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Michael McAleer

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Time-Varying Spillovers between Currency and Stock Markets in the USA: Historical Evidence From More than Two Centuries*

Semei Coronado
Independent Consultant

Rangan Gupta**
Department of Economics
University of Pretoria
South Africa

Besma Hkiri
Department of Finance and Economics
University of Jeddah
Saudi Arabia

Omar Rojas
Facultad de Ciencias Económicas y Empresariales
Universidad Panamericana
México

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* The authors are grateful to a reviewer for helpful comments and suggestions.
** Corresponding author: gupta.rangan@gmail.com

Abstract

In this paper, we analyze time-varying causality between the dollar-pound exchange rate and S&P 500 returns over the monthly period of September, 1791 to September, 2019. Based on a Dynamic Conditional Correlation-Multivariate Generalised Autoregressive Conditional Heterosckedasticity (DCC-MGARCH) framework, we find that evidence of unidirectional causality between the two returns is in general weak, and primarily restricted to the period following the breakdown of the Bretton Woods agreement. However, instantaneous spillovers across the returns of these two markets is quite strong, which in turn tends to suggest the existence of nonsynchronous trading and also high-frequency causal dependency, with the latter confirmed based on daily data covering 3 January 1900 – 4 October 2019. Moreover, the underlying DCC reveals that there is actually portfolio diversification opportunities for investors. Finally, an analysis of the second moments reveal much stronger evidence of volatility spillovers between these two assets, when compared to the return linkages. This result has important implications from the perspective of policy making aiming to reduce the impact of uncertainty on the real economy.

Keywords: Time-varying Granger causality; currency and equity markets; returns and volatilities.

JEL Codes: C32; F31; F31; G10

1. Introduction

Theoretically, the linkage between equity and currency markets is based on two main frameworks namely, the flow-oriented model of Dornbusch and Fischer (1980), and the stock-oriented model of Branson (1983) and Frankel (1983). According to the former, exchange rate changes can help predict developments in the equity market given that, following a depreciation of the domestic currency, the international competitiveness of domestic firms improves, and the ensuing rise in exports would translate into higher earnings and increased stock prices.

The latter postulates that developments in the stock market spills over to the currency market via the financial account, since a bullish (bearish) domestic stock market signals strong (weak) economic prospects, and hence, increases (decreases) capital inflows to cause the domestic currency to appreciate (depreciate). While either theoretical model posits unidirectional information spillovers between the equity and currency markets, empirical causality can be indeed bidirectional, if both these channels are at work simultaneously.

Given that establishing whether and to what extent there exist information spillovers among currency and stock markets is important in portfolio diversification for investors and risk management for policymakers, a large body of literature exists which has analysed the linkages between these two asset markets, both in developed and emerging economies (see Kanda et al. (2018) for a detailed review). A common feature in all these studies is that analysis is conducted on the relationship between the domestic stock market and the United States (US) dollar-based exchange rate of a specific country.

This should indeed not come as a surprise, given the importance of the US dollar as the official reserve currency since the second half of the 20th century. Naturally, the relationship between the stock market of the US and the dollar has not received any attention, and in this paper, this is specifically what we aim to analyse for the first time. For our purpose, in terms of the exchange rate, we look at the US dollar in terms of United

Kingdom (UK)'s sterling pound, and study the longest available monthly historical data on the domestic US equity market prices and the dollar, expressed in terms of the sterling pound, dating back to August in 1791.

Taking a historical perspective is important, given that we use the sterling pound as the base currency, which in turn was the primary reserve currency of much of the world in the 19th century and first half of the 20th century.[1] Moreover, with our analysis covering the period of August, 1791 to September, 2019 (with the latter governed by the availability of data at the time of writing this paper), is immune to any sample-selection bias, unlike the existing literature which primarily relies on post Bretton Woods system data.[2]

The data coverage of more than two centuries necessitates a usage of a time-varying approach to analyse the causal relationship between these two US markets, since static linear and nonlinear models only capture the average causality effect over the given sample or regime, and hence cannot describe the entire dynamics of information spillovers. In this regard, as far as the econometric framework is concerned, we use, the Dynamic Conditional Correlation-Multivariate Generalised Autoregressive Conditional Heterosckedasticity (DCC-MGARCH)[3] Hong tests (as developed by Lu et al. (2014)) for time-varying Granger causality, to investigate whether and to what extent the nature of causality between the equity and currency markets of the US changes across time.

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[1] The establishment of the US Federal Reserve System in 1913, the economic dominance of the US as an economic superpower from the second half of the 20th century onward, and due to the UK almost bankrupting itself fighting two World Wars, leading to occasional economic weaknesses during the second half of the 20th century, resulted in the sterling pound losing its status as the world's most important reserve currency. In fact, in the 1950s, 55% of global reserves were still held in sterling pounds, but the share was 10% lower within 20 years. As of September 2019, which corresponds to the end point of our analysis, the sterling pound represented the fourth largest proportion (by US dollar equivalent value) of foreign currency reserves.

[2] The exception is the work of Kanda et al. (2018), which analysed historical relationship between these two markets for the UK, India and South Africa over 1791:02-2017:07, 1920:08-2017:07, and 1910:02-2017:07 respectively, and found evidence of time-varying spillovers across these two markets.

[3] Though we use the underlying DCC-MGARCH model to perform our causality analysis, the problems associated with this approach in terms of algebraic non-existence, mathematical irregularity, and non-asymptotic properties are highlighted in McAleer (2019).

The main appeal of the DCC-MGARCH Hong tests is that we can analyse causality at each point in time, such that we can pin down time-varying financial contagion. In addition to detecting unidirectional time-varying causality, the method can also pick-up the overall (bidirectional) causal relationships. Furthermore, the framework can be used to establish any evidence of instantaneous information spillovers obtained from possible nonsynchronous trading.

The remainder of the paper is organized as follows: Section 2 outlines the basics of the DCC-MGARCH framework, while Section 3 presents the data and empirical results, along with a wide array of robustness tests. Finally, Section 4 concludes the paper and also includes implications of our results.

2. Methodology

Following Lu et al. (2014), we consider two stationary time series X_t and Y_t, and an information set I_t for the time series, with $t = 1,2, \dots, T$, and T being the sample size. Given $Z_t(j) = \binom{X_t}{Y_t}$, where j represents the lag order used in the dynamic correlation coefficient, the DCC-MGARCH model is defined as follows, in line with Engle (2002):

$$Z_t(j)|I_{t-1} \sim N(0, D_{t,j}R_{t,j}D_{t,j})$$

$$D_{t,j}^2 = diag(\omega_{t,j}) + diag(\kappa_{t,j}) \circ Z_t(j)Z_t{}'(j) + diag(\lambda_{t,j}) \circ D_{t-1,j}^2$$

$$u_{t,j} = D_{t-1,j}^{-1} Z_t(j) \tag{1}$$

$$Q_{t,j} = S \circ (u' - A - B) + Au_{t-1,j}u'_{t-1,j} + BQ_{t-1,j}$$

$$R_t, j = diag(Q_{t,j})^{-1} Q_{t,j} diag(Q_{t,j})^{-1}$$

For the widely used DCC-MGARCH(1,1) model, the dynamic correlation estimator with lag j is:

$$\rho_{pq,t}(j) = \overline{\rho}_{pq}(j) + \alpha_j(u_{p,t-1}u_{q,t-1-j} - \overline{\rho}_{pq}(j)) + \beta_j(\rho_{pq,t-1}(j) - \overline{\rho}_{pq}(j))$$

$$r_{pq,t}(j)\frac{\rho_{pq}(j)}{\sqrt{\rho_{11,t}}\rho_{22,t}(j)} \tag{2}$$

where $p, q = 1,2$.

Based on the choice of a positive integer M, and a kernel function $k(x)$, the unidirectional DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{1,t}(k)$:

$$H_{1,t}(k) = \frac{T\sum_{j=1}^{T-1} k^2\left(\frac{j}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{3}$$

where

$$C_{1T}(k) = \sum_{j=1}^{T-1}\left(1 - \frac{j}{M}\right) k^2\left(\frac{j}{M}\right)$$

$$D_{1T}(k) = \sum_{j=1}^{T-1}\left(1 - \frac{j}{T}\right)\left(1 - \frac{j+1}{T}\right) k^4\left(\frac{j}{M}\right)$$

The bidirectional DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{2,t}(k)$:

$$H_{2,t}(k) = \frac{T\sum_{j=2-T}^{T-2} k^2\left(\frac{j}{M}\right) r_{12,t}^2(j) - C_{2T}(k)}{\sqrt{2D_{2T}(k)}} \tag{4}$$

where

$$C_{2T}(k) = \sum_{j=1-T}^{T-1} \left(1 - \frac{|j|}{M}\right) k^2 \left(\frac{j}{M}\right)$$

$$D_{2T}(k) = \sum_{j=1-T}^{T-1} \left(1 - \frac{|j|}{T}\right) \left(1 - \frac{|j|+1}{T}\right) k^4 \left(\frac{j}{M}\right)$$

The instantaneous DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{3,t}(k)$:

$$H_{3,t} = \frac{T \sum_{j=0}^{T-2} k^2 \left(\frac{j+1}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{5}$$

where $C_{1T}(k)$ and $D_1 T(k)$ are estimated in $H_{1,t}(k)$.

Note that, the DCC-MGARCH Hong tests are asymptotically normally distributed. Given that it is not feasible to estimate all lagged dynamic correlations in DCC-MGARCH Hong tests, we follow Hong (2001) to deal with this by choosing a suitable kernel function, namely the Bartlett kernel[4]. It must be pointed out that the choice of non-uniform kernels and M has little impact on the size of the DCC-MGARCH Hong tests.

3. Data and Results

3.1. Data and Preliminary Analyses

We use monthly data on the S&P 500 stock price index and the dollar-pound exchange rate over the monthly period of August 1791 to September, 2019, with the two series obtained from Global Financial Data.[5] As required by the methodology, we work with

[4] The Bartlett kernel is defined as follows: $k(z) = \begin{cases} 1-|z|, & \text{if } |z|<1 \\ 0, & \text{if } |z|>1 \end{cases}$.

[5] http://www.globalfinancialdata.com/.

log-returns to ensure stationarity, and hence our effective sample starts in September, 1791. The data has been plotted in Figure A1 and summarized in Table A1 in the Appendix of the paper. From visual inspection, we notice the presence of volatility clustering as well as large outliers across both the series.

On average, equity return is positive, while the mean value of the dollar-pound exchange rate return is found to be negative, indicating mean appreciation of the dollar. Equity market is also found to be more volatile than the currency market, with both returns depicting non-normal distribution (as shown by the strong rejection of the Jarque-Bera test) due to negative skewness and excess kurtosis. The Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979), also reported in Table A1, confirms that both our returns series are devoid of any unit roots.

Before we present the results from the DCC-MGARCH Hong tests, for the sake of comparability and completeness, we conducted the standard linear Granger causality tests based on Vector Autoregressive (VAR) models of order 5, with the lag-length chosen by the Akaike Information Criterion (AIC). The null of no-Granger causality running from stock return to exchange rate return and vice versa, produced $\chi^2(5)$ statistics of 35.8867 and 88.5386, with *p*-values of 0.000 in both cases, thus suggesting that bi-directional causality exists. Of course the statistic test fails to provide information of the specific periods over which spillovers are concentrated.

Moreover, due to the sample period spanning 229 years of monthly data, over which both these markets have undergone massive evolution, it is expected that the relationship between these two variables depict nonlinearity and regime changes, to both of which the time-varying DCC-MGARCH Hong tests is robust to by design. In fact, the nonlinearity is confirmed by the Brock et al. (1996, BDS) test, when applied to the residuals obtained from each of the two equations of the VAR(5) model (as reported in Table A2 in the

Appendix of the paper), with the test overwhelmingly rejecting the null of *i.i.d.* residuals, to point towards uncaptured nonlinearity.[6]

In addition, the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to *M* structural breaks, allowing for heterogenous error distributions across the breaks, applied to the stock and exchange rate returns equations of the VAR(5) model individually, picked up the existence of the following break dates: 1827:06, 1861:07, 1895:08, 1940:01, and 1985:05 for the exchange rate return equation, and 1826:10, 1864:09, 1902:08, 1938:08, and 1976:05 for the stock return equation. The existence of both nonlinearity and regime changes, provide strong statistical reasons to investigate the causal relationship between these two markets using a time-varying approach, to which we turn to next via the implementation of the DCC-MGARCH Hong tests.

3.2. Main Results

In Figures 1(a) to 1(e), we plot the unidirectional, instantaneous, and bidirectional time-varying DCC-MGARCH Hong tests for information spillovers between the equity and foreign exchange markets, by setting $M = 5$, in accordance with the lag-length of the static test. The top panel of each figure depicts the value of the time-varying DCC-MGARCH Hong test (indicated as Causality), and at the bottom, we show shaded regions representing periods during which the test is statistically significant at the 5% level.

On the whole, there is overwhelming evidence of time-varying information spillovers between the currency and stock markets. The direction as well as statistical significance of the information spillovers between these markets is indeed time-varying. Considering the unidirectional information spillovers (see Figures 1(a) and 1(b)), we find that the pattern of causal relationships across the two markets, in terms of the periods where causality is found is similar, with strong evidence of causality post the breakdown of the

[6] Given this, we used the cross-bicorrelation test of Brooks and Hinich (1999) which permit us to identify existence of any nonlinear causal dependence between the two variables. In this case, when the two returns were separated into equal length of non-overlapping moving time windows (24 months) and frames (114), the null of no causality from stock returns to exchange rate returns, and from exchange rate returns to stock returns were rejected under 79 (69.3%) and 61 (53.5%) windows respectively, thus highlighting the need to look into a time-varying approach to study the causal dependence between these two variables. Complete details of these results are available upon request from the authors.

Bretton Woods agreement, i.e., from 1975 onwards. Causal evidence, though sporadic, is also detected in the early part of the sample till around 1875, but thereafter till the beginning of World War I, there is no evidence of causality, with the same pattern observed post World War II till about 1975. The interwar period shows weak evidence of causality.

While the unidirectional causality across the two markets is quite regular over the last 5 decades or so, the evidence of spillovers in the early part of the sample is primarily dominated by the role of the exchange rate return in driving the stock return, which in turn results in producing causality in 12.3% of the sample, compared to 6.9% of the sample in terms of predictability the other way round. Since it is likely that information spillovers between markets takes place in a contemporaneous fashion, we report the instantaneous DCC-MGARCH Hong tests in Figures 1(c) and 1(d). We observe a pattern suggesting that there is similar degree of instantaneous information spillovesr between the dollar-pound exchange rate returns and the S&P500 returns.

In fact, stock returns drive the exchange rate returns in 48.6% of the sample, while exchange rate returns affect the stock market returns instantaneously in 50.2% of the total number of observations. Given this, the bidirectional DCC-MGARCH Hong tests (see Figure 1(e)) highlight evidence of time-varying overall two-way instantaneous information spillovers between the equity and currency markets, which actually occurs in 47% of the sample period.

Overall, while unidirectional causality across the two markets is weak, but relatively stronger running from the currency market to the stock market, and primarily concentrated in the post-Bretton Woods era, evidence of instantaneous causality is quite dominant, and is likely due to nonsynchronous trading. But this can also be indicative of the fact that spillovers across these markets occur fast and at a higher frequency. We investigate this presumption in greater detail below as part of additional analyses using daily data.

[FIGURE 1]

Next, to get an understanding of the sign of the relationship between the two return time series, we plot in Figure 2, the underlying time-varying correlation obtained from the DCC-MGARCH model. In general, the relationship between the dollar-pound and stock returns is positive, which basically suggests that an increase (decrease) in stock returns is associated with a depreciation (appreciation) of the dollar, and hence diversification opportunities exist across these two assets. However, this was not the case between 1975 till around early 2000s, when the returns were negatively correlated, thus suggesting improvements or declines in the returns of these assets in the same direction.[7]

[FIGURE 2]

3.3. Additional Results

As discussed above, we test the possibility of high-frequency spillovers by using daily data of returns on these two variables over the period of January 3rd, 1900 to October 4th, 2019, as governed by data availability. Note that daily data on S&P 500 is not available over this period, and hence, we use the Dow Jones Industrial Average (DJIA) index instead. Again, the daily data set is obtained from Global Financial Data.

The various DCC-MGARCH Hong tests (with $M = 8$, based on the AIC) have been reported in Figures 3(a)-3(e), and when we compare the common period of January, 1900 to September, 2019 across the monthly and daily data sets, we find exceptionally strong evidence of bi-directional spillovers from the five tests – a finding in line with our suggestion that these two markets are associated with high frequency spillovers.[8, 9]

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[7] Using the average phase difference derived from a wavelet framework covering the frequencies of 0 to 1024 months, we basically obtained a similar picture in terms of the correlation, as depicted in Figure A2 in the Appendix of the paper. While interpreting the figure, one must remember that the relationship is in phase in the interval $[-\pi\backslash 2; \pi\backslash 2]$, but out of phase in the interval $[-\pi; -\pi\backslash 2]$. For complete technical details in this regard, the reader is referred to Tiwari et al. (2019). The figure also reveals the dominance of causality running from the currency to the stock market, in line with our DCC-MGARCH Hong test results.

[8] The pattern of the underlying correlation depicted a similar picture over the common period to the one derived under the monthly data set in Figure 2. Complete details of these results are available upon request from the authors.

[9] As an extra analysis, since both our variables occasionally exhibit large changes, we followed Laurent et al. (2016) to assume that the observed return series consist of a conditionally Gaussian Autoregressive Moving Average (ARMA)-GJR model contaminated by an additive jump component, to deal with these events. Using the test for additive jumps in this framework, which in turn is based on standardised returns, where the first two conditional moments of the non-contaminated observations are estimated in a robust

[INSERT FIGURE 3]

In a recent paper, Liu et al. (2020) point out that the flow-oriented and the stock-oriented models also result in second-moment spillovers. Given this, we analysed the causality-in-volatility using the DCC-MGARCH Hong tests (with $M = 5$ using the AIC), by first estimating a best-fitting GARCH model, namely the GJR model of Glosten et al. (1993) highlight the importance of leverage effect, on the individual monthly return series, then recovering the standardized residuals, and finally using these squared residuals in the time-varying model (following Çevik et al. (2018), to remove the volatility-on-volatility effect to apply the DCC-MGARCH Hong tests on conditional volatility series).

The results have been reported in Figures 4(a)-4(e), and provide evidence of relatively stronger volatility spillovers when compared to returns linkages, with again exceptionally high degree of instantaneous causality. Interestingly, the causality from stock market volatility to currency market volatility is found to be way stronger than the causality-in-volatilities in the opposite direction – a result opposite to those obtained under returns.[10]

[FIGURE 4]

Overall, these two additional analyses confirm the existence of instantaneous causality between the currency and stock markets of the US, both in terms of first and second moments.

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way, we detected 2467 and 129 jumps for the daily exchange rate and stock returns, respectively. A binary-logit model confirmed the significant positive relationship (with a coefficient of 0.8004 and a *p*-value of 0.0010) between the dummies associated with the identified dates of the jumps in the two series. Note that, the ARMA-GJR model picked up 105 and 30 jumps for the exchange rate and stock returns based on monthly data respectively, and weak (at the 10% level) positive association was observed thereafter based on the binary-logit model – a result which should not be surprising given that jumps are a more high-frequency concept. Furthermore, by identifying jumps as dates in which the changes in the two returns were greater than equal to 2.5%, as suggested by Baker et al. (2019), and then defining a dummy for these days to take the value of 1 and 0 otherwise, and multiplying the dummy with the returns series, yielded us the jumps data for exchange rate and equity returns. When we applied the linear Granger causality tests to daily data, we found spillovers in both directions (even in the case of monthly data), with the cross-spectra wavelet analysis confirming dominant jumps causality from the currency to the stock market, which in some sense is not surprising given the identification of more jumps in the former series by the ARMA-GJR model. Complete details of these results are available upon request from the authors.

[10] In general, these results of causality-in-volatility also carried over to the daily data set, and the underlying correlations in both the monthly and daily data sets were in general found to be positive. Complete details of these results are available upon request from the authors.

4. Conclusion

Given the importance of the US dollar as the reserve currency, the existing literature on the spillovers between currency and stock markets has considered the relationship between domestic stock returns (and volatility) and dollar-based local currency exchange rate returns (and volatility). Given this we, for the first time, analyze the relationship between these two markets for the US by using the dollar-pound exchange rate, and data over the monthly period of August, 1791 to September, 2019, with the long data sample allowing us to use the British sterling pound as the reserve currency, which was historically so until the mid-20th century. Since we deal with the longest available history of these two asset prices, with these two markets having undergone regime changes, we rely on a time-varying approach to detect causal relationships.

Using the DCC-MGARCH Hong tests, we find that while unidirectional return causality is primarily restricted to the post-1975 period, there is stronger evidence of instantaneous spillovers, suggesting both the possibility of nonsynchronous trading, and high-frequency causal relationships. The latter conclusion is confirmed when we find strong evidence of both predictability in the causal sense, as well as instantaneous causality, based on daily data covering January 3rd, 1900 to October 4th, 2019. With the underlying time-varying correlation suggesting that bullish or bearish stock market is associated with a depreciating or appreciating dollar relative to the pound, we confirm opportunities of diversification across the two markets. In addition, when we look at second-moments, we find stronger evidence of risk spillovers across these two markets using monthly data, compared to the corresponding monthly data-based causality effects of currency and stock returns. From the perspective of investors, our results suggest that holding both US equities and dollars in a portfolio is likely to provide diversification benefits. From the perspective of a policymaker, the existence of volatility spillovers suggest the fact that the impact of uncertainty shock originating in one market, i.e., currency or stocks, and negatively affecting the macroeconomy (Gupta et al. 2018) is likely to be persistent, since these shocks are contagious across the two markets under consideration. Finally, our results tend to suggest to an academician that more accurate predictability of these two asset returns are likely to be derived when one uses high-frequency, i.e., daily, rather than monthly data.

As a possible future line of research, it would be worthwhile to investigate the factors triggering the switch in the evidence, direction, as well as overall nature of the causality between the exchange rate and stock returns over the historical time period.

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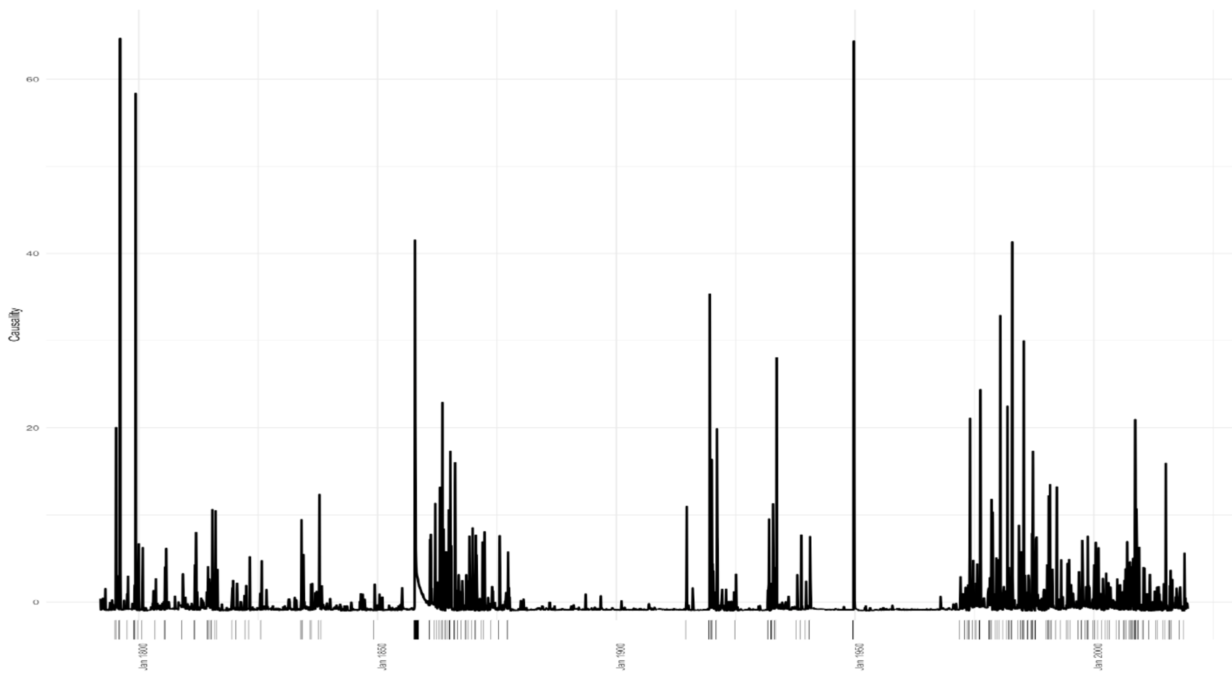
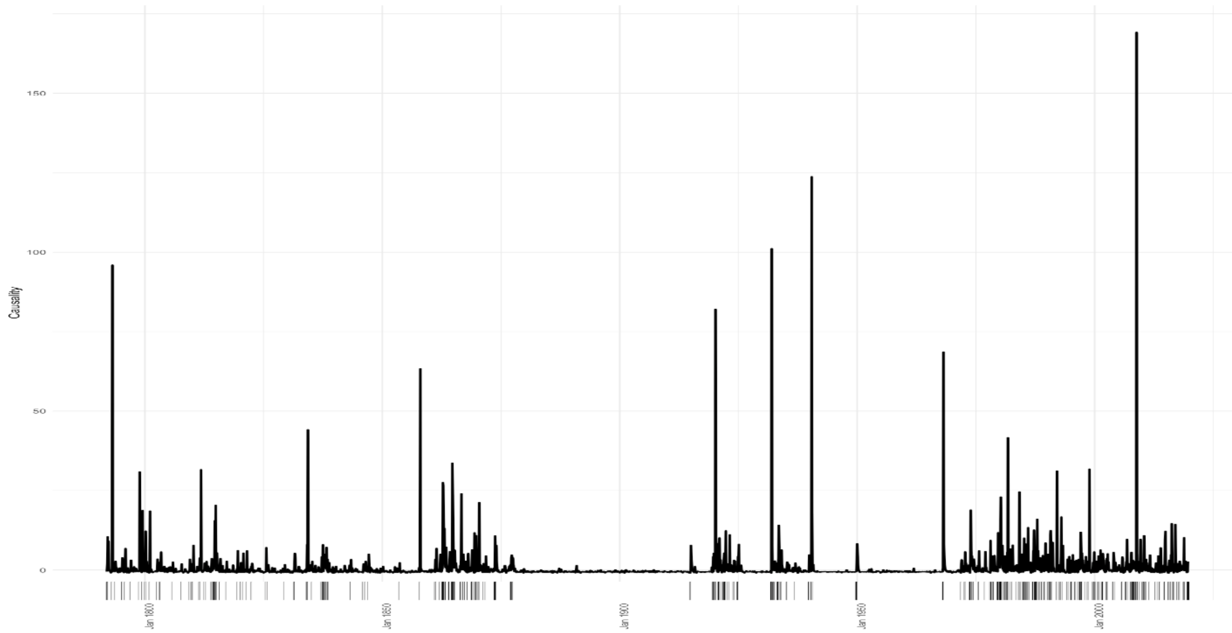
Figure 1

Monthly Results of DCC-MGARCH Hong Tests between Dollar-Pound Exchange Rate Return and S&P 500 Return: September 1791-September 2019

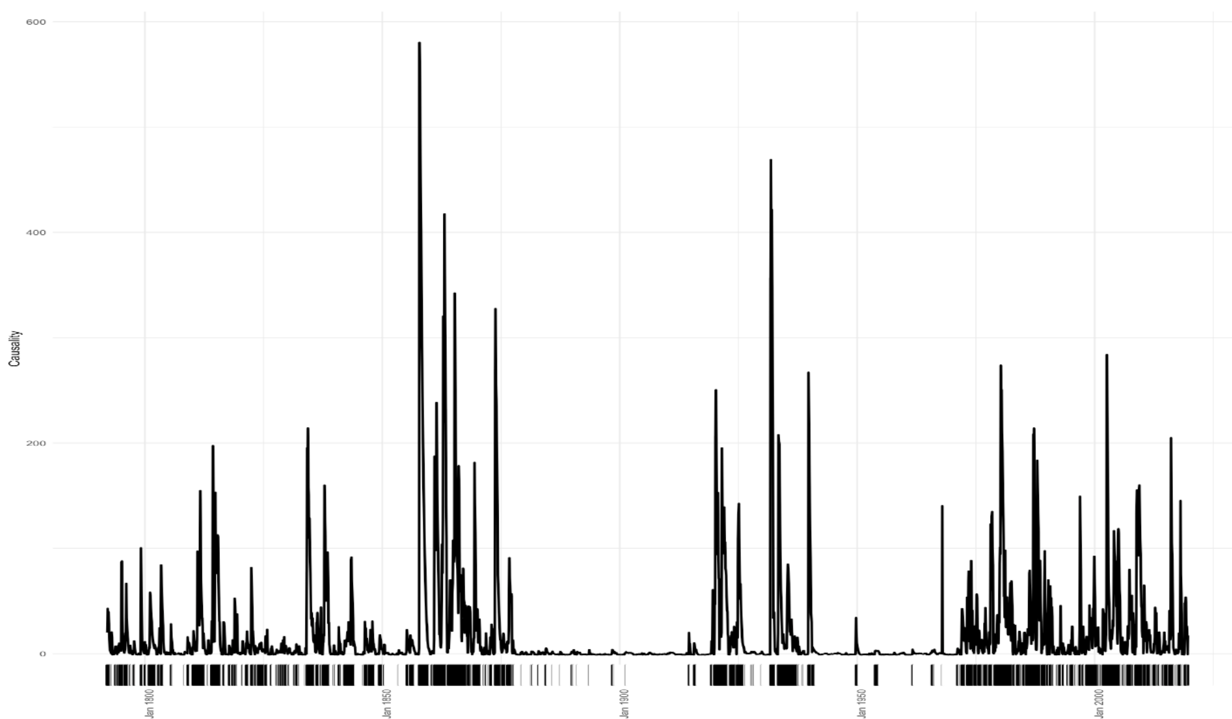
1(a). Unidirectional Causality Test: Stock Return to Currency Return



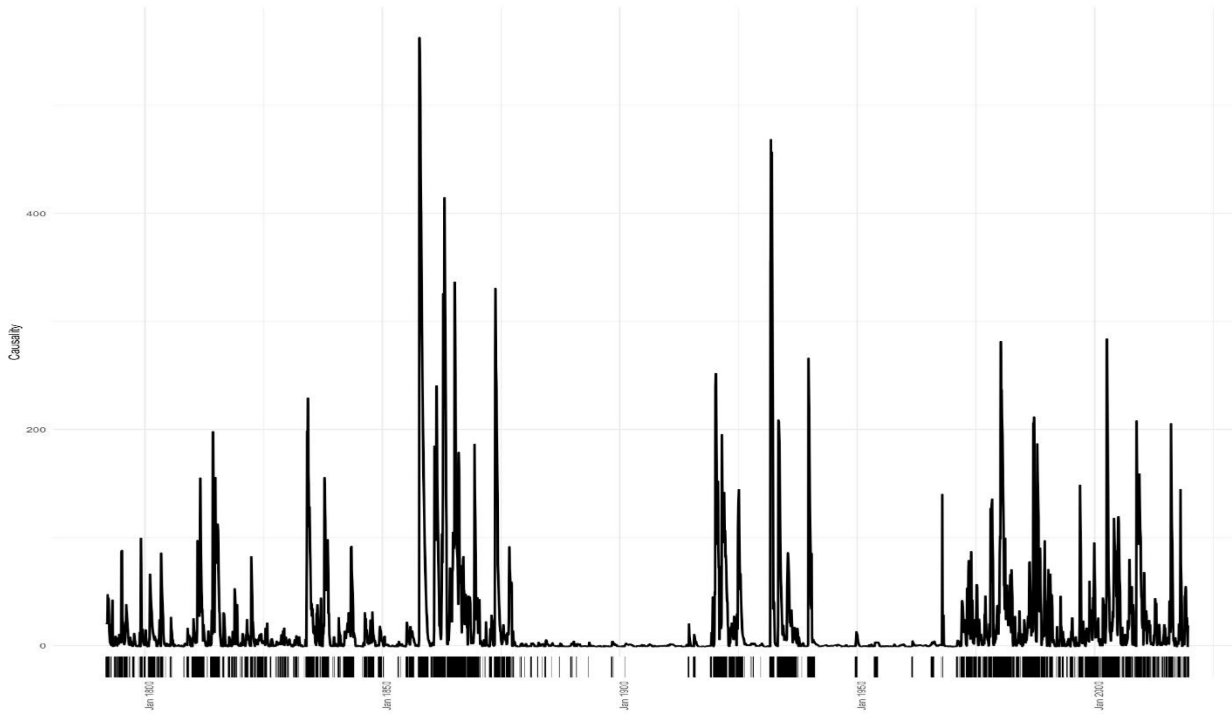
1(b). Unidirectional Causality Test: Currency Return to Stock Return



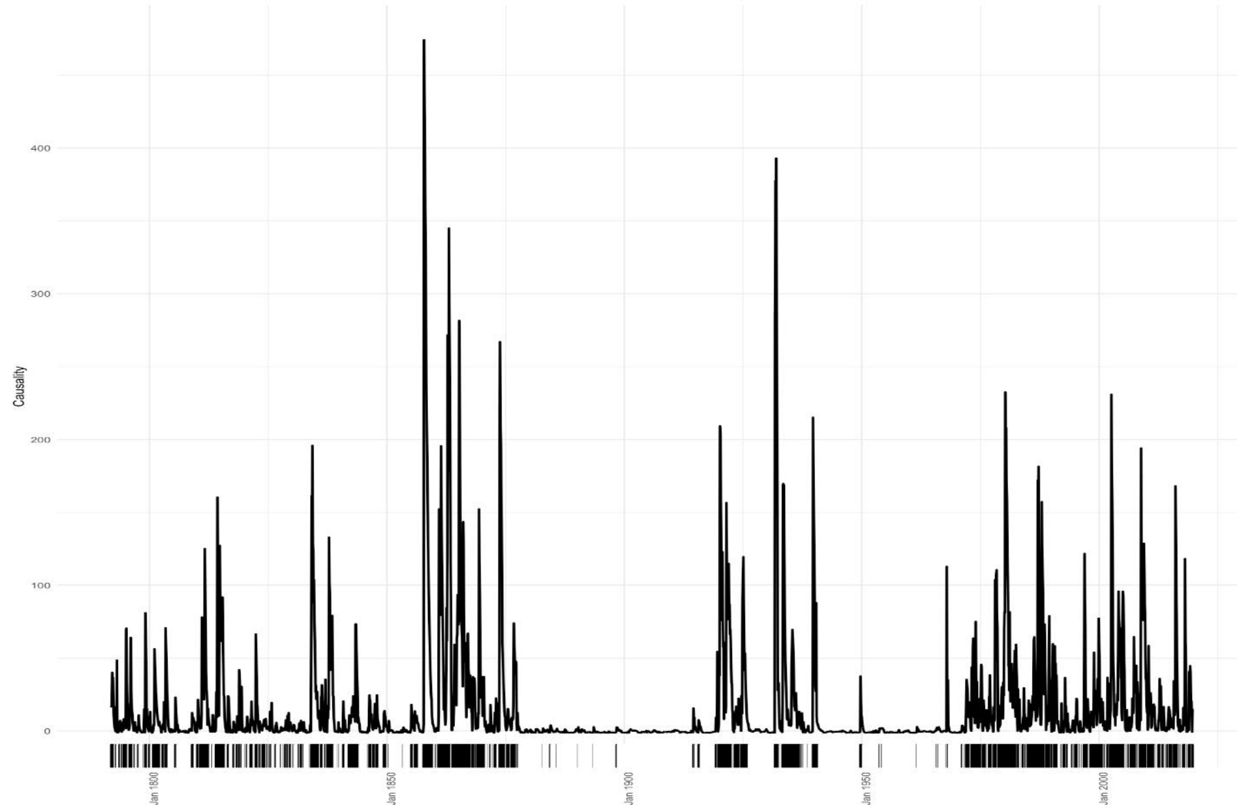
1(c). Instantaneous Causality Test: Stock Return to Currency Return



1(d). Instantaneous Causality Test: Currency Return to Stock Return



1(e). Bidirectional Causality Test between Currency Return and Stock Return



Notes: The top panel in Figures 1(a)-1(e) shows the time-varying DCC-MGARCH Hong test statistic (Causality); The shaded region below shows the period during which the test is statistically significant at the 5% level.

Figure 2

Dynamic Conditional Correlation (DCC) between Dollar-Pound Exchange Rate Return and S&P500 Return

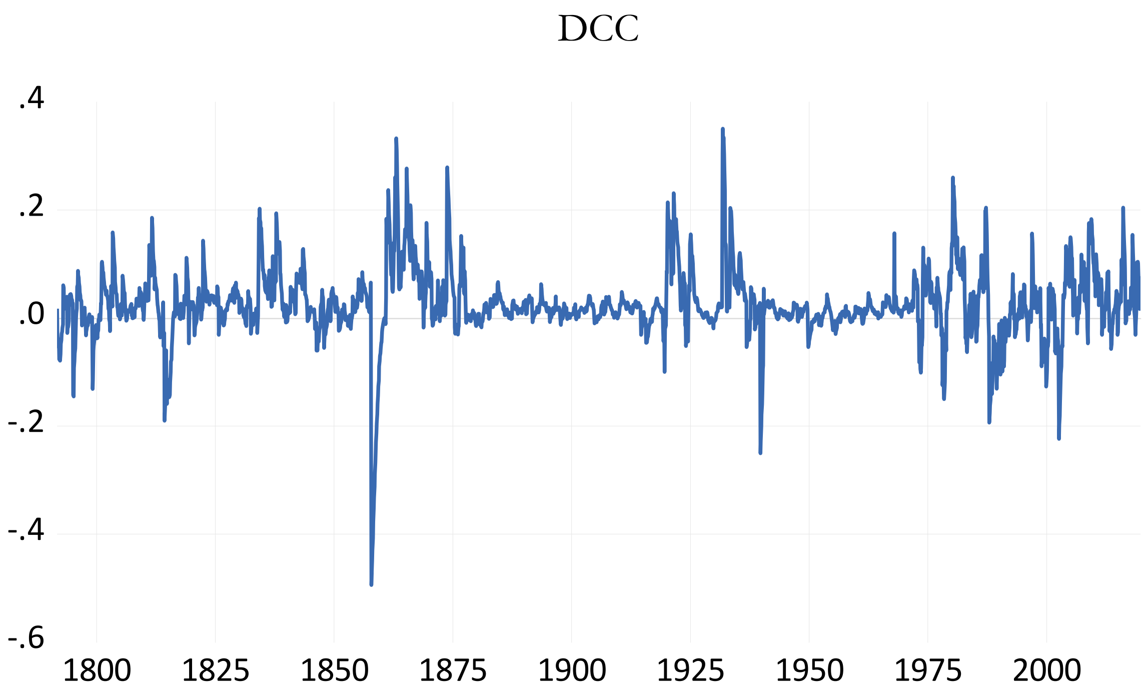
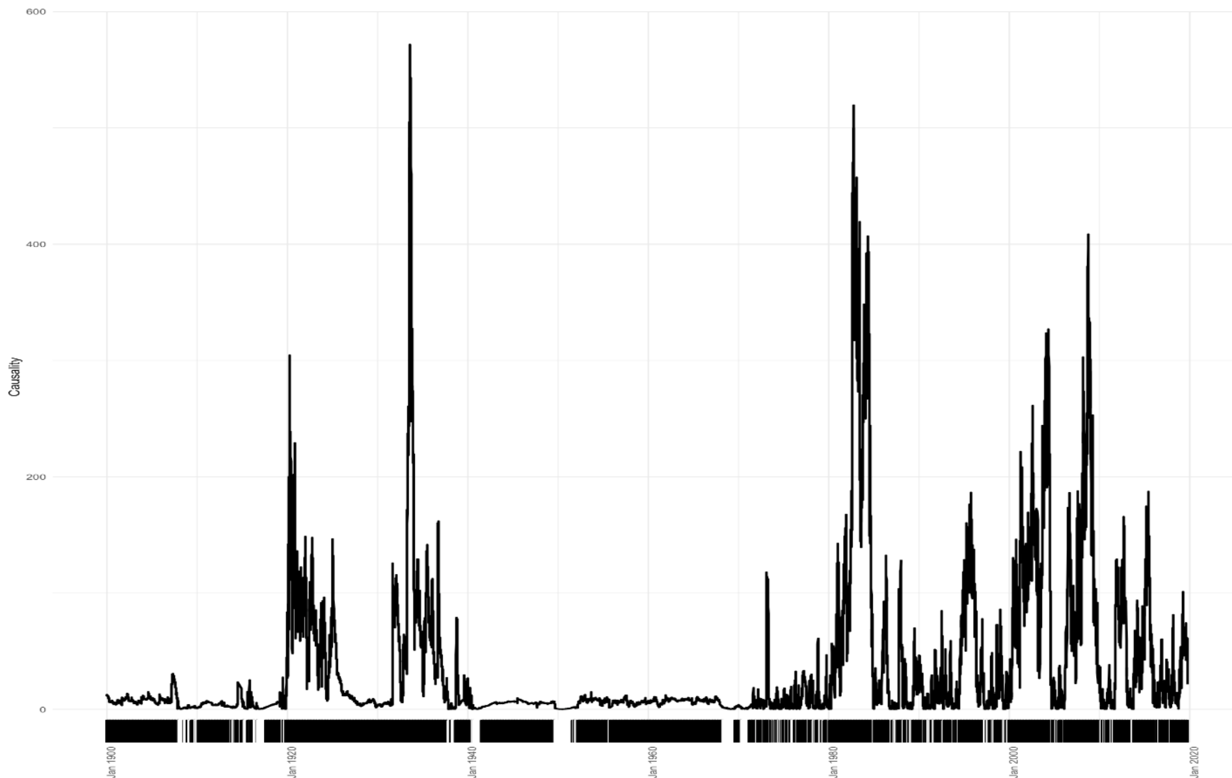


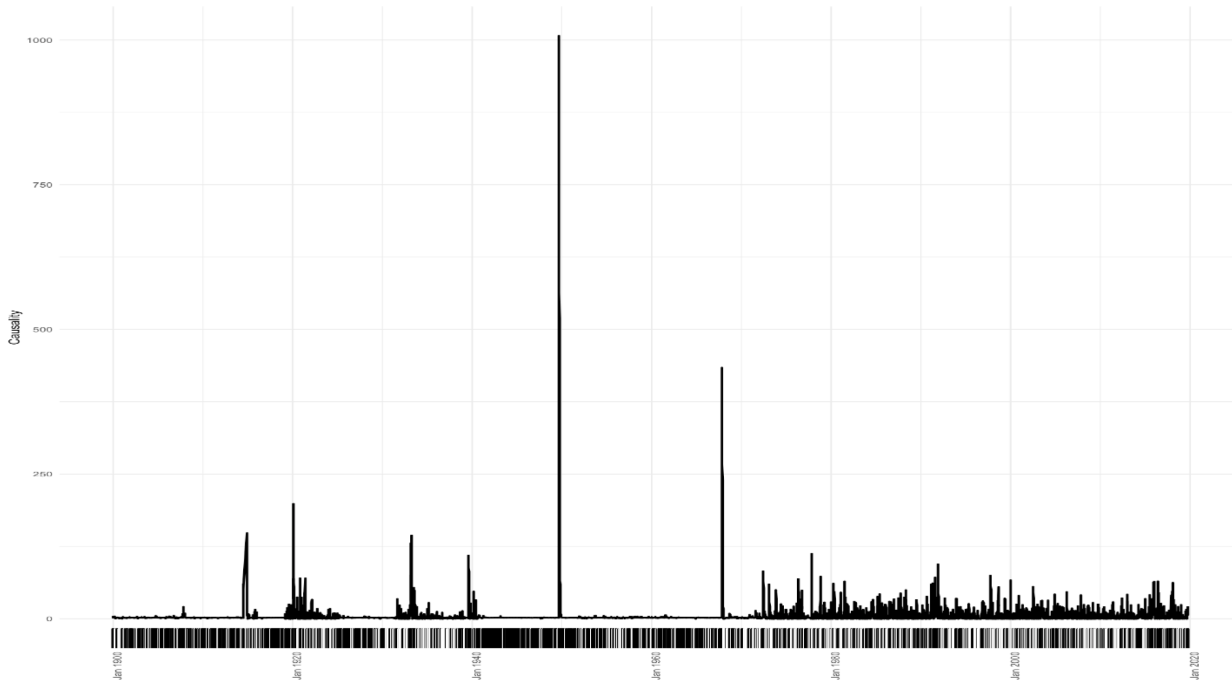
Figure 3

Daily Results of the DCC-MGARCH Hong Tests between Dollar-Pound Exchange Rate Return and S&P 500 Return: 3 January 1900 – 4 October 2019.

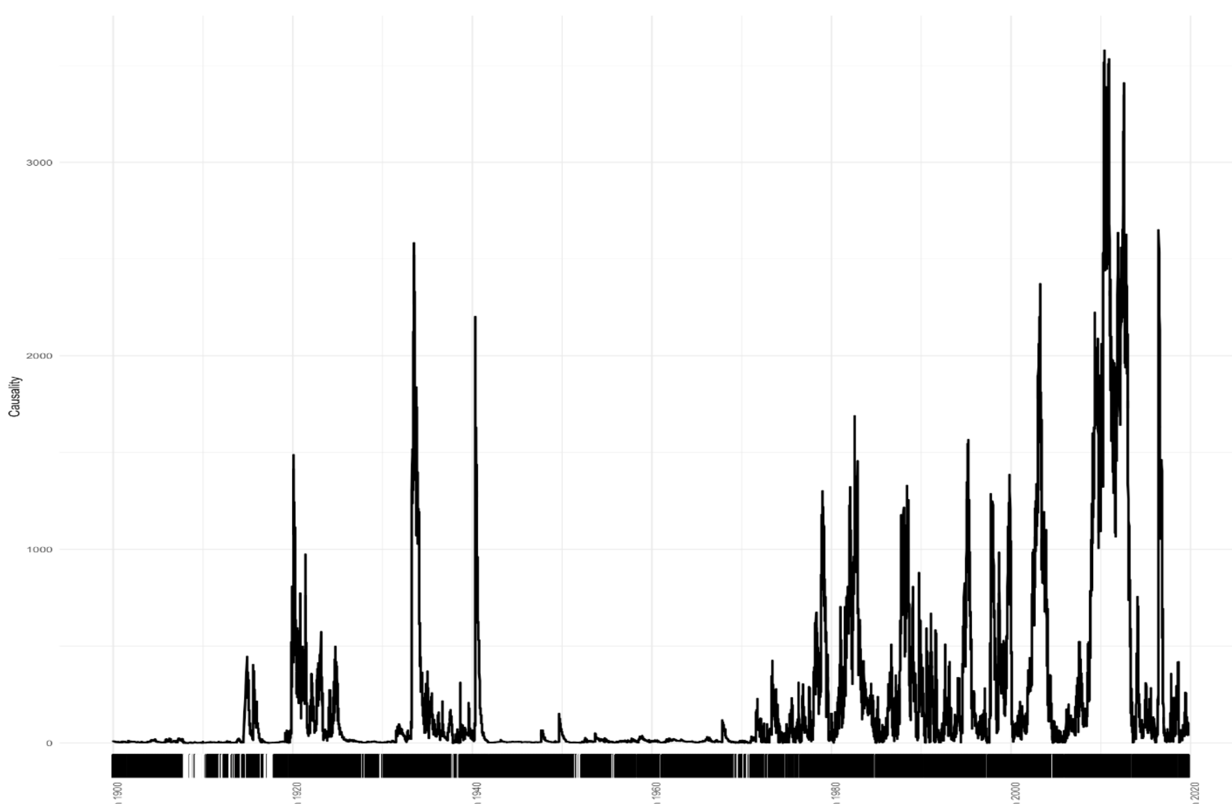
3(a). Unidirectional Causality Test: Stock Return to Currency Return



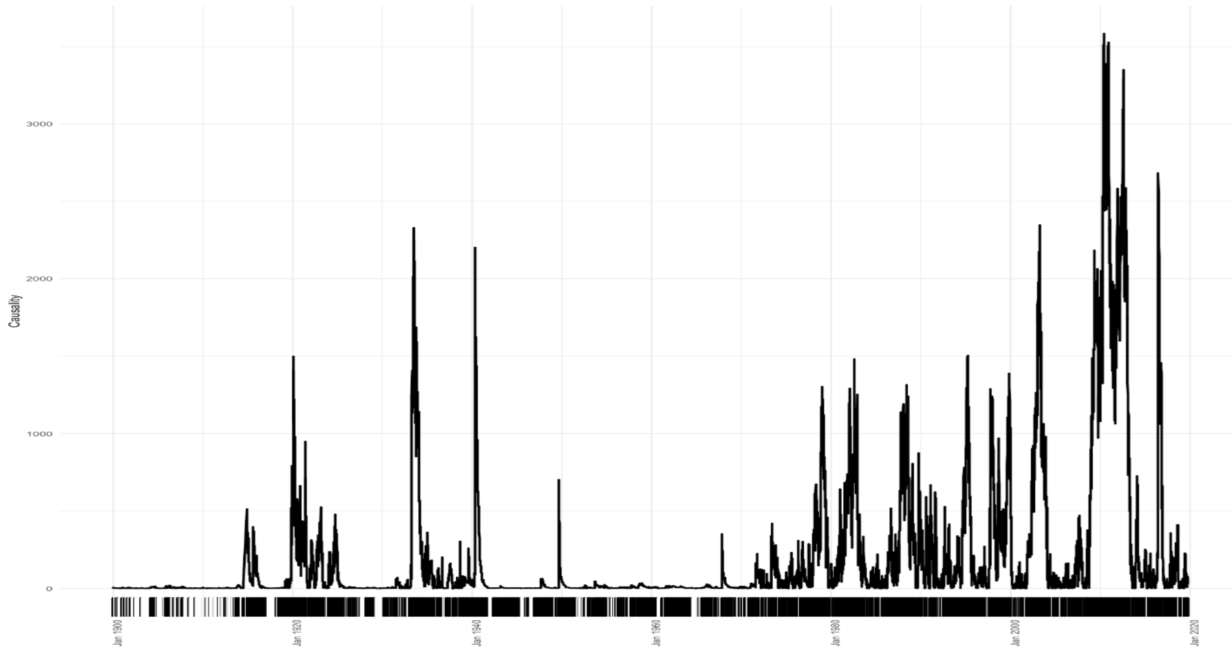
3(b). Unidirectional Causality Test: Currency Return to Stock Return



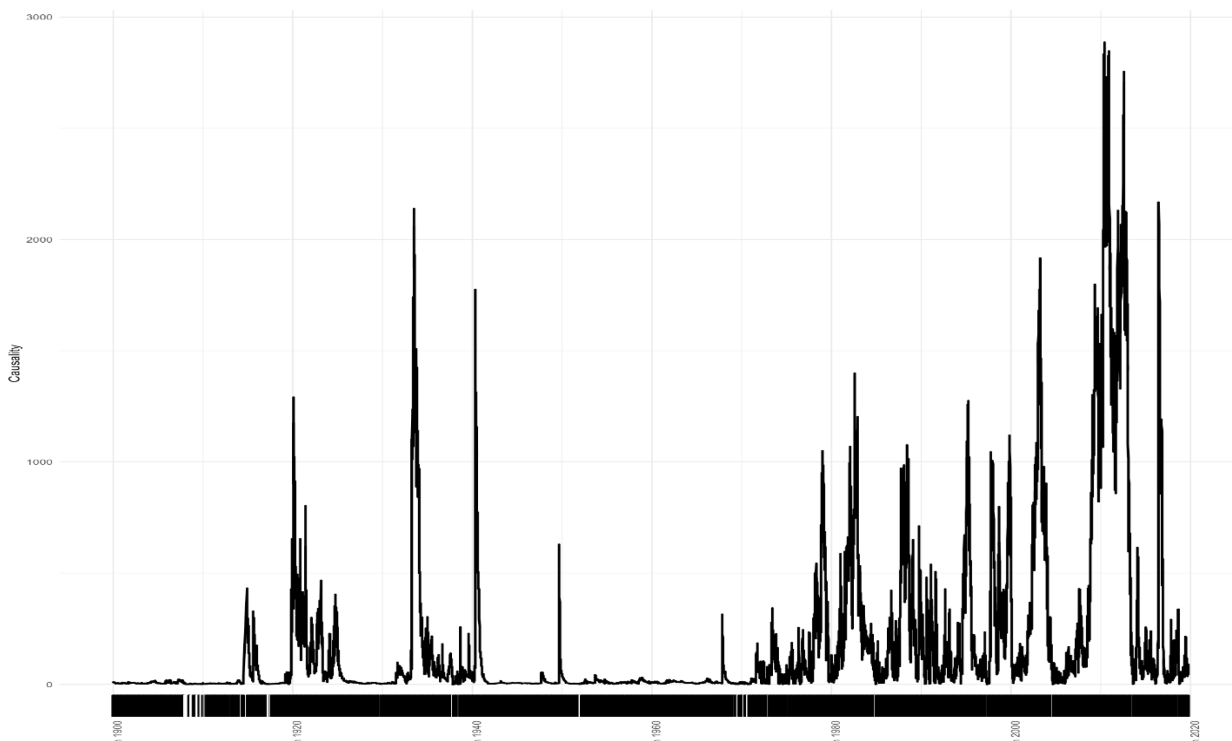
3(c). Instantaneous Causality Test: Stock Return to Currency Return



3(d). Instantaneous Causality Test: Currency Return to Stock Return



3(e). Bidirectional Causality Test between Currency Return and Stock Return

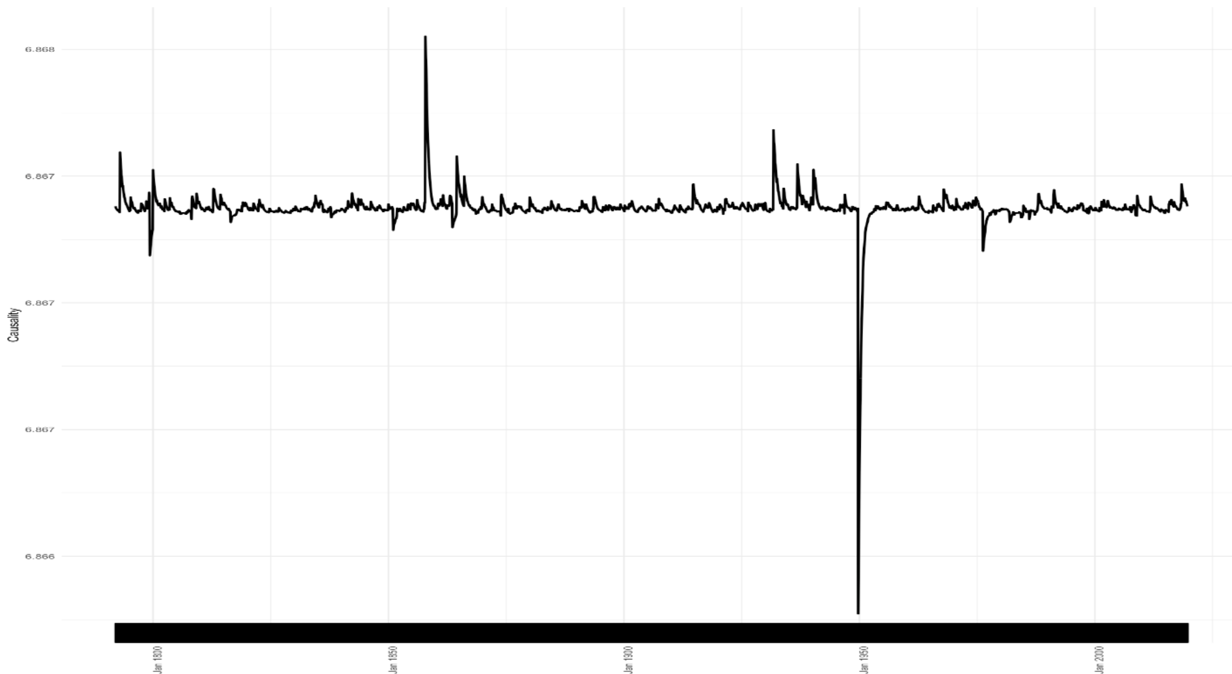


Note: See Notes to Figure 1.

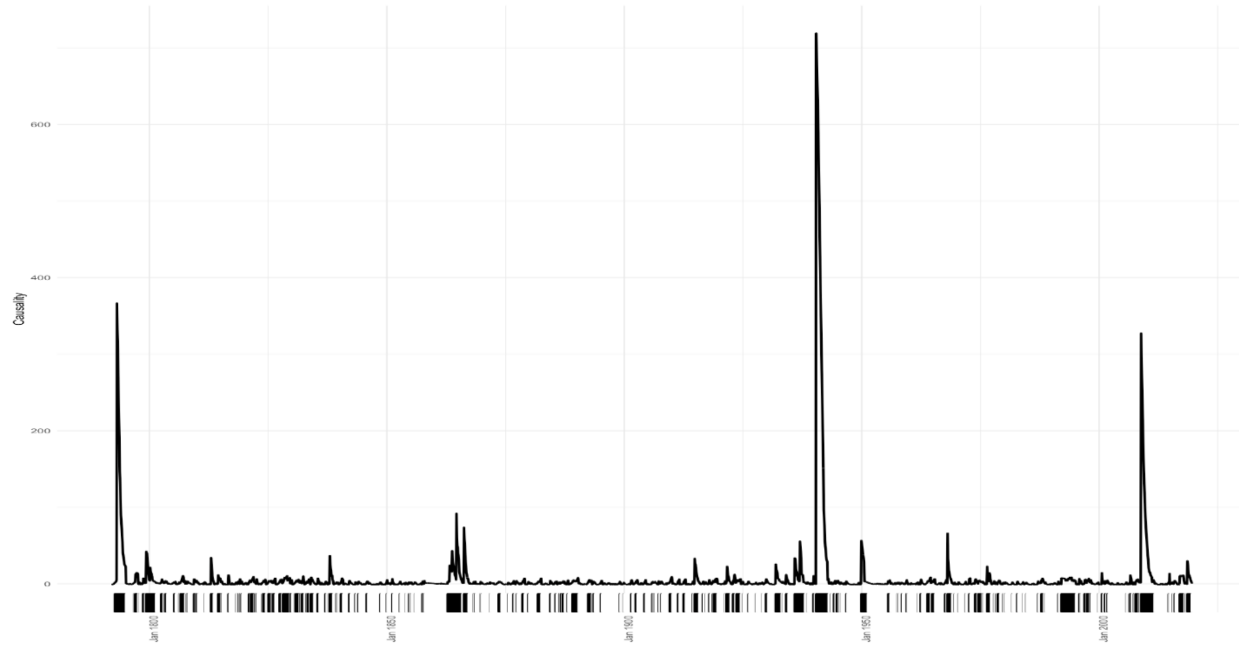
Figure 4

Monthly Results of the DCC-MGARCH Hong Tests between Dollar-Pound Exchange Rate Return Volatility and S&P 500 Return Volatility: September 1791 - September 2019

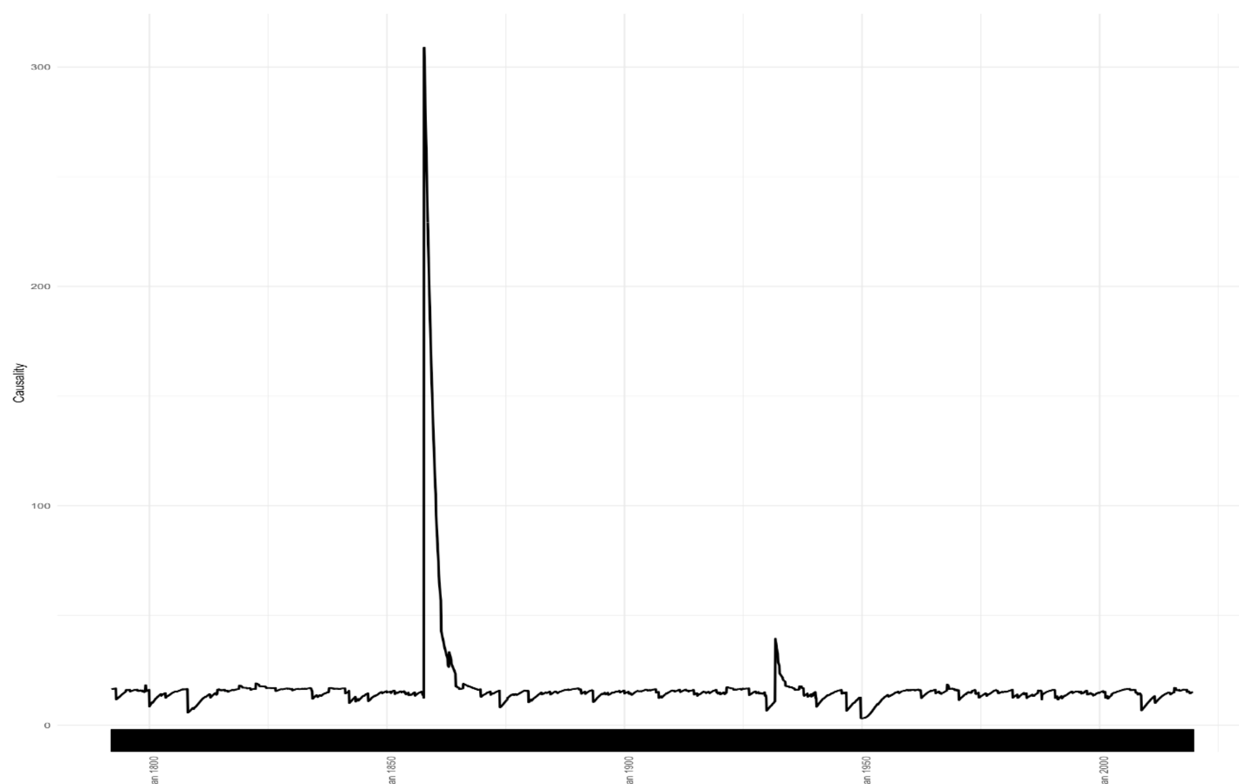
4(a). Unidirectional Causality: Stock Return Volatility to Currency Return Volatility



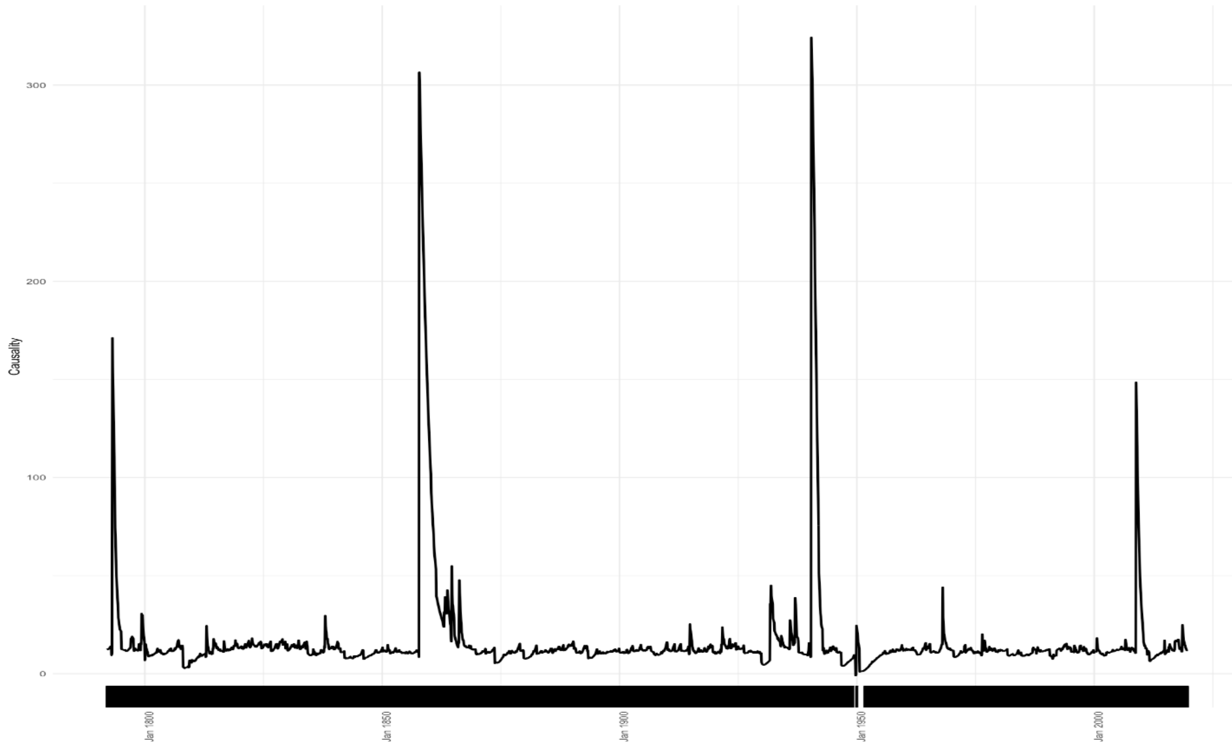
4(b). Unidirectional Causality: Currency Return Volatility to Stock Return Volatility



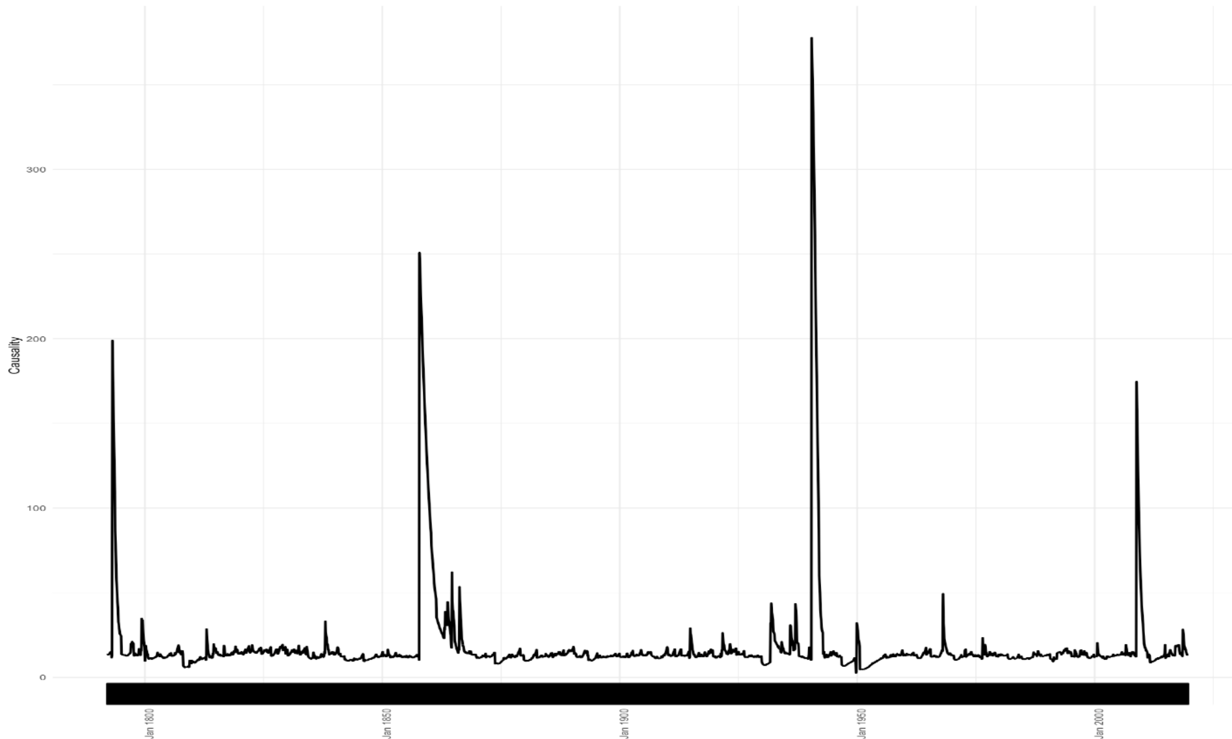
4(c). Instantaneous Causality: Stock Return Volatility to Currency Return Volatility



4(d). Instantaneous Causality: Currency Return Volatility to Stock Return Volatility



4(e). Bidirectional Causality Test between Currency Return Volatility and Stock Return Volatility



Note: See Notes to Figure 1.

APPENDIX

Table A1

Summary Statistics

	Variable	
Statistic	Dollar-Pound Exchange Rate Return	S&P500 Return
Mean	-0.0476	0.2565
Median	0.0000	0.2782
Maximum	60.4282	40.7459
Minimum	-61.1064	-30.7528
Std. Dev.	2.5774	3.8277
Skewness	-0.4139	-0.5903
Kurtosis	234.8025	14.8020
Jarque-Bera	6127811.0000	16043.4500
ADF-Test Statistic	-53.1233^{***}	-34.6029^{***}
Observations	2737	

Notes: Std. Dev: stands for standard deviation; The null hypotheses of the Jarque-Bera and ADF tests correspond to the null of normality and unit root respectively;
*** indicates significance at the 1% level.

Table A2

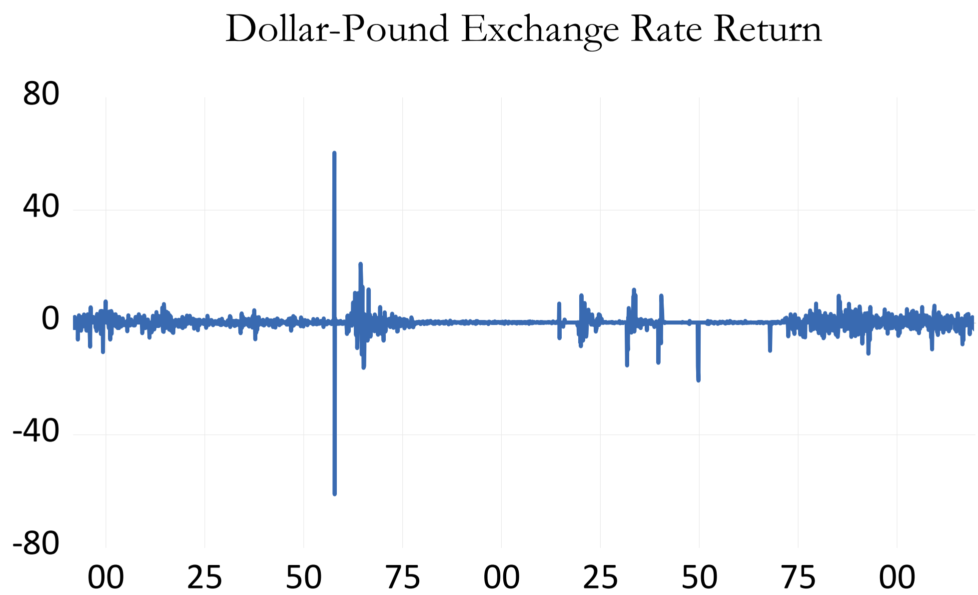
Brock et al. (1996, BDS) Test of Nonlinearity

Dependent Variable	*m*				
	2	3	4	5	6
Dollar-Pound Exchange Rate Return	24.5380***	29.5638***	34.3629***	38.9842***	44.0620***
S&P500 Return	10.1523***	13.4995***	15.8694***	17.7874***	19.7405***

Note: Entries correspond to the *z*-statistic of the BDS test with the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the exchange rate return and stock return equations with five lag each of the two variables; *** indicates rejection of the null hypothesis at 1 percent level of significance.

Figure A1

Data Plots



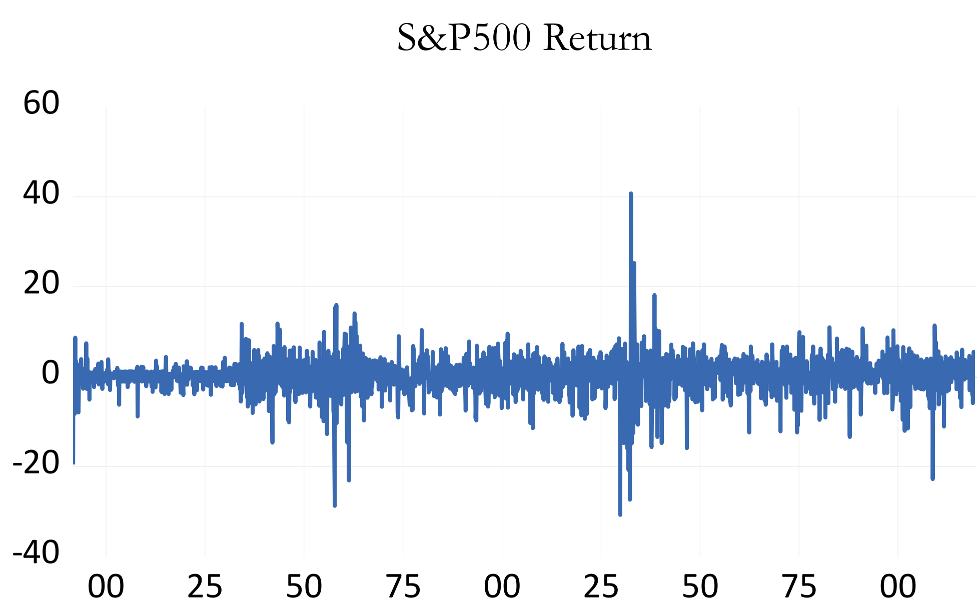


Figure A2

Wavelet-Based Average Phase Difference between Dollar-Pound Exchange Rate Return and S&P500 Return