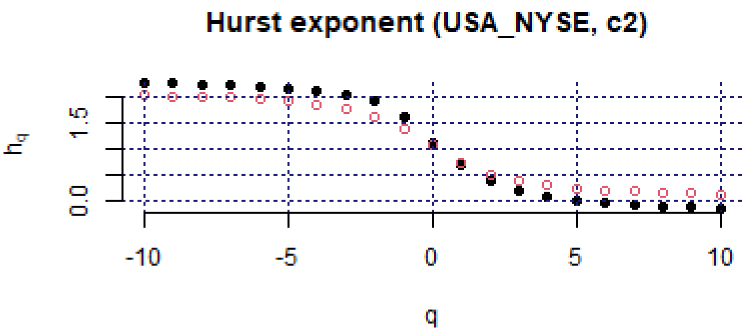

Mass exponent (SGP_SGX, c2)
tau(q)
q
-10 -5 0 5 10
-40 -20 0

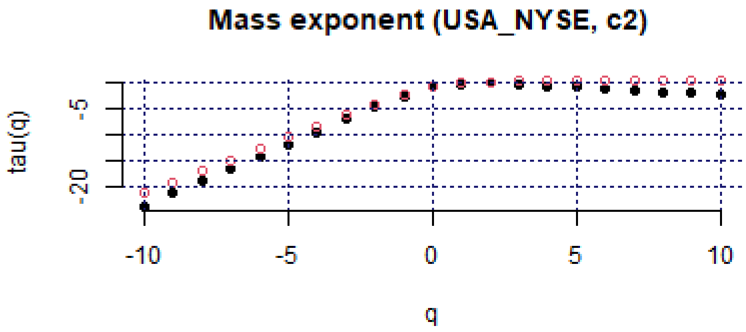

Hurst exponent (THA_SET, c1)
h_q
q
-10 -5 0 5 10
0.0 1.5


Mass exponent (THA_SET, c1)
tau(q)
q
-10 -5 0 5 10
-25 -10

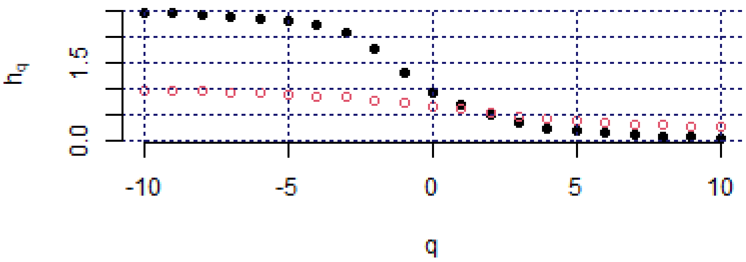

Hurst exponent (USA_NASDAQ, c2)
h_q
0.5
1.5
-10
-5
0
5
10
q


Mass exponent (USA_NASDAQ, c2)
tau(q)
-20
-5
-10
-5
0
5
10
q

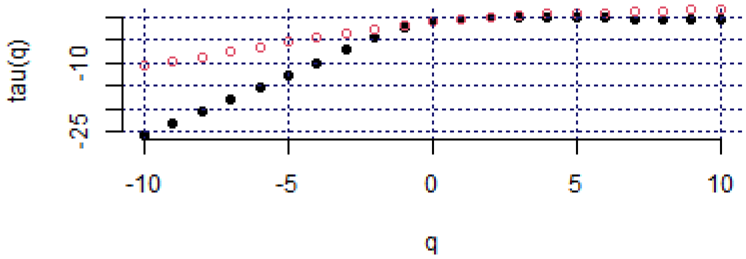

Hurst exponent (USA_NYSE, c2)
h_q
0.0
1.5
-10
-5
0
5
10
q


Mass exponent (USA_NYSE, c2)
tau(q)
-20
-5
-10
-5
0
5
10
q

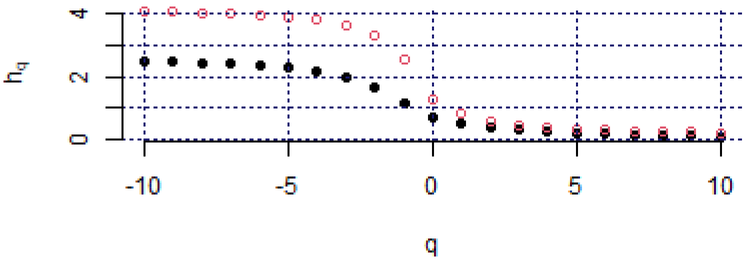
Hurst exponent (ZAF_JALSH, c1)



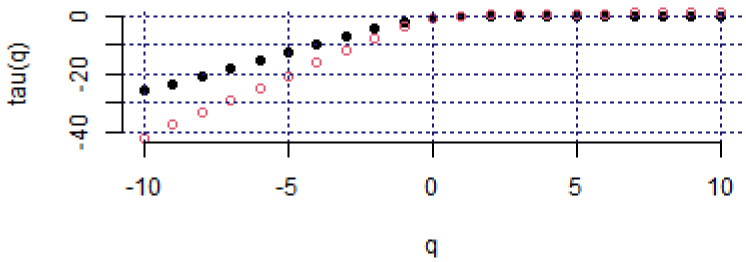
Mass exponent (ZAF_JALSH, c1)



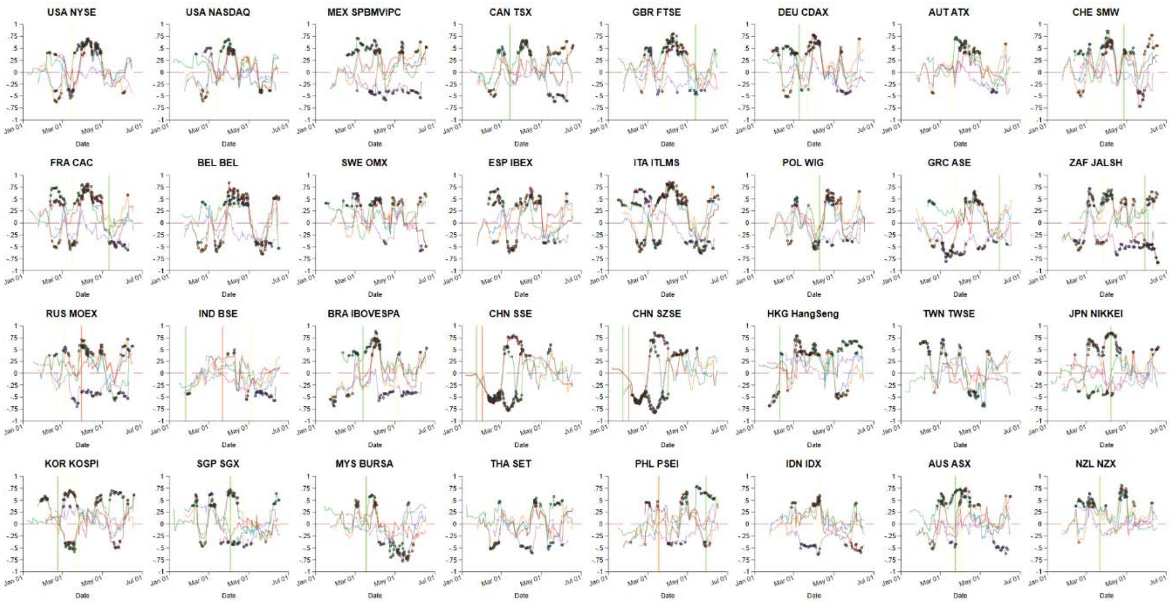
Hurst exponent (ZAF_JALSH, c2)



Mass exponent (ZAF_JALSH, c2)



Section 2: Differenced COVID-19 log variables with log of traded value



Confirmed cases (Δ*log*, global) Confirmed cases (Δ*log*, USA) Mobility change (Residential, Δ%)

Deaths (Δ*log*, global) Deaths (Δ*log*, USA)

Section 3: Differenced log COVID-19 variables and differenced log traded value