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On the Efficiency of Foreign Exchange Markets in times of the COVID-19 Pandemic

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Abstract

We employ multifractal detrended fluctuation analysis (MF-DFA) to provide the first look at the efficiency of forex markets during the initial period of ongoing COVID-19 pandemic, which has disrupted the financial markets globally. We use high frequency (5-min interval) data of six major currencies traded in the forex market for the period from 01 October 2019 to 31 March 2020. Prior to the application of MF-DFA, we examine the inner dynamics of multifractality using seasonal-trend decompositions using loess (STL) method. Overall, the results confirm the presence of multifractality in forex markets, which demonstrates, in particular: (i) a decline in the efficiency of forex markets during the period of COVID-19 outbreak, and (ii) the heterogeneity in the effects on the strength of multifractality of exchange rate returns under investigation. The largest effect is observed in the case of AUD as it shows the highest (lowest) efficiency before (during) COVID-19 assessed in terms of low (high) multifractality. During COVID-19 period, CAD and CHF exhibit the highest efficiency. Our findings may help policymakers in shaping a comprehensive response to improve the forex market efficiency during such a black swan event.

Keywords: COVID-19 pandemic; forex market; MF-DFA; high frequency; efficiency

JEL Classifications: C10; C32; G10; G15

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1. Introduction:

The outbreak of COVID-19 pandemic has jolted the global economy in a very short time span. Many countries around the world have been obligated to impose, among others, travel restrictions, border shutdowns, lockdowns, and social distancing in order to control the epidemic propagation. These measures have severe impacts on supply channels, economic activities, and international trade at all scales. In its April 2020 World Economic Outlook, the International Monetary Fund predicted that the global economy might contract by -3% in 2020.¹ Financial markets are also witnessing a massive disruption with a very aggressive revaluation and adjustment process across the world amid this global pandemic. For instance, on 16 March 2020, the Dow Jones Industrial Average dropped by 12.9%, and the S&P 500 index lost nearly 12% in a single day. It was the worst percentage drop since the infamous "Black Monday" crash of 1987. Stock markets are in turmoil as the pandemic has badly restricted the economic activity due to protection measures and suspension of major events.

It is now well-known that sudden 'large' shocks, such as the global financial crisis of 2008, cause structural changes in both commodity and financial markets, which can then have potential asymmetric effects on market efficiency, portfolio allocation and volatility spillovers (e.g., Rapach and Strauss, 2008; Managi and Okimoto, 2013; Mensi et al., 2015). Since the onset of COVID-19 pandemic, foreign exchange (forex) market, which is, by far, the largest financial market², has also witnessed unprecedented movements, and it is thus subject to a close watch by the global portfolio investors, market regulators, and policymakers. Most of the central banks scrambled to adjust the

¹<https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020>

² Forex market is the largest financial market in terms of average daily trading volumes (with a record of US\$ 6.6 trillion in April 2019, compared to US\$ 5.1 trillion recorded previously in April 2016) and geographical presence. <https://www.bloomberg.com/news/articles/2019-09-16/global-currency-trading-surges-to-6-6-trillion-a-day-market>

monetary frameworks to address the feedback loop between exchange rate movements depreciation and capital outflows in a bid to weather the financial setbacks from the Covid-19 outbreak. The concerns of policymakers stem from the simultaneous decrease in aggregate and foreign demand which could put pressure on the currencies along with the flow of foreign aid across countries from international donor agencies and financial institutions. Then, both corporate and institutional investors are worried about the eventual fall of their portfolio investments and seek possible safe havens for their financial assets as the dollar funding cost in the forex market demonstrated a sharp rise during this turmoil. While the current aggregate volatility levels are atypical, the COVID-19 impact may vary from one currency to another due to their market standing, risk sensitivities, and the nature of policy response the government has been putting in place. For instance, the Australian dollar (AUD) hit a 17-year low of \$0.59215, and the New Zealand dollar hit an 11-year low at \$0.5850 cents. On the other hand, the currencies viewed as safe haven, including Japanese yen (JPY) traded at 107.42 yen per US\$ while the Swiss Franc (CHF) rose to US\$ 0.9598 per CHF.

While investigating the impact COVID-19 on forex markets, a critical aspect that needs to be addressed is the efficiency of the forex market. The extant research shows that the efficiency in the forex market remains difficult to detect (Katusiime et al., 2015), and the market efficiency of exchange rates changes over time, in particular, during the crisis-like situations (Levich et al., 2019). The inefficiency in the forex market generates different puzzling anomalies and delayed overshooting (Li and Miller, 2015). The efficiency of the forex market is estimated by using various approaches like pairwise co-integration test (Layton and Tan, 1992), linear unit root tests (Giannellis and Papadopoulos, 2009), correlation functions (Podobnik et al., 2002), network anal-

ysis (Jeong et al., 2000), and Pedroni's panel co-integration method (Makovský, 2014). The existing mainstream literature on financial markets is mainly based on the fundamental assumption of the normal distribution of stock prices and the random walk hypothesis (RWH) of Bachelier (Bachelier, 1900). However, the econophysics literature rejects the RWH hypothesis. It suggests that the asset prices have different fundamental properties (Mandelbrot, 1967, Mandelbrot, 1971, Mandelbrot, 1997), including fat tail (Gopikrishnan et al., 2001), long-term correlation (Alvarez-Ramirez et al., 2008), volatility clustering (Kim and Eom, 2008), fractals multifractals (He et al., 2007) and chaos (Adrangi et al., 2001). Since then, fractal analysis has widely been applied in the financial market research. By using R/S analysis, (Peters, 1994, Edgar, 1991) proved mono-fractal properties in several financial markets. However, mono-fractals cannot describe height-height correlation function (Barabási and Vicsek, 1991), while Multifractal Detrended Fluctuation Analysis (MF-DFA) can overcome this weakness (Kantelhardt et al., 2002, Alvarez-Ramirez et al., 2008). The strand of finance literature employing MF-DFA method also includes (Podobnik and Stanley, 2008, Wang et al., 2010, Mandelbrot et al., 1997, Kumar and Deo, 2009, Oh et al., 2010).

In the context of forex market efficiency, Ning et al. (2018) investigate the multifractal properties of both GBP and EUR exchange rates from 2015 to 2017 through the MF-DFA method. Their results reveal evidence of significant nonlinear multifractal properties. Han et al. (2019) examine the multifractal properties of four significant exchange rates (EUR, GBP, CAD and JPY) and show that fat-tail distribution and long-range correlation cause their multifractal properties. The recent work by (Shahzad et al., 2018) confirms the higher level of efficiency in JPY, while GBP is the least efficient currency. While it is too early to estimate the exact magnitude of economic and financial impacts of COVID-19 pandemic, this paper provides a first look at the forex

market using a sophisticated MF-DFA approach to understand the patterns of large movements in major currencies and the extent to which the forex market risk evolves due to the pandemic.

This study contributes to the literature in three distinct manners. First, we use five-minute high-frequency data of six major exchange rates (AUD, CAD, CHF, EUR, GBP, and JPY) against the US dollar to draw new and useful information about the impacts of COVID-19 on the forex market efficiency. Second, we employ the seasonal-trend decomposition using loess (STL) to decompose intraday exchange rate returns. The STL method is advantageous in that it enables us to unearth the inner dynamics of asset returns in addition to improved reliability and decomposition of information by removing the seasonal components (Laib et al., 2018a). Third, we use the robust multifractal MF-DFA technique to provide an in-depth comparison of the multifractal behaviour of sample currencies before and during COVID-19 outbreak. The MF-DFA is a generalisation of the DFA approach (Kantelhardt et al., 2002) and allows the estimation of multiple scaling exponents within time series.

Our main findings show evidence of a significant change in the strength of multifractality pointing to a general decline in the efficiency of forex markets exchange rate efficiency during the COVID-19 period as compared to the period before the pandemic. The differences in the degree of efficiency might have their roots in how investors perceived currencies as assets as well as the fundamentals that determined their underlying value. In any case, the price efficiency of any asset is based on the premise that its prices have incorporated all relevant information. Considering various channels through which prices adjust in the forex markets, the difference in the speed of adjustment of prices may reflect overshooting. Dornbush (1976) shows that an unanticipated change in the money supply leads to the exchange rate overshooting because consumer prices cannot move immediately to reflect the money supply change. Building on this analogy, it can be

argued that a temporary disequilibrium in the forex markets may represent the adjustment of prices to a set of information which arrives through a channel relatively faster than other channels.

The emergence of the COVID-19 outbreak received an immediate response from the investors while the policymakers' interventions may take time. The forex markets tend to become inefficient under such volatile conditions. The findings of our study are thus helpful for policymakers and regulators because they can ensure the efficiency of forex markets and the stability of their respective currencies with well-coordinated and gradual responses against this backdrop.

The remainder of the study is organised as follow. Section 2 presents the data and methodology. Section 3 reports and discuss the empirical results. Section 4 provides some concluding remarks.

2. Data and Methodology

2.1. Data description

We use high-frequency data (five-minute intervals) to reveal the inner dynamics of the forex market efficiency under the impacts of COVID-19 pandemic. Due to improved continuity in the distribution function, the high-frequency data more accurately accounts for long memory and structural changes. The high-frequency data sample consists of six major currencies traded in forex markets, including the Australia dollar (AUD), the Canadian dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), and the Japanese Yen (JPY). All prices are quoted in the indirect quotes of US dollars (e.g., amounts of foreign currency per one unit of US dollar). The data from 01 October 2019 to 31 March 2020 is collected from TrueFx and converted into five-minute windows using the 'high-frequency' toolkit in R developed by (Boudt et al., 2020).³

³ The detailed documentation is available at <https://cran.r-project.org/web/packages/highfrequency/highfrequency.pdf>

COVID-19 was first reported by Chinese authorities on 31 December 2019 to the World Health Organization (WHO). Based on this date, the intraday exchange rate data is divided into two periods of 3 months trading each (Zhu et al., 2020). The prices ranging from 1st October 2019 to 31st December 2019 are set as before COVID-19 period, while prices from 1st January 2020 to 31st March 2020 are set as during COVID-19. The intraday five-minute exchange rate fluctuations are presented in Figure 1. We calculate the intraday forex return as in Eq. (1).

$$r_i(t) = \ln p_i(t) - \ln p_i(t - \Delta t) \quad (1)$$

where, $p_i(t)$ denotes the closing price of currency 'i' at time t , Δt is the time interval Δt (five-minutes).

***** Table 1 and Figure 1 about Here*****

Table 1 shows some descriptive statistics of the six exchange rates used in this study. The average five-min returns are nearly zero before COVID-19. However, the returns on AUD, CAD, EUR, and GBP turn negative during the COVID-19 outbreak, while those of JPY and CHF remain positive during this time. The GBP has the highest volatility with a range of 2 basis point to -0.6 basis point before COVID-19. The AUD return series is the most volatile during the COVID-19 outbreak with a range of 1.1 basis points to -1.6 basis points. The skewness values of all exchange rates were positive before COVID-19, but they become negative during the pandemic outbreak for AUD, CAD and GBP. The kurtosis coefficient of all return series is greater than 3, indicating their fat-tailed behaviour. Figure 1 shows the trends of all exchange rates before and during the COVID-19. A consistent movement with small fluctuations can be noticed before COVID-19, while during the first quarter of 2020, relatively large fluctuations in the exchange rate have been observed.

2.2. Methodology

To measure the efficiency of exchange rates, the multifractal detrended fluctuation analysis (MF-DFA) method is applied. Prior to MF-DFA, we employ seasonal-trend decomposition using Loess (STL) method for decomposing time series (Cleveland et al., 1990). As we are using five-minute returns, the STL method helps handle any type of seasonality because it is robust to outliers and flexible enough to allow seasonal component variations over time. In addition to the improved reliability and decomposition through removing the seasonal components, it also reveals the inner dynamics of asset returns (Laib et al., 2018a). From a technical perspective, the STL method breaks each exchange rate return time series into a deterministic trend (T_i), seasonal (S_i) component, and stochastic remainder (R_i) component (Laib et al., 2018b, Miloş et al., 2020), such as:

$$r_i(t) = T_i + S_i + R_i \quad (2)$$

To carry out the STL decomposition, the R package "stats" has been used (Laib et al., 2018a, Shiskin, 1965, Miloş et al., 2020).⁴ For our 24-hour trading data with five-minute frequency, we set the span of the loess window for seasonal extraction equal to 288, which is the number of trading prices in one day. The results of the STL decomposition of intraday exchange rates are shown in Figure 2. For illustration purposes, four graphs for the Australian dollar (AUD) in panel A present the original time series of daily returns (1st row), the seasonal component (2nd row), the trend component (3rd row), and the remainder component (4th row). The presence of a seasonal pattern in the Australian dollar (AUD) can be noticed and in agreement with earlier findings (De Bondt and Thaler, 1987, Miloş et al., 2020). The trend component shows, however, a declining trend after mid-March 2020. As to the remainder component, it does not follow any

⁴ The details of STL are available at <https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/stl>

pattern. The findings of the STL decomposition for other exchange rate returns are reported in Figure 2, panel B to L.

***** Figure 2 about here*****

2.2.1. Multifractal Detrended Fluctuation Analysis (MF-DFA)

Once the STL decompositions are obtained, we apply the MF-DFA technique to compute the multifractality in the time series following a five-step procedure. Formally, let $\{Z_{t,t=1,\dots,N}\}$ be a possible non-stationary time series and 'N' be the length of the series (number of observations). Then, the MF-DFA method can be summarised as follow:

Step 1: Construct the profile $X_{(k)}$ for MF-DFA estimation such as:

$$X_{(k)} = \sum_{t=1}^k (z_t - \bar{z}) \quad (3)$$

where, $k = 1, 2, 3, \dots, N$ and $\bar{z} = \frac{1}{N} \sum_{t=1}^N z_{(t)}$ explains the average of the whole time series.

Step 2: Divide the profile $X_{(k)}$ into $N_s = \lfloor N/s \rfloor$ non-overlapping boxes of same length s . While the length N of the series is usually not a multiple of the considered time scale s , it disregards a short part of the profile $X_{(k)}$ at the end. It is not necessary to disregard this part of the series, and the same procedure will be repeated starting from the opposite side. Thus, $2N_s$ segments are obtained all together. Peng et al. (1994) initiated the process with $10 < s < N_s/5$.

Step 3: Calculate the local trend for each of the $2N_s$ parts by k^{th} order polynomial fit. After that, the variance is given by

$$F^2(s, m) = \frac{1}{s} \sum_{j=1}^s \{X[(m-1)s + j] - x_m(j)\}^2 \quad (4)$$

for the segments between $m = 1$ and $m = N_s$, while for the segments between $m = N_{s+1}$ and $m = 2N_s$ this is given by

$$F^2(s, m) = \frac{1}{s} \sum_{j=1}^s \{X[N - (m - N_s)s + j] - x_m(j)\}^2 \quad (5)$$

Step 4: In Equations (4) and (5), $x_{m(j)}$ represents the polynomial fit of the segments. After averaging, we will obtain the q th-order fluctuation function for any $q \neq 0$ given by

$$F_{q(s)} = \left\{ \frac{1}{2N_s} \sum_{\rho=1}^{2N_s} [F^2(s, m)]^{q/2} \right\}^{1/q} \quad (6)$$

while for $q = 0$ it is equal to

$$F_{0(s)} = \exp \left\{ \frac{1}{4N_s} \sum_{\rho=1}^{2N_s} \ln[F^2(s, m)] \right\} \quad (7)$$

The parameter q allows us to distinguish between segments with large and small fluctuations. Its negative and positive values show small and large fluctuations, respectively. The DFA case is given for $q=2$. Note that $F_{q(s)}$ is the increasing function of s .

Step 5: Compute the relationship between $F_{q(s)}$ and s . The task consists of establishing the scaling exponent of the fluctuation function for any fixed q . If $F_{q(s)}$ is a power law, the time series are in the log-log scale for that particular q .

$$F_{q(s)} \sim S^{h(q)} \quad (8)$$

Through the least-square fit, the slope of $\ln F_q(s)$ is the generalised Hurst exponent $h(q)$ which describes the fractal structure of the time series. An increase in s scale shows how fast $F_q(s)$ of local fluctuations grows. If $h(q)$ is constant at different values of q , then the series is monofractal. Otherwise, the series is said to be multifractal. In the case of multifractal series, $h(q)$ describes the

scaling behaviour of segments with large fluctuations when q is positive, while it depicts the scaling behaviour of segments with small fluctuations when q is negative. Usually, the multifractal series comes with smaller $h(q)$ at positive q values. The range of $h(q)$ indicates the level at which the series is multifractal and can be estimated by $\Delta h = h_{(q_{min})} - h_{(q_{max})}$. Specifically, it is called the multifractal spectrum width that represents the interval between the maximum probability and the minimum probability, and thus measures the degree of the multifractality property. A decline in $h(q)$ value occurs as the q value goes up (Zunino et al., 2008), and a higher value of Δh indicates the presence of higher multifractality in time series (Cajueiro et al., 2009; Anagnostidis et al., 2016). The richer the multifractality, the higher the degree of market inefficiency because of long-range autocorrelation properties and fat-tail characteristics. Since the multifractality is negatively correlated with market efficiency, the higher the width of the multipole spectrum, the lower the degree of market efficiency (Caraianni, 2012; Domino, 2011). The MF-DFA turns into the DFA at $q = 2$. More broadly, the Hurst exponent describes the fractal structure of the time series. When $h(q) = 0.5$, the fluctuation related to q is said to follow a random walk. It is persistent when $h(q) > 0.5$ and anti-persistent when $h(q) < 0.5$.

The estimated $h(q)$ from the MF-DFA can also be presented as a function of Renyi exponent $\tau(q)$ such as:

$$\tau(q) = qh(q) - 1 \quad (9)$$

The singularity strength $h(q)$ and the singularity spectrum $D(q)$ can be calculated via Legendre transform, or be related with $h(q)$ with the following equations:

$$h(q) = \frac{d\tau(q)}{dq} = hq - qh'(q) \quad (10)$$

$$D(q) = qh(q) - \tau(q) = 1 + q[\alpha - h(q)] \quad (11)$$

The multifractal spectrum $D(q)$ describes the fractal dimension of the ensemble formed by all the points that share the same singularity exponent $h(q)$. The width of the multifractal spectrum is the difference between $h(q)_{max}$ and $h(q)_{min}$, representing the maximum and minimum probability, respectively. A higher width of the multipole spectrum potentially indicates a lower level of efficiency in the forex market (Domino, 2011; Caraiani, 2012). Note that for we use the R package "MF-DFA" developed by (Laib et al., 2018a, Laib et al., 2018b) the MF-DFA analysis.⁵ We have used the time scales ranged from 10 to N/5 intraday (5-minute exchange rate) observations.

3. Empirical Results and Discussions

Figure 3 shows the MF-DFA findings for the remainder component of all exchange rates under consideration for 2019 (before COVID-19) and 2020 (during COVID-19) periods. It indicates the fluctuation function $\log_2(F_q(s))$ versus $\log_2(s)$ plot ($q = -10, q = 0, \text{ and } q = 10$), the value of the generalized Hurst exponent $h(q)$ over the range of $q \in [-10, 10]$, Renyi exponent, $\tau(q)$ and the multifractal spectrum f_α .

***** Figure 3 About Here*****

For illustration, Figure 3-A shows the standard MF-DFA findings for remainder components of the AUD for 2019. The top left panel of Figure 3-A shows the fluctuation function $\log_2(F_q)$ versus $\log_2(s)$ plot at $q = -10, q = 0, \text{ and } q = 10$, which is well-shaped and is present as a straight line. We calculate the slope of the generalised Hurst exponents for both the short and long term. The results show the highest value of $h(q)$ of 0.58 at $q = -10$, declined to 0.53 at $q = 0$ and the lowest value of 0.45 at $q = 10$ in 2019. Likewise, in 2020, the highest value of $h(q)$ of 0.71 at

⁵ The detail documentation is available at <https://www.rdocumentation.org/packages/MF-DFA/versions/1.1/topics/MF-DFA>

$q = -10$, declined to 0.49 at $q = 0$ and the lowest value of 0.28 at $q = 10$. This declining trend of the generalised Hurst exponent $h(q)$ confirms its dependence on the value of q , which suggests the existence of multifractality in the time fluctuations of the remainder component for the AUD in 2019. We obtain similar results and patterns for the series of exchange rate returns of the remaining five currencies. Their results are presented in Figure 3, from 3-B to 3-L.

Furthermore, the Hurst component for 2019 ($h(q) = 0.52$) and 2020 ($h(q) = 0.46$) at $q = 2$ scaling component (the setting for stationarity of return series) indicates high persistence in 2019 and low persistence in 2020 in the remaining components. Figure 3-A and Figure 3-B (bottom left) show Renyi exponent, $\tau(q)$, which is nonlinear in case of multifractal series. In the case of AUD for 2019 and 2020, $\tau(q)$ exhibits an exponential shape indicating multifractality in the exchange rate returns. Finally, the multifractal spectrum f_α in Figure 3-A and Figure 3-B (bottom right) show a single-humped shape, confirming the presence of multifractality in the AUD returns series. The results and patterns for the exchange rate returns of other five currencies, displayed in Figure 3 from 3-B to 3-L, are also in line with these results.

Concerning the strength of multifractality, we report the width of the generalised Hurst exponents, Δh , for 2019 (before COVID-19) and 2020 (during COVID-19) over the range of $q \in [-10, 10]$ in Table 2. The strength of multiple spectra in Figure 3 also demonstrates the comparative strength of multifractality across exchange rates before and during COVID-19 pandemic outbreak. The larger the range, the more the multifractality dwells in the series (Kantelhardt et al., 2002). The finding evidences a declining pattern of Hurst exponents $h(q)$ for all six exchange rates we consider in 2019 and 2020, confirming the time fluctuations of multifractality of the remainder components (Laib et al., 2018a).

***** Table 2 about here*****

More concretely, the GBP shows the highest multifractality in 2019 with the highest width of generalised Hurst exponent ($\Delta h = 0.49$), followed by the CAD ($\Delta h = 0.41$), thus indicating the highest level of unevenness in the local fluctuations in the GBP and CAD exchange rate return series. By contrast, AUD and JPY have the lowest degree of multifractality with respective Hurst exponent width of $\Delta h = 0.13$ and $\Delta h = 0.22$, which corresponds to the highest level of evenness in the local fluctuations in the AUD and JPY exchange rate returns. The Euro ($\Delta h = 0.31$) and the CHF ($\Delta h = 0.36$) stay in the middle in terms of multifractality before COVID-19 period. Taken together, among the six intraday exchange rate returns, the GBP and CAD currencies witness the highest multifractal degree, while the AUD and JPY exhibit the lowest multifractal degree before COVID-19.

The COVID-19 resulted in significant movements and affected the strength of intraday multifractality in the first three months of 2020 with the marked changes in the strength of multifractality of currencies. More specifically, during the COVID-19 period, we observe the highest multifractality for the AUD ($\Delta h = 0.42$) followed by the JPY ($\Delta h = 0.40$), while the CAD ($\Delta h = 0.25$) and the CHF ($\Delta h = 0.30$) have the lowest multifractality. The multifractal properties are indicative of the financial markets' efficiency (Anagnostidis et al., 2016). Therefore, based on multifractal properties observed, the AUD, JPY, and EUR showed decrease in their individual efficiency level during the COVID-19 period while the CAD, CHF, and GBP showed an improvement in the degree of their efficiency during the COVID-19 period. The AUD showed the most extreme behaviour among the six selected currencies as it was the most efficient currency before the COVID-19 while it became relatively less efficient during the COVID-19 period.

Similarly, in terms of relative efficiency among the six currencies, the JPY was the second most efficient currency before the COVID-19 period, while during the COVID-19 outbreak it got

badly effected and became one of the inefficient currencies. In overall terms, the increase in multifractality confirms that COVID-19 has adversely impacted the efficiency of the forex market as the market touches a new level of inefficiency during the COVID-19 outbreak. Our findings are broadly in line with (Shahzad et al., 2018).

It is worth noting that the persistence of the return series is an important determinant of multifractality. In 2019, the classical Hurst exponent ($q = 2$) shows a persistent behaviour (positive autocorrelation) for the JPY ($h(q) = 0.54$), the AUD ($h(q) = 0.52$) and the GBP ($h(q) = 0.50$), which means that positive (negative) values in the previous period would be most probably chased by positive (negative) values in the subsequent period. The remaining three currencies, including CAD ($h(q)=0.48$), CHF ($h(q)=0.47$) and EUR ($h(q)=0.46$), exhibit anti-persistent behaviour with an observed negative autocorrelation. This evidence implies that any change (positive/negative) in previous time periods would probably be followed by an opposite (negative/positive) change in subsequent times.

The influence of the COVID-19 can be noticed in the persistence behaviour of forex markets. During the COVID-19 period, three out of six currencies analysed have changed the pattern of their persistence. In 2020, the pattern of CHF ($h(q) = 0.52$) and EUR ($h(q) = 0.51$) shifted from anti-persistent to persistent behaviour. The value of the Hurst exponent ($q = 2$) for the AUD declined from ($h(q) = 0.52$) in 2019 to ($h(q) = 0.49$) in 2020. We observe no change in the persistence levels for the GBP and the JPY before and during COVID-19 outbreak period. Similarly, the CAD was found to be anti-persistent before and during the COVID-19 outbreak period. Overall, there is an increase in the persistence level among these exchange rates.

The AUD and JPY currencies have shown the most peculiar behaviour during the COVID-19 pandemic. In relative terms, both the currencies demonstrated a high degree of inefficiency

during the COVID-19 period as opposed to an increase in the degree of efficiency before the COVID-19 period in our sample. On the other hand, the CAD was at the lowest end in efficiency terms before COVID-19 period, while it demonstrated the highest degree of efficiency during the COVID-19 period. These differences might have their roots in how these currencies as financial assets are perceived by investors as well as in the fundamentals that determine their underlying value. The AUD is known as a commodity currency because it is sensitive to fluctuations of commodity prices (Lodewijks and Mmnademi, 2017). There is also evidence that it is highly correlated with Chinese economic conditions because of raw material exports to Chinese industries.⁶ With the economic slowdown in the Chinese economy, the demand for the AUD currency decreased. Moreover, as the COVID-19 cases rose in China and other countries, the AUD depreciated against the USD in the forex market. The decrease in interest rates decided by Reserve Bank of Australia due to lower inflation expectations will prompt investors to shift to markets offering higher returns.

The recovery in the AUD value relative to the USD towards the end of March 2020 represents the risk appetite of investors.⁷ The results of our analysis show that the AUD became more inefficient after the COVID-19 outbreak, which suggests profitable investment opportunities. In the meanwhile, the JPY currency, which generally is considered a safe haven, lost its value amid rising COVID cases in neighbouring China.⁸ For its part, the CAD depreciated against the USD due to COVID-19 outbreak fears and the Canadian central bank left room for interest rate cuts if

⁶ <https://www.dailyfx.com/forex/fundamental/forecast/weekly/aud/2020/03/07/Australian-Dollar-at-Mercy-of-COVID-19-as-Chinas-Economy-Slows.html>

⁷ <https://www.thestar.com.my/business/business-news/2020/04/08/dollar-drops-aussie-sterling-gain-as-risk-appetite-increases>

⁸ <https://www.fxstreet.com/news/usd-jpy-the-japanese-yen-losing-its-safe-haven-status-rabobank-202002201011>

required⁹. We cautiously explain it as an outcome of the central bank's timely intervention to provide room for economic recovery and stability that, in turn, boosted the investor confidence in the Canadian economy and its currency. Thus, we see a lower volatility in CAD/USD from before to during COVID-19 period.

In a nutshell, the varying impacts of COVID-19 on the multifractality and efficiency of the forex markets under consideration can be explained by the structure of these markets and the behaviour of traders during the COVID-19 pandemic. A significant portion of international news headlines evoked uncertainty, negative sentiments and emotions of fear and sadness (Aslam et al., 2020a). In such a turbulent environment, investors tend to shy from trading activity to avoid financial losses, which adversely affects the financial markets (Mukerji and Tallon, 2001, Levy and Galili, 2006). The COVID-19 is not only affecting the trading behaviour but also the multifractal behaviour of financial markets with considerable uncertainty (Aslam et al., 2020b) and complex issues associated with a low degree of information determinacy. These factors potentially explain the differences regarding the overall effects of COVID-19 on the forex market efficiency, along with heterogeneous expectations of investors and traders about the fundamentals underlying a currency as well as strong trade ties with a severely affected country such as the case of the AUD and reversal of safe haven perception as in the case of the JPY.

The efficiency in the forex markets also depends on the policy response from governments on both fiscal and monetary sides that are subject to several factors linked to prevailing economic and political environment, among others. For example, an unanticipated change in the money supply may lead to exchange rate overshooting as the consumer prices cannot move immediately to reflect the money supply change (Dornbush, 1976). Building on this analogy, it can be argued that

⁹ <https://www.theglobeandmail.com/investing/markets/inside-the-market/market-news/article-canadian-dollar-falls-ahead-of-polo-z-speech-as-coronavirus-worries/>

a temporary disequilibrium in the forex markets may represent the adjustment of prices to a set of information which arrives through a channel relatively faster than other channels. The COVID-19 pandemic crisis emerging from China received a quick response from the investors while the adjustments made by policymakers may take time due to rather measured interventions like recent deployment of central bank dollar swap lines.

4. Conclusion, policy implications and future research

This paper provides a first look at the forex market efficiency amid the COVID-19 pandemic as the associated economic and social costs of this outbreak have concerned the society, policymakers, market operators, and individual investors. For this purpose, we conducted a comparative analysis of the efficiency level of six major currencies traded in the forex markets, including AUD, CAD, CHF, EUR, GBP and the JPY. Our study is thus vital as it provides an insightful analysis of fractals in the six major international forex markets. The intraday data of five-minute frequency from 01 October 2019 to 31 March 2020 is divided into before and during the COVID-19 periods with a 3-month trading window each. The robust MF-DFA and STL methods are employed to capture the presence of multifractality in the sample exchange rates. These methods provide insight into the long-range dependence of these exchange rates in terms of their multifractal structures.

Market efficiency is pivotal in both resource allocation and capital formation, which leads to economic development and stability (Rizvi and Arshad, 2016). The findings of this study show varying degree of forex markets efficiency before and during the COVID-19 outbreak. Investors in the forex market can structure their investment and risk management strategies to exploit market inefficiencies (Dragotă and Țilică, 2014). In this scheme of things, the estimated Hurst coefficient $h(q)$ provides an insight into dynamics and trending characteristic of forex markets which are useful for investors in aligning their strategies according to the market conditions. During the COVID-

19, both AUD and CAD exchange rates exhibit anti-persistent behaviour ($0 < H < 0.5$), suggesting mean-reverting characteristics in the two currencies. Thus, it implies that a higher value of a financial asset in the prior periods of a time series may decline in the subsequent periods according to a mean-reversion process. For the remaining four currencies, a high value of H exponent ($0.5 < H < 1$) is indicative of long memory in the time series, where the future value of a series depends partially on its values in prior periods.

In non-technical terms, this evidence suggests that the markets for the sample currencies are not efficient, both before and during the Covid-19 pandemic. The AUD and JPY demonstrate the highest degree of efficiency before the COVID-19, whereas the CAD and CHF currencies demonstrate such trends during the COVID-19. While only three out of six major currencies (CAD, CHF, and GBP) experienced an improvement in the efficiency level during the COVID-19, most currency returns generally tend to be more persistent.

Since the COVID-19 pandemic is an ongoing crisis, we believe that no single policy response can be considered successful in the short term. The extant literature suggests minimum intervention in forex markets, while effective management of internal risks in the forex markets (Han et al., 2020), and financial liberalisation (Kawakatsu and Morey, 1999) improve market efficiency. The changes in the level of market efficiency in the considered forex markets may be driven by the investors' herd behaviour emanating from the crisis and sentiment of fear prevailing in the market regarding the underlying fundamentals of the economy. Such behaviour may lead to higher autocorrelations and hence a decrease in the level of market efficiency. Policymakers may potentially address such behavioural anomalies by ensuring stability in the underlying macroeconomic fundamentals. For market participants, it is suggested to reassess the investment and risk management framework to

mitigate the new and somewhat higher level of risk to which their positions are exposed during the tumultuous outbreak of the COVID-19.

While we acknowledge that the findings of this study should be viewed with caution given the sample period under analysis, it does pave the way for the future research focusing on the effects of the COVID-19 outbreak on the forex markets in both the short and long run, the effectiveness of policy responses in maintaining their stability, and volatility transmissions using larger sample and window of analysis. It is expected that the changes in investors behaviour across two-time horizons will potentially result in the transformation of market linkages and correlations. Thus, the fractals models can further be used to explore the fractal contagion effects caused by the COVID-19 pandemic. Moreover, investigating the primary source of the increase in this multifractality to understand the psychological aspects of investment behaviours may potentially be an interesting direction for future research.

References

- ADRANGI, B., CHATRATH, A., DHANDA, K. K. & RAFFIEE, K. 2001. Chaos in oil prices? Evidence from futures markets. *Energy Economics*, 23, 405-425.
- ALVAREZ-RAMIREZ, J., ALVAREZ, J. & RODRIGUEZ, E. 2008. Short-term predictability of crude oil markets: a detrended fluctuation analysis approach. *Energy Economics*, 30, 2645-2656.
- ANAGNOSTIDIS, P., VARSAKELIS, C. & EMMANOUILIDES, C. J. 2016. Has the 2008 financial crisis affected stock market efficiency? The case of Eurozone. *Physica A: Statistical Mechanics and its Applications*, 447, 116-128.
- ASLAM, F., AWAN, T. M., SYED, J. H., KASHIF, A. & PARVEEN, M. 2020a. Sentiments and Emotions Evoked by News Headlines of Coronavirus Disease (COVID-19) Outbreak. *Humanities and Social Sciences Communications*, 7, 1-9.
- ASLAM, F., MOHTI, W. & FERREIRA, P. 2020b. Evidence of Intraday Multifractality in European Stock Markets during the recent Coronavirus (COVID-19) Outbreak. *International Journal of Financial Studies*, 8, 31.
- BACHLIER, L. 1900. Theory of speculation in the random character of stock market prices. MIT, Cambridge, MA.
- BARABÁSI, A.-L. & VICSEK, T. 1991. Multifractality of self-affine fractals. *Physical Review A*, 44, 2730.
- BOUDT, K., CORNELISSEN, J., PAYSEUR, S., NGUYEN, G., SCHERMER, M. & BOUDT, M. K. 2020. Package ‘highfrequency’.
- CAJUEIRO, D. O., GOGAS, P. & TABAK, B. M. 2009. Does financial market liberalization increase the degree of market efficiency? The case of the Athens stock exchange. *International Review of Financial Analysis*, 18, 50-57.
- CARAIANI, P. 2012. Evidence of multifractality from emerging European stock markets. *PloS one*, 7.
- CLEVELAND, R. B., CLEVELAND, W. S., MCRAE, J. E. & TERPENNING, I. 1990. STL: A seasonal-trend decomposition. *Journal of official statistics*, 6, 3-73.
- DE BONDT, W. F. & THALER, R. H. 1987. Further evidence on investor overreaction and stock market seasonality. *The Journal of finance*, 42, 557-581.
- DOMINO, K. 2011. The use of the Hurst exponent to predict changes in trends on the Warsaw Stock Exchange. *Physica A: Statistical Mechanics and its Applications*, 390, 98-109.
- DRAGOTĂ, V. & ȚILICĂ, E. V. 2014. Market efficiency of the Post Communist East European stock markets. *Central European Journal of Operations Research*, 22, 307-337.
- EDGAR, P. E. 1991. Chaos and Order in the Capital Markets, A New View of Cycles, Prices and Market Volatility. John Wiley Sons, Inc., New York.
- GIANNELLIS, N. & PAPADOPOULOS, A. P. 2009. Testing for efficiency in selected developing foreign exchange markets: An equilibrium-based approach. *Economic Modelling*, 26, 155-166.
- GOPIKRISHNAN, P., PLEROU, V., GABAIX, X., AMARAL, L. & STANLEY, H. 2001. Price fluctuations and market activity. *Physica A: Statistical Mechanics and its Applications*, 299, 137-143.
- HAN, C., WANG, Y. & NING, Y. 2019. Comparative analysis of the multifractality and efficiency of exchange markets: evidence from exchange rates dynamics of major world currencies. *Physica A: Statistical Mechanics and its Applications*, 535, 122365.
- HAN, C., WANG, Y. & XU, Y. 2020. Nonlinearity and efficiency dynamics of foreign exchange markets: evidence from multifractality and volatility of major exchange rates. *Economic Research-Ekonomska Istraživanja*, 33, 731-751.
- HE, L.-Y., FAN, Y. & WEI, Y.-M. 2007. The empirical analysis for fractal features and long-run memory mechanism in petroleum pricing systems. *International Journal of Global Energy Issues*, 27, 492-502.
- JEONG, H., TOMBOR, B., ALBERT, R., OLTVAI, Z. N. & BARABÁSI, A.-L. 2000. The large-scale organization of metabolic networks. *Nature*, 407, 651-654.

- 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, 87-114.
- KATUSIIME, L., SHAMSUDDIN, A. & AGBOLA, F. W. 2015. Foreign exchange market efficiency and profitability of trading rules: Evidence from a developing country. *International Review of Economics & Finance*, 35, 315-332.
- KAWAKATSU, H. & MOREY, M. R. 1999. Financial liberalization and stock market efficiency: an empirical examination of nine emerging market countries. *Journal of Multinational Financial Management*, 9, 353-371.
- KIM, S. & EOM, C. 2008. Long-term memory and volatility clustering in high-frequency price changes. *Physica A: Statistical Mechanics and its Applications*, 387, 1247-1254.
- KUMAR, S. & DEO, N. 2009. Multifractal properties of the Indian financial market. *Physica A: Statistical Mechanics and its Applications*, 388, 1593-1602.
- LAIB, M., GOLAY, J., TELESKA, L. & KANEVSKI, M. 2018a. Multifractal analysis of the time series of daily means of wind speed in complex regions. *Chaos, Solitons & Fractals*, 109, 118-127.
- LAIB, M., TELESKA, L. & KANEVSKI, M. 2018b. Long-range fluctuations and multifractality in connectivity density time series of a wind speed monitoring network. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 28, 033108.
- LAYTON, A. P. & TAN, A. 1992. Multivariate cointegration testing of the efficiency of Australia's spot forex market. *Accounting & Finance*, 32, 63-70.
- LEVICH, R., CONLON, T. & POTÌ, V. 2019. Measuring excess-predictability of asset returns and market efficiency over time. *Economics Letters*, 175, 92-96.
- LEVY, O. & GALILI, I. 2006. Terror and trade of individual investors. *The Journal of Socio-Economics*, 35, 980-991.
- LI, J. & MILLER, N. C. 2015. Foreign exchange market inefficiency and exchange rate anomalies. *Journal of International Financial Markets, Institutions and Money*, 34, 311-320.
- LODEWIJKS, J. & MMNADEMI, M. S. 2017. Global Economy and the Australian Dollar. *Expert Journal of Economics*, 5.
- MAKOVSKÝ, P. 2014. Modern approaches to efficient market hypothesis of FOREX—the central European case. *Procedia Economics and Finance*, 14, 397-406.
- MANDELBROT, B. 1967. The variation of some other speculative prices. *The Journal of Business*, 40, 393-413.
- MANDELBROT, B. B. 1971. When can price be arbitrated efficiently? A limit to the validity of the random walk and martingale models. *The Review of Economics and Statistics*, 225-236.
- MANDELBROT, B. B. 1997. The variation of the prices of cotton, wheat, and railroad stocks, and of some financial rates. *Fractals and scaling in finance*. Springer.
- MANDELBROT, B. B., FISHER, A. J. & CALVET, L. E. 1997. A multifractal model of asset returns.
- MILOȘ, L. R., HAȚIEGAN, C., MILOȘ, M. C., BARNA, F. M. & BOȚOC, C. 2020. Multifractal Detrended Fluctuation Analysis (MF-DFA) of Stock Market Indexes. Empirical Evidence from Seven Central and Eastern European Markets. *Sustainability*, 12, 535.
- MUKERJI, S. & TALLON, J.-M. 2001. Ambiguity aversion and incompleteness of financial markets. *The Review of Economic Studies*, 68, 883-904.
- NING, Y., HAN, C. & WANG, Y. 2018. The multifractal properties of Euro and Pound exchange rates and comparisons. *Physica A: Statistical Mechanics and its Applications*, 509, 578-587.
- OH, G., KIM, S. & EOM, C. 2010. Multifractal Analysis of Korean Stock Market. *Journal of the Korean Physical Society*, 56, 982-985.
- PENG, C.-K., BULDYREV, S. V., HAVLIN, S., SIMONS, M., STANLEY, H. E. & GOLDBERGER, A. L. 1994. Mosaic organization of DNA nucleotides. *Physical review e*, 49, 1685.
- PETERS, E. E. 1994. *Fractal market analysis: applying chaos theory to investment and economics*, John Wiley & Sons.

- PODOBNIK, B., GROSSE, I. & STANLEY, H. E. 2002. Stochastic processes with power-law stability and a crossover in power-law correlations. *Physica A: Statistical Mechanics and its Applications*, 316, 153-159.
- PODOBNIK, B. & STANLEY, H. E. 2008. Detrended cross-correlation analysis: a new method for analyzing two nonstationary time series. *Physical review letters*, 100, 084102.
- RIZVI, S. A. R. & ARSHAD, S. 2016. How does crisis affect efficiency? An empirical study of East Asian markets. *Borsa Istanbul Review*, 16, 1-8.
- SHAHZAD, S. J. H., HERNANDEZ, J. A., HANIF, W. & KAYANI, G. M. 2018. Intraday return inefficiency and long memory in the volatilities of forex markets and the role of trading volume. *Physica A: Statistical Mechanics and its Applications*, 506, 433-450.
- SHISKIN, J. 1965. *The X-11 variant of the census method II seasonal adjustment program*, US Government Printing Office.
- WANG, Y., WEI, Y. & WU, C. 2010. Cross-correlations between Chinese A-share and B-share markets. *Physica A: Statistical Mechanics and its Applications*, 389, 5468-5478.
- ZHU, N., ZHANG, D., WANG, W., LI, X., YANG, B., SONG, J., ZHAO, X., HUANG, B., SHI, W. & LU, R. 2020. A novel coronavirus from patients with pneumonia in China, 2019. *New England Journal of Medicine*.
- ZUNINO, L., TABAK, B. M., FIGLIOLA, A., PÉREZ, D., GARAVAGLIA, M. & ROSSO, O. 2008. A multifractal approach for stock market inefficiency. *Physica A: Statistical Mechanics and its Applications*, 387, 6558-6566.

Table 1. List of Exchange rates with corresponding summary statistics (5-minute interval)

Currency	Australian dollar-AUD	Canadian dollar-CAD	Swiss Franc-CHF	Euro-EUR	British Pound-GBP	Japanese Yen-JPY
Summary Statistics of Exchange rate returns						
2019* (Before COVID-19)						
Mean	0.000002	0.000001	0.000002	0.000002	0.000004	0.000000
Std. Dev.	0.000229	0.000164	0.000197	0.000172	0.000379	0.000175
Minimum	-0.003934	-0.004323	-0.003187	-0.003072	-0.006215	-0.002948
Maximum	0.003485	0.005343	0.003490	0.003598	0.020735	0.004551
Skewness	0.408098	0.818122	0.429145	0.792372	9.226872	0.360279
Kurtosis	22.960322	114.113335	26.032817	37.991999	501.914380	53.750461
Observations	18950	18950	18950	18950	18950	18950
2020** (During COVID-19)						
Mean	-0.000007	-0.000004	0.000000	-0.000001	-0.000003	0.000001
Variance	0.000720	0.000399	0.000399	0.000393	0.000535	0.000476
Minimum	-0.016646	-0.015399	-0.004651	-0.004142	-0.009830	-0.005915
Maximum	0.011148	0.004472	0.012390	0.007217	0.009860	0.014995
Skewness	-1.367940	-3.624304	1.678191	0.821631	-0.600611	3.188010
Kurtosis	61.144564	143.700572	65.516308	25.499180	35.421532	96.912052
Observations	18362	18362	18362	18362	18362	18362

* 2019 (01-Oct-2019 to 31-Dec-2019)

** 2020 (01-Jan-2020 to 31-Mar-2020)

Table 2. Generalised Hurst exponents for six exchange rates for 2019 and 2020 and their range over $q \in [-10, 10]$.

Order q	AUD-19	CAD-19	CHF-19	EUR-19	GBP-19	JPY-19	AUD-20	CAD-20	CHF-20	EUR-20	GBP-20	JPY-20
-10	0.5825	0.6915	0.6586	0.6410	0.7076	0.6315	0.7065	0.5907	0.6988	0.7164	0.7854	0.7405
-8	0.5695	0.6748	0.6424	0.6238	0.6930	0.6173	0.6921	0.5752	0.6814	0.6990	0.7707	0.7243
-6	0.5542	0.6531	0.6214	0.6012	0.6739	0.5998	0.6732	0.5546	0.6580	0.6743	0.7506	0.7016
-4	0.5397	0.6259	0.5949	0.5724	0.6496	0.5814	0.6493	0.5290	0.6279	0.6397	0.7226	0.6705
-2	0.5311	0.5922	0.5631	0.5387	0.6209	0.5697	0.6183	0.5036	0.5935	0.5976	0.6829	0.6308
0	0.5280	0.5456	0.5243	0.5014	0.5817	0.5632	0.5696	0.4816	0.5577	0.5564	0.6298	0.5825
2	0.5205	0.4787	0.4742	0.4606	0.5032	0.5382	0.4903	0.4541	0.5201	0.5173	0.5676	0.5229
4	0.5025	0.4003	0.4156	0.4182	0.3819	0.4968	0.4026	0.4161	0.4808	0.4793	0.5078	0.4538
6	0.4810	0.3407	0.3632	0.3808	0.2972	0.4589	0.3423	0.3819	0.4462	0.4469	0.4631	0.3972
8	0.4627	0.3035	0.3252	0.3527	0.2492	0.4313	0.3056	0.3570	0.4205	0.4226	0.4331	0.3603
10	0.4485	0.2796	0.2991	0.3325	0.2200	0.4118	0.2821	0.3392	0.4021	0.4048	0.4127	0.3363
Δh	0.1340	0.4119	0.3595	0.3085	0.4876	0.2197	0.4244	0.2515	0.2967	0.3116	0.3727	0.4042

Figure 1-A). AUD

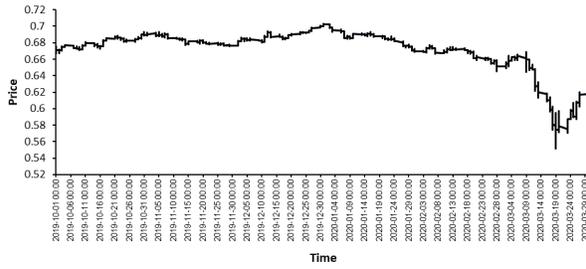


Figure 1-B). CAD

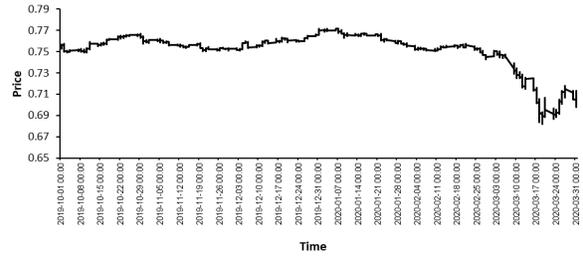


Figure 1-C). CHF

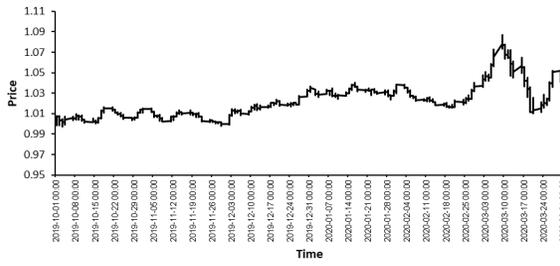


Figure 1-D). EUR

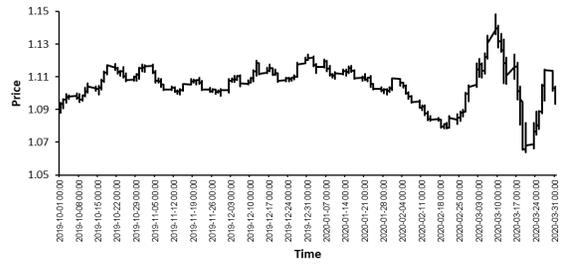


Figure 1-E). GBP

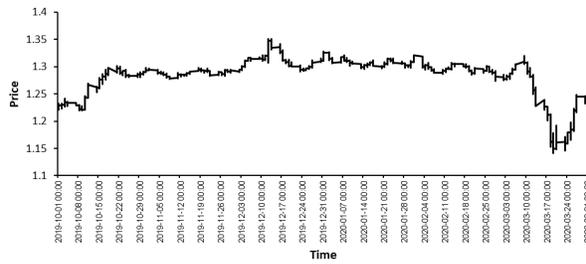


Figure 1-F). JPY

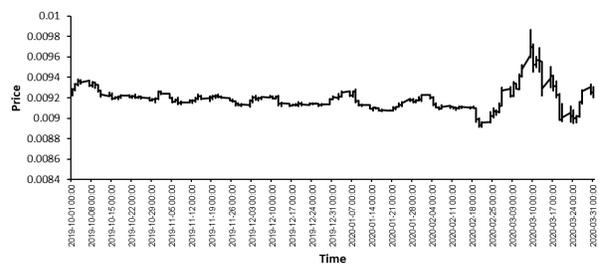


Figure 1: Time trend of five-minute currency rates from 01-Oct-2019 to 31-Mar-2020

Figure 2-A). STL decomposition AUD-2019

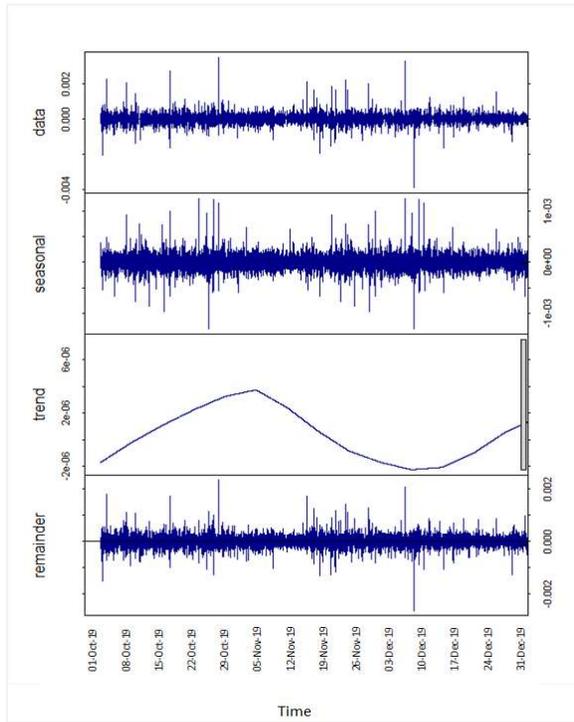


Figure 2-B). STL decomposition AUD-2020

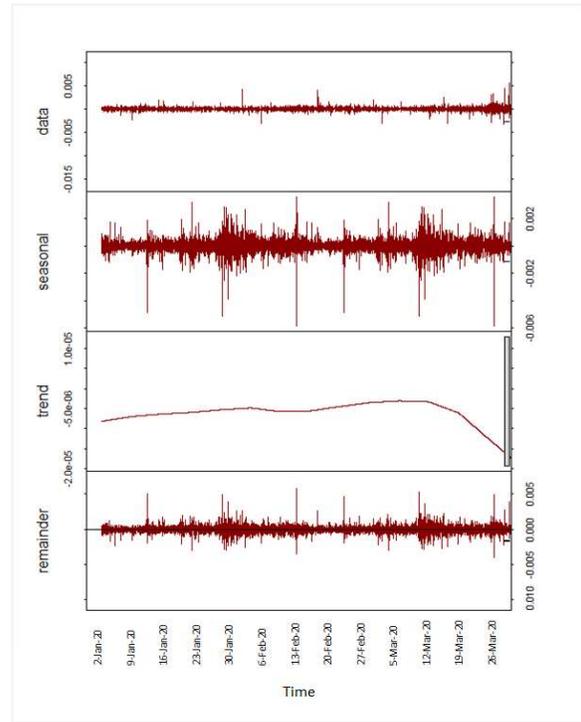


Figure 2-C). STL decomposition CAD-2019

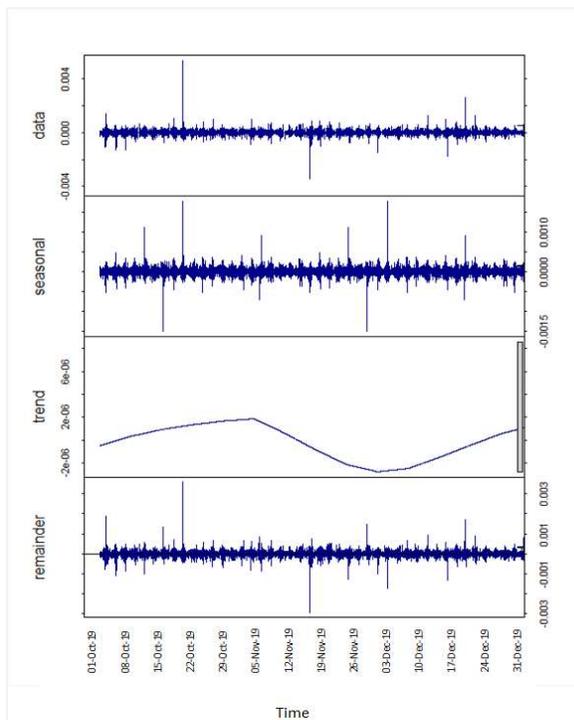


Figure 2-D). STL decomposition CAD-2020

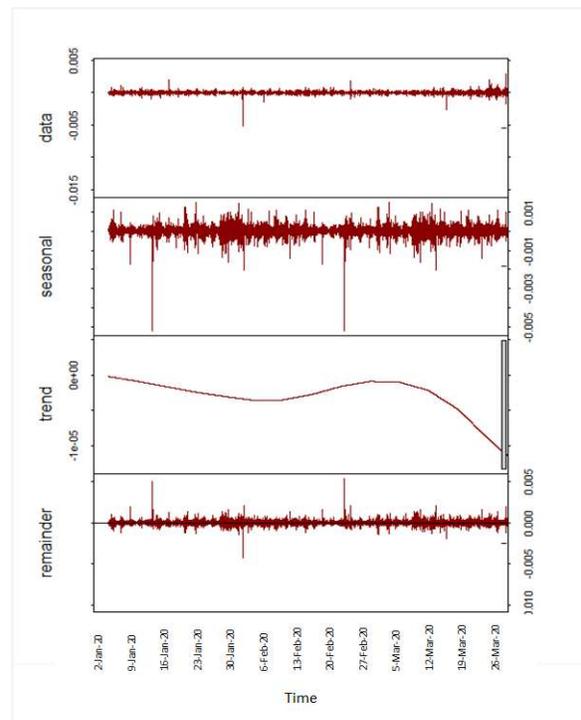


Figure 2-E). STL decomposition CHF-2019

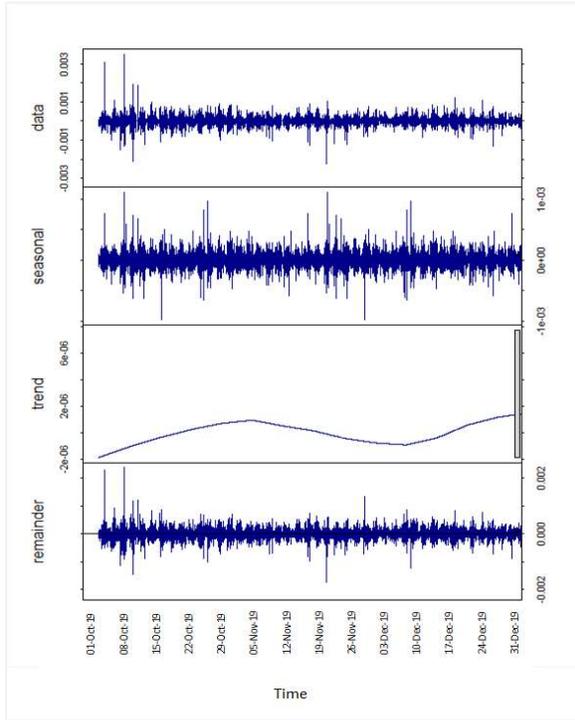


Figure 2-F). STL decomposition CHF-2020

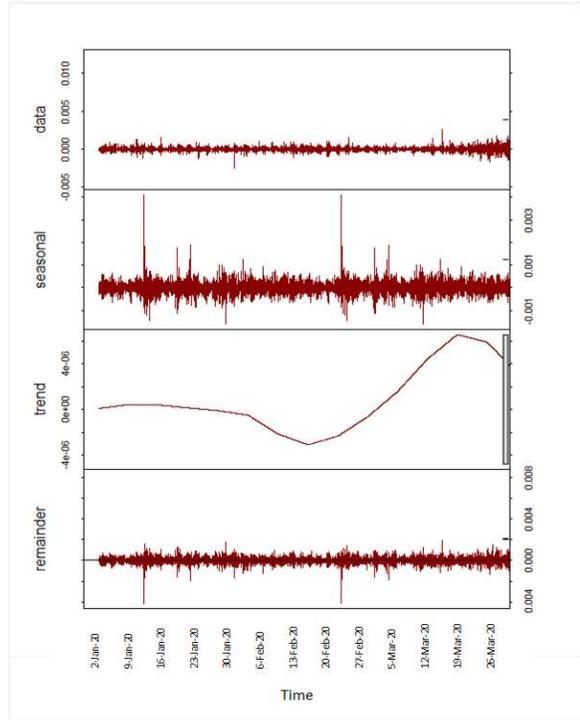


Figure 2-G). STL decomposition EUR-2019

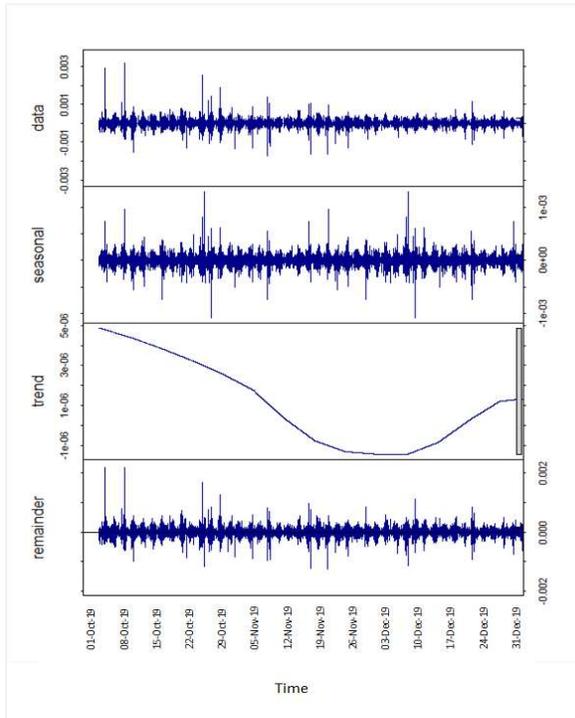


Figure 2-H). STL decomposition EUR-2020

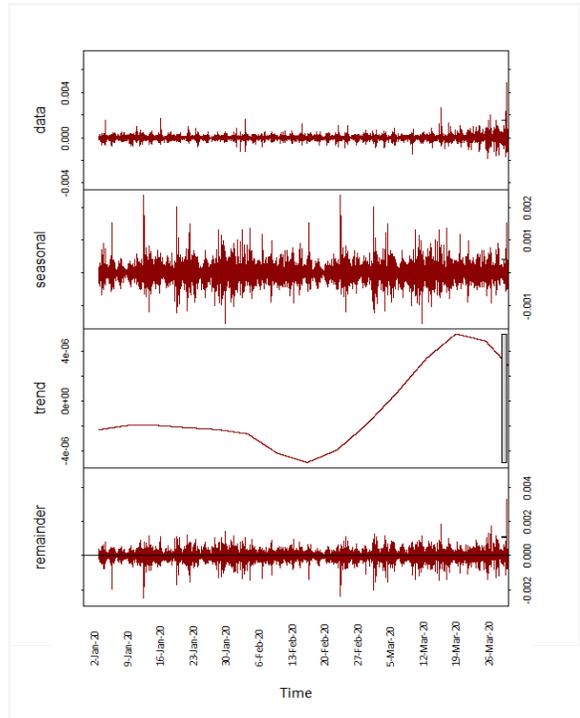


Figure 2-I). STL decomposition GBP-2019

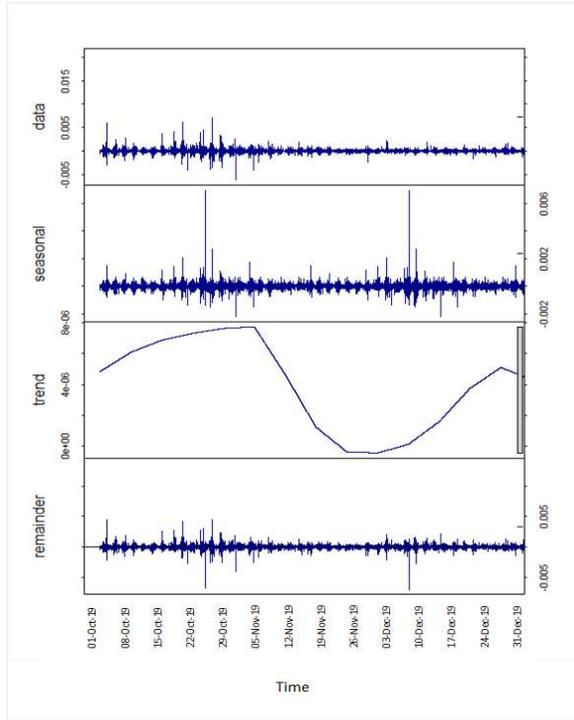


Figure 2-J). STL decomposition GBP-2020

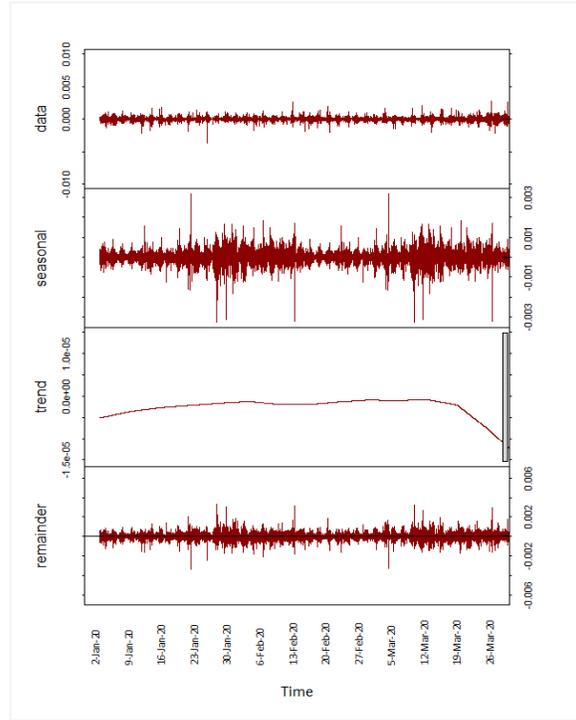


Figure 2-K). STL decomposition JPY-2019

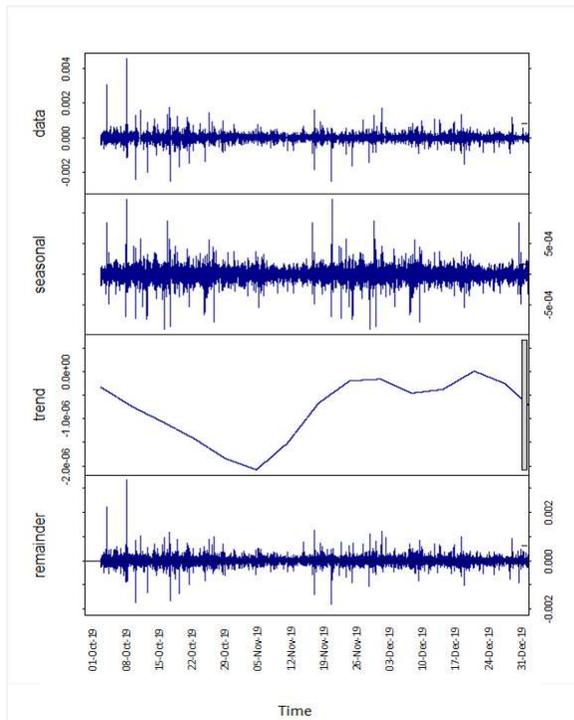


Figure 2-L). STL decomposition JPY-2020

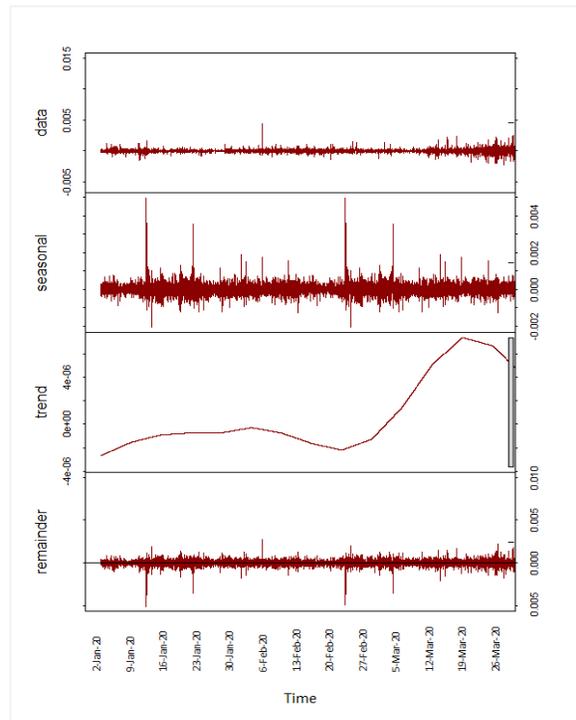


Figure 2: STL decomposition of Intraday (five-minute) exchange rate returns for 2019 (blue) and 2020 (red). (1st row) Original five-minute time series (2nd row) seasonal component (3rd row) trend component (4th row) remainder.

Figure 3-A). MF-DFA AUD-2019

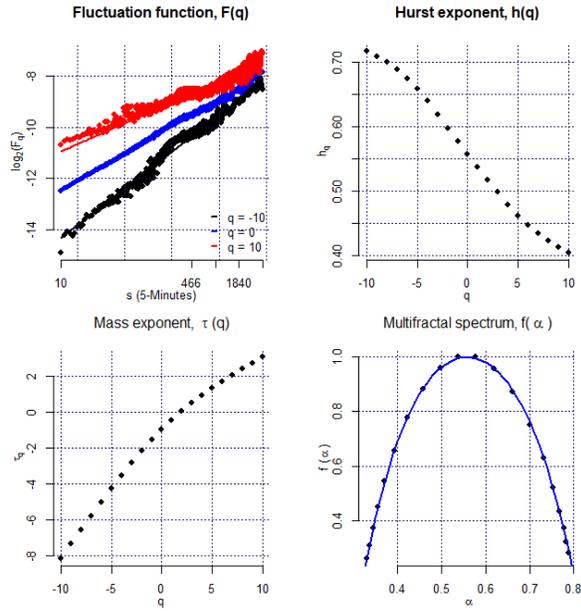


Figure 3-B). MF-DFA AUD-2020

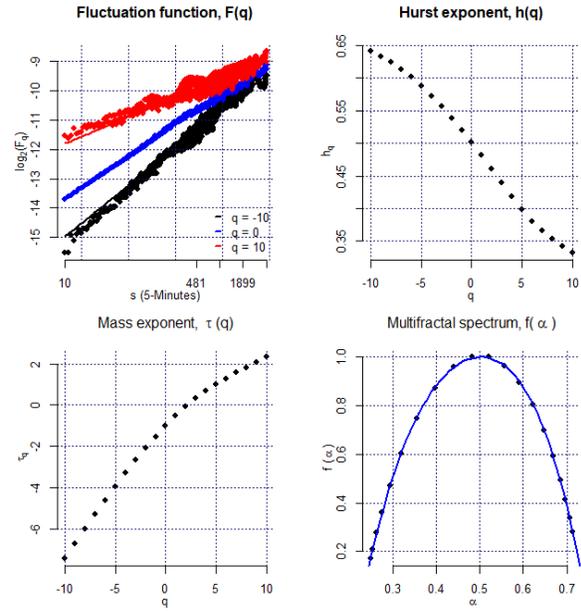


Figure 3-C). MF-DFA CAD-2019

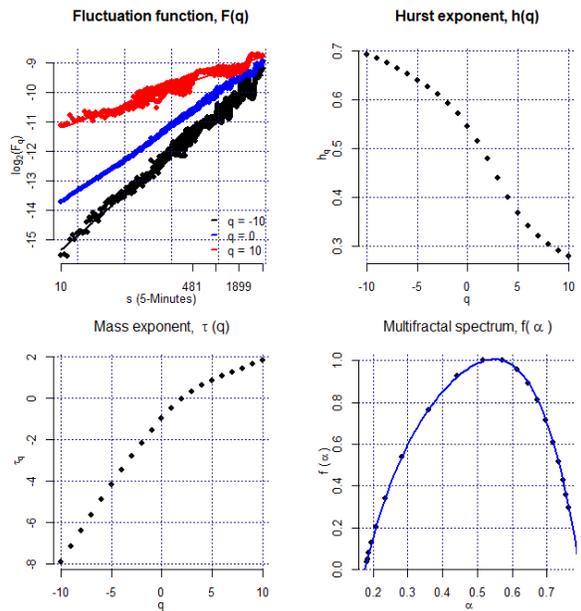


Figure 3-D). MF-DFA CAD-2020

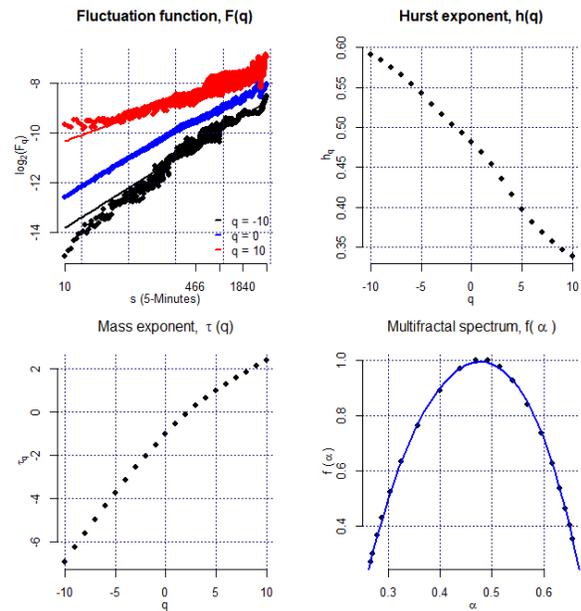


Figure 3-E). MF-DFA CHF-2019

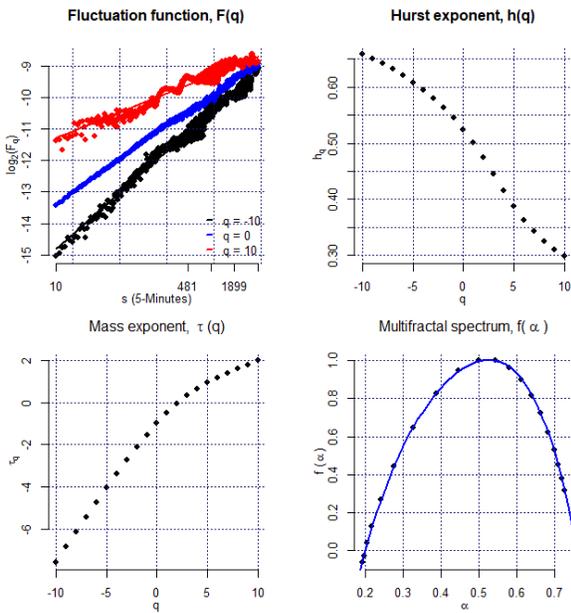


Figure 3-F). MF-DFA CHF-2020

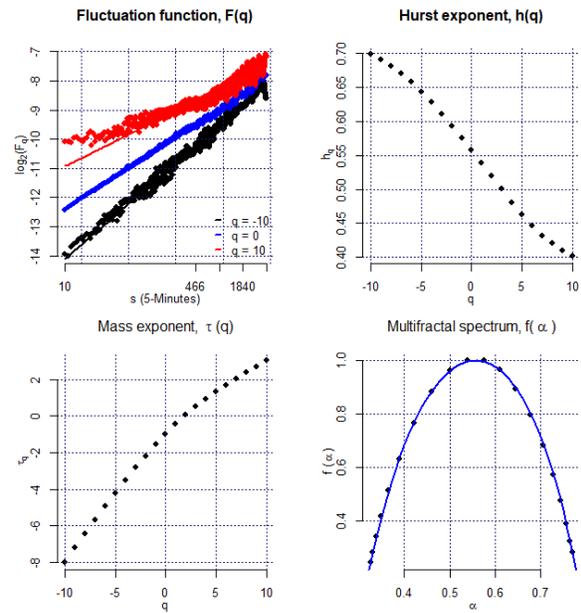


Figure 3-G). MF-DFA EUR-2019

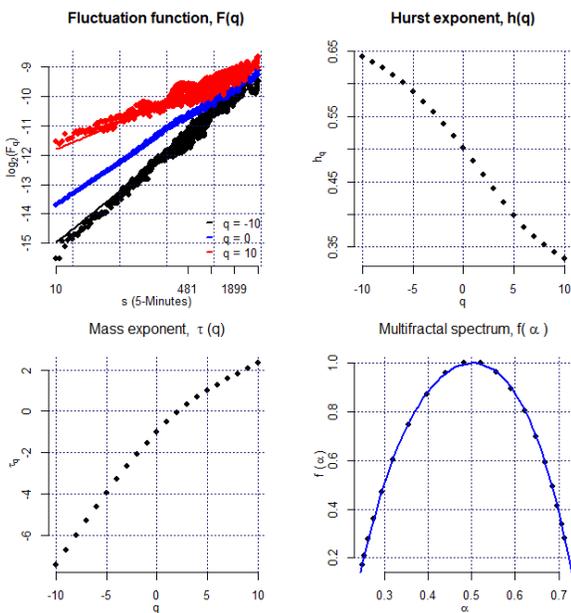


Figure 3-H). MF-DFA EUR-2020

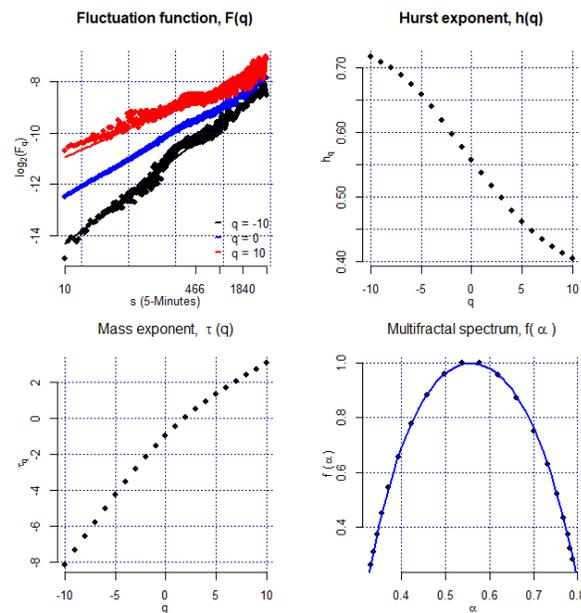


Figure 3-I). MF-DFA GBP-2019

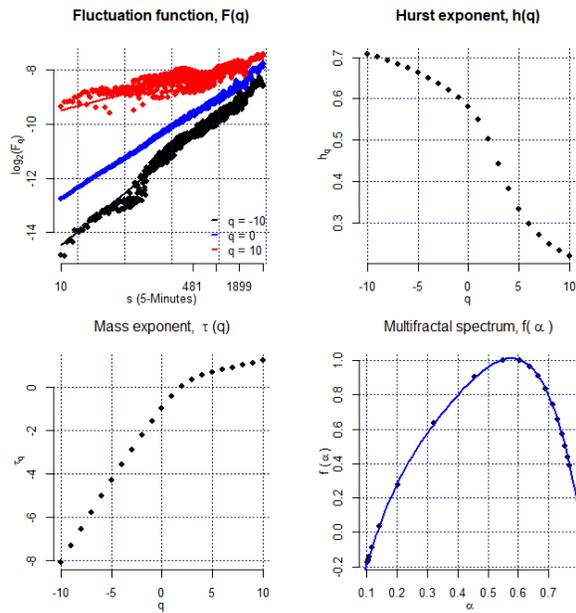


Figure 3-J). MF-DFA GBP-2020

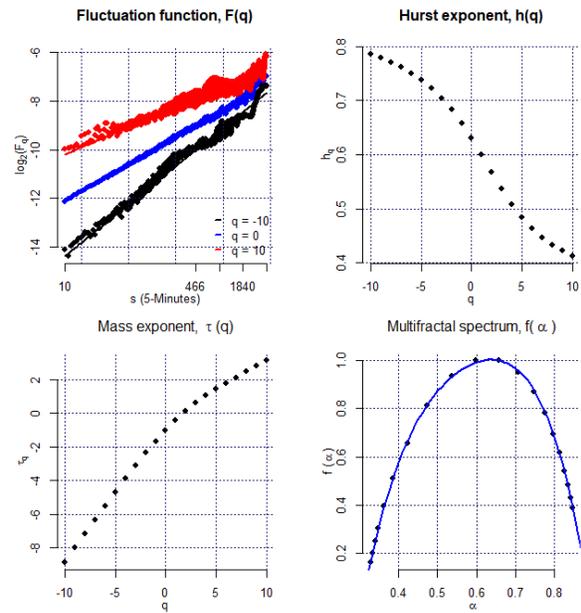


Figure 3-K). MF-DFA JPY-2019

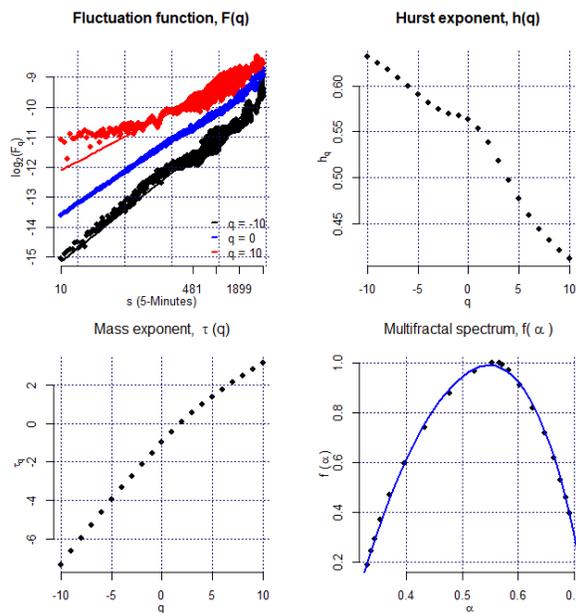


Figure 3-L). MF-DFA JPY-2020

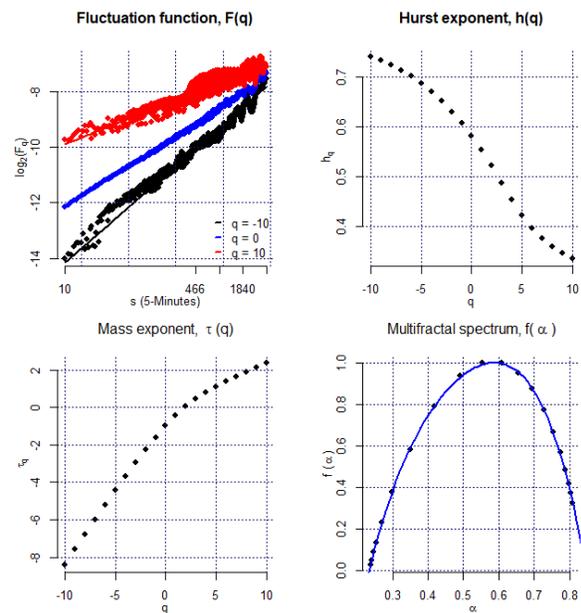


Figure 3: The MF-DFA results of intraday time series of exchange returns. (Top Left) Fluctuation functions for $q=-10$, $q=0$, $q=10$ (Top Right) Generalized Hurst exponent for each q . (Bottom Right) Mass exponent, $\tau(q)$. (Bottom Left) Multifractal spectrum.