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Time-Varying Causality between Equity and Currency Returns in the United Kingdom: Evidence from Over Two Centuries of Data

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Abstract

We analyse the dynamics of the causal interaction between the stock and foreign exchange markets for the United Kingdom using monthly data going as far back as 1791. First, we consider static causality tests, yielding mixed results. Given the evidence of structural breaks in the relationship between equity and currency returns, we use next the Dynamic Conditional Correlation-Multivariate Generalised Autoregressive Conditional Heterosckedasticity time-varying tests for Granger causality. The time-varying testing strategy we implement allows us to detect whether any causal relationship exists at each point in time between stock price and exchange rates returns. We find overwhelming evidence of time-varying information spillovers between the equity and currency returns. We check the robustness of our findings by running the entire battery of tests for two emerging market economies, namely, India and South Africa starting in 1920 and 1910 respectively. On the whole, the United Kingdom results are comparable to those in India and South Africa. As such, our results encompass the fragmented findings from our static tests as well as those in the extant literature.

JEL codes: C12, C18, C32, F31, G15

Keywords: Time-varying Granger causality, equity returns, currency returns

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1 Introduction

Establishing whether and to what extent there exist information spillovers among financial markets is important in portfolio diversification as well as risk management for policymakers, regulators, financial institutions, multinational firms and investors.

Against this backdrop and that of increased global financial integration, understanding how the equity and currency markets are related to one another is key. The theoretical literature on the linkages between the equity and currency markets is based on two main models: the flow-oriented (Dornbusch and Fischer, 1980) and the stock-oriented (Frankel, 1983; Branson, 1983) models.

According to the flow-oriented model, exchange rate changes can help predict developments in the equity market. The model postulates that, following a depreciation of the domestic currency, the international competitiveness of domestic firms improves. The ensuing rise in exports would translate into higher earnings and increased stock prices.

On the other hand, the stock-oriented model postulates that developments in the stock market spill-over to the currency market via the financial account. For instance, one possible channel is the effect of an increased demand for financial assets such as stocks on the exchange rate. A bullish domestic stock market signals better economic prospects. Hence, capital inflows increase and the domestic currency appreciates (Caporale et al., 2014).

While either theoretical model posits a unidirectional information spillover between the equity and currency markets, empirical causality can be bidirectional (Caporale et al., 2014; Granger et al., 2000).

Against this backdrop, an extensive strand of the literature examines empirically the linkages between the equity and currency markets both in developed as well as emerging economies. Recent studies include: Wong (2017); Sui and Sun (2016); Ho and Huang (2015); Caporale et al. (2014); Chkili and Nguyen (2014); Liang et al. (2013); Liu and Wan (2012); Tudor and Popescu-Dutaa (2012); Chkili et al. (2011); Pan et al. (2007); Ramasamy and Yeung (2005); Granger et al. (2000); Kanas (2000).

By and large, the literature is inconclusive on the empirical nature of the relationship between the equity and currency markets. The lack of empirical consensus can be attributed to a number of factors such as the sample and frequency of the data used in the study, the degree of capital control and the size of the equity market in the country being analysed (Pan et al., 2007; Granger et al., 2000). In the same perspective, another important aspect explaining the conflicting results from the literature is of a methodological nature. For instance, some models differ on the assumption about the nature of the data generating process of variables. Indeed, as

we will show, such different approaches have a significant implication for the findings. Depending on these factors, results may either corroborate the flow-oriented model, the stock-oriented hypothesis or both. In yet other cases, there could be no evidence of any interactions between the two markets.

That said, a key aspect of the nature of the relationship between the stock and foreign exchange market is that it is not stable across time due to structural breaks in the data. Using different sample periods or regimes for the same countries, some studies find evidence of a switching nature of the information spillover between the equity and currency markets. (Ho and Huang, 2015; Liu and Wan, 2012; Chkili et al., 2011; Ramasamy and Yeung, 2005).

This study contributes to the extant body of the literature by providing new evidence on the dynamics of information spillovers between the equity and currency markets in a developed market economy, namely the United Kingdom. Studies investigating the causality between equity and currency returns in the United Kingdom are rather scant, and much like the existing literature on different countries, yield conflicting results. To illustrate, in a recent study, Wong (2017) finds no support for causality in either direction between equity and currency returns in the United Kingdom. Yet, Tudor and Popescu-Dutaa (2012) and Stavarek (2004) argue that there do indeed exist interactions between the equity and currency markets in the United Kingdom, with the former leading the latter. On the contrary, Nieh and Lee (2001) find very limited (one-day) evidence of currency market developments leading equity markets outcomes.

Against such an unsettled backdrop about the nature of causality between equity and currency returns, we first implement a set of parametric and nonparametric Granger causality tests as is the practice in most studies in the literature. However, these tests are essentially static; they only capture the average causality effect over the given sample or regime and hence cannot describe the entire dynamics of information spillovers (Lu et al., 2014). For these reasons, we use, for the first time in this literature, the Dynamic Conditional Correlation-Multivariate Generalised Autoregressive Conditional Heterosckedasticity (DCC-MGARCH) Hong tests for time-varying Granger causality to investigate whether and to what extent the nature of information spillover between the United Kingdom equity and currency markets changes across time.

The key appeal of the DCC-MGARCH Hong tests is that causality at each point in time can be analysed. As such, we can pin down time-varying financial contagion. In addition to detecting unidirectional time-varying causality, the tests also show the overall (bidirectional) causal relationships. Furthermore, the tests can

be used to establish any evidence of instantaneous information spillover obtaining from nonsynchronous trading (Lu et al., 2014).

Our contribution is also novel in that, unlike existing studies in the literature which rely on relatively shorter samples, we consider a very wide span of time, using data on foreign exchange rates and stock prices as far back as possible.

We find that the time-varying Granger causality tests results encompass findings based on the static counterparts. There is overwhelming evidence that the nature and significance of the causal relationship between equity and currency returns varies across time. As such, contingent upon a particular point in time and when detected, information spillovers between the equity and currency markets can be explained using either the flow-oriented model, stock-oriented model or both.

To assess the robustness of our findings, we run the same set of tests for similarly wide samples of Indian and South African data. We reach comparable results: static causality tests portray an inconclusive picture of the nature of causality between the equity and currency returns. On the other hand, the DCC-MGARCH Hong causality tests detect overwhelming evidence of time-varying information spillovers between the equity and currency markets.

The remainder of the paper is structured as follows: Section 2 presents the methodology while Section 3 discusses the results. Section 4 concludes.

2 Methodology

This section presents the static as well as time-varying causality tests we implement in order to investigate the information spillover effects between the equity and currency markets for India, South Africa and the United Kingdom. We discuss the traditional Granger causality test which assumes a linear data generating process (DGP) of variables as well as time-invariant regression parameters. On the other hand, if the DGP is nonlinear, possibly due to structural breaks, then inferences from the linear Granger causality can be misleading. Against this backdrop, we outline two nonparametric and nonlinear alternatives to the traditional Granger causality test: the Diks and Panchenko (2006) and the Transfer Entropy causality tests. Evidence of structural breaks in the relationship between variables implies that the way in which the variable relate to one another is time-variant. Hence, we present the DCC-MGARCH Hong tests used to investigate time-varying causality between the variables under study. Lastly, we discuss the data used in the paper.

2.1 Linear Granger causality test

Let X_t and Y_t denote two stationary time series processes. Y_t does not Granger-cause X_t if for $h > 0$, the mean squared error (MSE) of X_{t+h} based on $(X_t, X_{t-1}, \ldots)$ corresponds to the MSE of a prediction of X_{t+h} based on both $(X_t, X_{t-1}, \ldots)$ and $(Y_t, Y_{t-1}, \ldots)$. We say that Y_t is not linearly informative about future X_t (Hamilton, 1994; Granger, 1969).

Using a bivariate VAR model where p denotes the autoregressive lag order, Y_t fails to Granger-cause X_t if the coefficient matrices Φ_i are lower triangular, for all i in

$$\begin{pmatrix} X_t \\ Y_t \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \phi_{11}^{(1)} & 0 \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} \end{pmatrix} \begin{pmatrix} X_{t-1} \\ Y_{t-1} \end{pmatrix} + \ldots + \begin{pmatrix} \phi_{11}^{(p)} & 0 \\ \phi_{21}^{(p)} & \phi_{22}^{(p)} \end{pmatrix} \begin{pmatrix} X_{t-p} \\ Y_{t-p} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \quad (1)$$

Testing whether Y_t Granger-causes X_t in the above VAR framework involves estimating the following model by OLS

$$X_t = c_1 + \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + u_t \quad (2)$$

We conduct an F test based on the null hypothesis $H_0 : \beta_1 = \cdots = \beta_p = 0$. To implement the test, we compute the sum of squares residuals (SSR) from Equation (2) as $RSS_1 = \sum_{t=1}^{T} \hat{u}_t^2$ and compare it with the SSR from the univariate autoregression for X_t, that is $RSS_0 = \sum_{t=1}^{T} \hat{\epsilon}_t^2$, where $X_t = c_0 + \gamma_1 X_{t-1} + \ldots + \gamma_p X_{t-p} + \epsilon_p$ is estimated by OLS. If $F_{stat} = \frac{(RSS_0 - RSS_1)/p}{RSS_1/T-2p-1}$ is greater than the critical value for an $F(p, T-2p-1)$ distribution, then we reject the null hypothesis that Y_t does not Granger-cause X_t (See Hamilton, 1994, for details).

2.2 Transfer Entropy causality test

Transfer entropy is a dynamic and non-symmetric measure of causality between two time series that was proposed by Schreiber (2000). Following the approach in Bekiros et al. (2017), we let the time series variable X_t follow a Markov process of degree k. The state i_{n+1} of X_t depends on all previous k states of X_t, that is,

$$p(i_{n+1}|i_n, i_{n-1}, \ldots, i_0) = p(i_{n+1}|i_n, i_{n-1}, \ldots, i_{n-k+1}) \quad (3)$$

where: $p(A|B) = p(A, B)/p(B)$ is the conditional probability of A given B. As such, the probability of state i_{n+1} of $Y_{1,t}$ conditional on all its previous states corresponds with the probability of i_{n+1} conditional on its k previous states. If X_t depends on another series Y_t then we assume that the state of X_t, that is, i_{n+1} depends on

previous states of variable Y_t, denoted j_n. The Transfer Entropy from Y_t to X_t is the average information contained in Y_t (the source) about the next state of X_t (the destination) that was not yet included in X_t's past. Formally, the Transfer Entropy is defined by

$$TE_{Y_t \to X_t}(k, \ell) = \sum_{i_{n+1}, i_n^{(k)}, j_n^{(\ell)}} \left(p\left(i_{n+1}, i_n^{(k)}, j_n^{(\ell)}\right) \log_2 \frac{p\left(i_{n+1} | i_n^{(k)}, j_n^{(\ell)}\right)}{p\left(i_{n+1} | i_n^{(k)}\right)} \right) \tag{4}$$

where i_n (j_n) denotes the n elements of the series X_t (Y_t); $p(A, B)$ is the joint probability of A and B. The joint probability of state i_{n+1} with its k predecessors as well as those of state j_n is defined as

$$p\left(i_{n+1}, i_n^{(k)}, j_n^{(\ell)}\right) = p\left(i_{n+1}, i_n, \ldots, i_{n-k+1}, \ldots, j_{n-\ell+1}\right) \tag{5}$$

As such, Transfer Entropy defined as above assumes that events at a given time can depend on events at time k as well as previously. In addition, Transfer Entropy can be considered as a nonlinear variant of the Granger causality test where causality is model-independent and asymmetric (See Bekiros et al., 2017, for details).

2.3 Diks and Panchenko causality test

Diks and Panchenko (2006) propose a nonlinear and nonparametric Granger causality test that alleviates the risk of bias in rejecting the null hypothesis of no Granger-causality in a previous test by Hiemstra and Jones (1994). For two strictly stationary time series X_t and Y_t, consider the delay vectors $X_t^{\ell X} = (X_{t-\ell_X+1}, \ldots, X_t)$ and $Y_t^{\ell Y} = (Y_{t-\ell_Y+1}, \ldots, Y_t)$ with $\ell_X,\ \ell_Y \geq 1$.

The null hypothesis that $X_t^{\ell X}$ contains no additional information about Y_{t+1} beyond that in $Y_t^{\ell Y}$ is defined as

$$H_0 : Y_{t+1} | \left(X_t^{\ell X}; Y_t^{\ell Y}\right) \sim Y_{t+1} | Y_t^{\ell Y} \tag{6}$$

The null hypothesis implies that the distribution of the $(\ell_X + \ell_Y + 1)$ - dimensional vector $W_t = \left(X_t^{\ell X}, Y_t^{\ell Y}, Z_t\right)$ (where $Z_t = Y_{t+1}$) is invariant. Hence, we can drop the time index and assume $\ell_X = \ell_Y = 1$. The distribution of Z conditional on $(X, Y) = (x, y)$ is identical to that of Z conditional on $Y = y$. The joint probability density function and its marginal satisfy

$$\frac{f_{X,Y,Z}(x, y, z)}{f_Y(y)} = \frac{f_{X,Y}(x, y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y, z)}{f_Y(y)} \tag{7}$$

Diks and Panchenko (2006) demonstrate that the null hypothesis implies

$$q \equiv E\left[f_{X,Y,Z}\left(X,Y,Z\right)f_{Y}\left(Y\right)-f_{X,Y}\left(X,Y\right)f_{Y,Z}\left(Y,Z\right)\right]=0 \tag{8}$$

Consider $\hat{f}_W\left(W_i\right)$, a local density estimator of a d_W-variate random vector W at W_i.

$$\hat{f}_W\left(W_i\right)=\left(2\epsilon_n\right)^{-d_W}\left(n-1\right)^{-1}\sum_{j,j\neq i}I_{ij}^{W}$$

where $I_{ij}^{W}=I\left(||W_i-W_j||<\varepsilon_n\right)$ with $I\left(\cdot\right)$ denoting the indicator function and ε_n the bandwidth depending on the sample size n.

The test statistic is a scaled sample variant of q in Equation (8)

$$T_n\left(\varepsilon_n\right)=\frac{n-1}{n\left(n-2\right)}\cdot\sum_{i}\left(\hat{f}_{X,Y,Z}\left(X_i,Y_i,Z_i\right)\hat{f}_{Y}\left(Y_i\right)-\hat{f}_{X,Y}\left(X_i,Y_i\right)\hat{f}_{Y,Z}\left(Y_i,Z_i\right)\right) \tag{9}$$

Diks and Panchenko (2006) show that if $\varepsilon_n=Cn^{-\beta}\left(C>0,\frac{1}{4}<\beta<\frac{1}{3}\right)$ then, for $\ell_X=\ell_Y=1$, the test statistic in Equation (9) satisfies

$$\sqrt{n}\ \frac{\left(T_n\left(\varepsilon_n\right)-q\right)}{S_n}\xrightarrow{D}N\left(0,1\right) \tag{10}$$

where $\xrightarrow{D}$ denotes convergence in distribution and S_n, an estimator of the asymptotic variance of $T_n\left(\cdot\right)$. Diks and Panchenko (2006) implement a one-tailed version of the test. If the left-hand side of Equation (10) is very large, then the null hypothesis is rejected.

2.4 DCC-MGARCH Hong tests for time-varying causality

Following Lu et al. (2014), the DCC-MGARCH Hong tests strategy first consists in estimating an ARMA-GARCH model for each stationary series. The objective is to remove the autocorrelation effect and generate series of residuals denoted X_t and Y_t. Then, the DCC-MGARCH model for $Z_t(j)=\left(\begin{smallmatrix}X_t\\Y_t\end{smallmatrix}\right)$ (where j represents the lag order) is used to estimate the dynamic correlations with lag j. The DCC-MGARCH

model is defined as[1]

$$\begin{aligned} Z_t(j)|I_{t-1} &\sim N\left(0, D_{t,j}R_{t,j}D_{t,j}\right) \\ D_{t,j}^2 &= \text{diag}\{\omega_{i,j}\} + \text{diag}\{\kappa_{i,j}\} \circ Z_t(j)Z_t^{'}(j) + \text{diag}\{\lambda_{i,j}\} \circ D_{t-1,j}^2 \\ u_{t,j} &= D_{t-1,j}^{-1}Z_t(j) \\ Q_{t,j} &= S \circ \left(\iota\iota^{'} - A - B\right) + Au_{t-1,j}u_{t-1,j}^{'} + BQ_{t-1,j} \\ R_{t,j} &= \text{diag}\{Q_{t,j}\}^{-1}Q_{t,j}\text{diag}\{Q_{t,j}\}^{-1} \end{aligned} \tag{11}$$

The dynamic correlation estimator in the DCC-MGARCH(1,1) with lag order j is

$$\begin{aligned} \rho_{pq,t}\left(j\right) &= \overline{\rho_{pq}}\left(j\right) + \alpha_j\left(u_{p,t-1}u_{q,t-1-j} - \overline{\rho_{pq}}\left(j\right)\right) + \beta_j\left(\rho_{pq,t-1}\left(j\right) - \overline{\rho_{pq}}\left(j\right)\right) \\ & r_{pq}\left(j\right)\frac{\rho_{pq}\left(j\right)}{\sqrt{\rho_{11,t}\rho_{22,t}\left(j\right)}} \end{aligned} \tag{12}$$

where $p, q = 1, 2$.

Using the dynamic correlation estimators from the DCC-MGARCH estimation and based on the choice of a positive integer M and a kernel function $k\left(x\right)$, the unidirectional DCC-MGARCH Hong test from Y_t to X_t, denoted $H_{1,t}\left(k\right)$, is

$$H_{1,t}\left(k\right) = \frac{T\sum_{j=1}^{T-1}k^2\left(\frac{j}{M}\right)r_{12,t}^2\left(j\right) - C_{1T}\left(k\right)}{\sqrt{2D_{1T}\left(k\right)}} \tag{13}$$

where

$$\begin{aligned} C_{1T}\left(k\right) &= \sum_{j=1}^{T-1}\left(1 - \frac{j}{T}\right)k^2\left(\frac{j}{M}\right); \\ D_{1T}\left(k\right) &= \sum_{j=1}^{T-1}\left(1 - \frac{j}{T}\right)\left(1 - \frac{j+1}{T}\right)k^4\left(\frac{j}{M}\right) \end{aligned}$$

The bidirectional DCC-MGARCH Hong test, denoted $H_{2,t}\left(k\right)$, is

$$H_{2,t}\left(k\right) = \frac{T\sum_{j=2-T}^{T-2}k^2\left(\frac{j}{M}\right)r_{12,t}^2\left(j\right) - C_{2T}\left(k\right)}{\sqrt{2D_{2T}\left(k\right)}} \tag{14}$$

[1] see Engle (2002) for details.

where

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

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

$$H_{3,t}(k) = \frac{T \sum_{j=0}^{T-2} k^2 \left(\frac{j+1}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{15}$$

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

It is not possible to estimate all lagged dynamic correlations in DCC-MGARCH Hong tests. Also, the choice of non-uniform kernels and the positive integer M hardly affects Hong tests' size. In addition, as is often the case in financial markets, the lagged dynamic correlations tend to 0 with large lags. Hence, empirical applications in financial markets use the Bartlett kernel. As such, only the dynamic correlations with lags $j = 0, \pm 1, \pm 2, \ldots, \pm M$ need to be estimated.[2]

Under the null hypothesis that X_t and Y_t are mutually independent, $\alpha_j \sim N\left(0, \frac{\sigma_{1,j}^2}{T}\right)$ and β_j represents a nuisance parameter in the DCC-MGARCH model (See Engle and Sheppard, 2001). As such, we cannot have the asymptotic distribution of dynamic correlations $r_{12,t}(j)$. Nonetheless, we have that $\sqrt{T} r_{12,t}(j) = \mathcal{O}_p(1)$ from the estimation of the DCC-MGARCH model under the null hypothesis. Letting

$$\overline{\rho_{pq}}(j) = \rho_{pq,0}(j) = \hat{\rho}_j = \frac{\sum_{t=j}^{T} X_t Y_{t-j}}{\sqrt{\sum_{t=1}^{T} X_t^2 \sum_{t=1}^{T} Y_t^2}}$$

We therefore have $\rho_{11,t12,t}(j) = \hat{\rho}_j + \hat{\alpha}_j \sum_{s=1}^{t} \hat{\beta}_j^{s-1} \xi_{t-s,j}$, where $\xi_{t,j} = u_{1,t} u_{2,t-j} - \hat{\rho}_j$. Ignoring the second term, we have that $\rho_{11,t12,t}(j)$ corresponds to $\hat{\rho}_j$. Hence, $H_{s,t}(k) \overset{as.}{\sim} N(0,1)\,(s = 1,2,3)$, that is, the DCC-MGARCH Hong tests are asymptotically normally distributed. We can use these distributions in empirical applications.

[2]The Bartlett kernel is defined as $k(z) = \begin{cases} 1 - |z|, & \text{if } |z| < 1 \\ 0, & \text{otherwise} \end{cases}$. If $j \geq M$, $k\left(\frac{j}{M}\right) = 0$. Hence, only correlations with lag $M > j > -M$ are required (See Lu et al. (2014) and Hong (2001) for details).

2.5 Data

We use monthly data on the stock price index (FTSE All Share Index, Bombay Stock Exchange Sensitive Index and Johannesburg All Share Index for the United Kingdom, India and South Africa, respectively) as well as the corresponding local currency exchange rate to the US dollar. The data are obtainable from the Global Financial Database.

The sample size for each country is contingent on data availability for a period going as far back as possible. Hence, we have samples covering February 1791 to July 2017, August 1920 to July 2017 and February 1910 to July 2017 for the United Kingdom, India and South Africa and respectively.

We compute the monthly returns as the natural logarithm difference $r_t = 100 \times (log\,(p_t) - log\,(p_{t-1}))$, where p_t represents the monthly foreign exchange rates or the monthly stock market index. Figures (1) to (3) show the time series plots of the variables. From visual inspection, we notice the presence of volatility clustering as well as large outliers across all the series.

[Figures (1) to (3)]

Furthermore, we report in Table (1) descriptive statistics for the monthly equity and currency returns. We observe that equity returns are generally greater and more volatile than currency returns.

Looking at higher moments for the United Kingdom variables, we notice a negative skewness for the foreign exchange rates returns and a positive skewness for the stock returns. This suggests that it is highly likely to experience losses in the currency market and gains in the equity market. On the other hand, the outcome is dissimilar for India and South Africa. Returns variables in both countries exhibit positive and negative skewness for the exchange rates and stock returns, respectively.

[Table (1) here]

Next, all returns variables across all countries exhibit positive kurtosis exceeding 3 (for a normal distribution). To statistically corroborate these observations, the Jarque-Bera test rejects the null hypothesis of normally distributed returns for all the returns variables.

Lastly, we report the outcome of the Augmented Dickey-Fuller unit root test which concludes that all the returns series are stationary.

3 Results

In this section, we first present and discuss results of static and time-varying causality tests between the equity and currency returns for the United Kingdom as well as the outcome of the structural break tests providing a motivation to consider time-varying causality tests. Thereafter, as a robustness check of findings in the United Kingdom case, we discuss comparable outcomes for India and South Africa.

3.1 Main empirical findings: the United Kingdom

3.1.1 Linear Granger causality test

Firstly, we test for linear Granger causality[3] between the equity and currency returns in the United Kingdom. Table (2) (Panel A) presents the results. Essentially, we fail to reject the null hypothesis of no Granger causality at the all conventional levels of significance for both directions. Therefore, the linear Granger causality test suggests that past information from any one of the returns variable does not help in forecasting returns in the other series. That is, in a sense, the equity and currency markets do not interact.

The linear Granger causality test fails to detect any causal relationship between the equity and currency returns. However, some studies in the extant literature, also in a linear Granger causality spirit (See Tudor and Popescu-Dutaa, 2012; Stavarek, 2004; Nieh and Lee, 2001, for example), argue that there do indeed exist evidence of information spillover between the two markets. As such, relying on the linear Granger causality test results could be misleading. In fact, the linearity assumption about the DGP of variables is at odds with the fact that financial series feature nonlinearities. As such, we implement nonparametric and nonlinear tests.

3.1.2 Transfer Entropy causality test

Secondly, we consider Transfer entropy causality results. Transfer entropy measures the amount of information transferred between two time series. There is evidence of causality from one series to another if the estimated transfer entropy is larger than that obtained when testing against the same, but randomly shuffled time series.

Using Box Kernel and Kraskov estimator methods to estimate the densities, Figures (4) and (5) show histograms of estimated transfer entropies for the randomised time series (1000 series). The dashed line represents the actual transfer entropy. There is evidence of causality whenever a positive information entropy is

[3]Based on a VAR(1) model, where the lag order is determined by the AIC and SIC.

larger than the histogram. Our analysis uses the information dynamics toolbox (See Lizier, 2014).

Based on the Box Kernel approach, results show that there is evidence of causality running from stock market returns to exchange rates returns and *vice versa*. However, using the Kraskov estimator approach, no causality of any type is detected. Table (2) (Panel B) reports the results.

The difference in causality results for the two density estimation processes highlights the challenges in density estimation for noisy time series. Transfer entropy is highly dependent on the underlying kernel density estimation process used.

3.1.3 Diks and Panchenko test

Lastly, turning to the Diks and Panchenko (2006) nonlinear Granger causality test, results show that there is evidence of two-way information spillover between the equity and currency markets. We reject the null hypothesis of no Granger causality at the 1% level of significance in both tests. Table (2) (Panel C) reports the outcome of the tests.

[Table (2) here]

3.1.4 Recapitulation

In all, the static Granger causality tests yield mixed results. On the one hand, the linear Granger (1969) causality test concludes that there is no information spillover between the equity and currency markets. On the other hand, the Diks and Panchenko (2006) test points to the contrary; there is indeed evidence of bidirectional causality between the equity and currency returns in the United Kingdom. In between and based on different density estimation techniques, the Transfer Entropy causality test offers two opposite conclusions: one corroborating the Granger (1969)'s test outcome (Kraskov estimator) and the other supporting the Diks and Panchenko (2006)'s test finding (Box Kernel). Against this inconclusive backdrop, we test for the presence of structural breaks in the relationship between the equity and currency returns as these could affect the ability of static tests to detect or not causality. Indeed, given the extensive time period we consider in this paper, structural breaks may be inevitable, thereby invalidating the static causality tests findings as they provide a "one-shot", average causality account.

3.1.5 Structural breaks test

The observation that the returns series feature volatility clustering over the very long span of time we consider in this study implies that there could be structural breaks in the way the series relate to one another. We therefore formally test for the presence of structural breaks in the relationship between equity and currency returns. We implement the Bai and Perron (2003) test for multiple breakpoints on individual equations of a VAR(1) model of the exchange rates and stock returns.[4]

[Table (3) here]

As can be observed from Table (3), there is evidence of multiple structural breaks in the relationship between equity and currency returns. This finding motivates our strategy to investigate whether the nature of information spillover from one returns series to the other is contingent upon time.

3.1.6 Time-varying Granger causality tests

We show in Figures (6) to (8) the unidirectional, instantaneous as well as the bidirectional time-varying DCC-MGARCH Hong tests[5] for information spillover between the stock and foreign exchange markets. The top panel of each figure depicts the value of the time-varying DCC-MGARCH Hong test. 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 spillover between the equity and currency markets. The direction as well as statistical significance of the information spillover between the equity and currency markets change over time. Considering the unidirectional information spillover (See Figure (6)), the following pattern emerges: there is evidence that information spillovers from the stock market to the currency market ($st \rightarrow ex$) weakly dominates that in the opposite direction ($st \leftarrow ex$).

[Figure (6) here]

Since it is likely that information spillover between markets takes place in a contemporaneous fashion due to nonsynchronous trading, we report the instantaneous DCC-MGARCH Hong tests (See Figure (7)). We observe a pattern suggesting that the instantaneous information spillover from the equity market to the currency

[4] Bai-Perron tests of 1 to M globally determined breaks with Trimming = 0.15, Max. breaks = 5, Sig. level = 0.05.

[5] We use $M = 12$. $M = 6$ and $M = 24$ yield comparable results.

market ($st \Rightarrow ex$) and that in the opposite direction ($st \Leftarrow ex$) by and large counterbalance one another. As such, the stock market has no contemporaneous edge on the foreign exchange market and *vice versa*.

[Figure (7) here]

Next, the bidirectional DCC-MGARCH Hong tests (See Figure (8)) show the time-varying overall two-way instantaneous information spillover between the equity and currency markets ($st \Leftrightarrow ex$).

3.2 Robustness checks: India and South Africa

Having established the shortcoming of static tests in detecting causality as well as the overwhelming evidence that causality between equity and currency returns is contingent upon time in the United Kingdom, we run a similar analysis as a robustness check using emerging market data, that is, considering the Indian and South African cases.

3.2.1 Linear Granger causality test

Firstly, similar to the United Kingdom findings, the linear Granger causality test[6] between the equity and currency returns fails to reject the null hypothesis of no Granger causality at the 5% level of significance for all the pairs of variables for both India and South Africa (See Table (4) (Panel A)).

[Table (4) here]

As such, the linear Granger causality test concludes that equity and currency returns bear no predictive power for one another.

3.2.2 Transfer Entropy causality test

Secondly, we consider Transfer Entropy tests. Using the Box Kernel and Kraskov estimator methods for density estimation, Figures (9) to (12) depict histograms of estimated transfer entropies for one thousand randomised time series for India and South Africa.

Mirroring the United Kingdom case, results based on the Box Kernel approach show that there is conclusive evidence of causality from the stock market returns to the exchange rates returns for India and South Africa. However, only the South African case matches that of the United Kingdom regarding evidence of causality

[6] Based on a VAR(1) model, where the lag order is determined by both the AIC and SIC.

running from currency to equity returns. No such causality is detected for India. The Kraskov estimator approach detects no causality of any type between equity and currency returns for both India and South Africa, as was the case for the United Kingdom. Table (4) (Panel B) summarises the findings.

[Figures (9) to (12) here]

3.2.3 Diks and Panchenko test

Thirdly, the Diks and Panchenko (2006) test, results conclude that there is evidence of two-way information spillover between the equity and currency markets in the case of South Africa much like in the United Kingdom case. For India, the test detects only evidence of one-way information spillover from equity to currency returns (See Table (4) (Panel C)).

3.2.4 Structural breaks test

Next, we implement the Bai and Perron (2003) test for multiple breakpoints[7] on individual equations of a VAR(1) model of equity and currency returns for India and South Africa. (See Table (5)) Corroborating the United Kingdom results, the test detects multiple structural breaks in the relationship between equity and currency returns in India and South Africa; thereby motivating our approach to test for time-varying causality.

[Table (5) here]

3.2.5 Time-varying Granger causality tests

Finally, we show in Figures (13) to (18) the unidirectional, instantaneous as well as the bidirectional time-varying DCC-MGARCH Hong tests[8] for time-varying causality between the equity and currency returns for India and South Africa.

As was the case for the United Kingdom, we find overwhelming evidence of time-varying causality between the equity and currency returns for India and South Africa.

Similar to the United Kingdom findings, unidirectional causality (See Figures (13) and (14) for India and South Africa, respectively) tests show patterns suggesting that information spillover from the stock market to the currency market ($st \rightarrow ex$)

[7] Bai-Perron tests of 1 to M globally determined breaks with Trimming = 0.15, Max. breaks = 5, Sig. level = 0.05.

[8] We use $M = 12$. $M = 6$ and $M = 24$ yield comparable results.

dominates that in the opposite direction ($st \leftarrow ex$), that is, the equity market has an edge in predicting developments in the currency market.

[Figures (13) and (14) here]

Also, the instantaneous DCC-MGARCH Hong tests (See Figures (15) and (16) for India and South Africa, respectively) show a similar outcome as that for unidirectional causality for both countries: information spillover from the equity market to the currency market ($st \Rightarrow ex$) has a contemporaneous edge on that in the opposite direction ($st \Leftarrow ex$). However, this finding does not corroborate that in the United Kingdom case where the stock market is found to have no contemporaneous edge on the foreign exchange market and *vice versa*.

[Figures (15) and (16) here]

Figures (17) and (18) depict the overall bidirectional instantaneous informational spillover between the equity and currency markets in India and South Africa, respectively.

[Figures (17) and (18) here]

3.2.6 Recapitulation

The findings that (1) static causality tests yield mixed results on the existence and nature of information spillovers between the equity and currency markets and (2) the predictive power of one returns series over the other is contingent upon time are robust to the choice between a developed market economy (*e.g.* the United Kingdom) and an emerging market counterpart (*e.g.* India or South Africa). Be that as it may, some differences are worth highlighting. Based on the instantaneous causality tests outcomes, stock price returns tend to have greater power in nowcasting exchange rate returns in many more instances for both India and South Africa. On the other hand, results suggest that current equity returns are useful in nowcasting exchange rate returns and vice versa in the United Kingdom. Also, there is no uniformity in the patterns of causality or lack thereof between equity and currency returns across countries. Nonetheless, there exist overlapping periods featuring the same patterns.

4 Conclusion

There is no denying the fact that information spillovers between the equity and currency markets do occur, albeit at varying degrees and directions across time

as evidenced using the DCC-MGARCH Hong tests. At one extreme, there are periods where there is evidence of information spillover in either direction between the equity and currency markets. At the other extreme, there are times when we find no evidence of any interaction between the two markets. That said, we generally observe that equity returns tend to give much more impulses to developments in the currency market than is the case in the opposite direction. Nevertheless, results also tend to suggest that, contingent upon time and if detected, the causal relationship between the equity and currency markets can be looked at through the lens of either the flow-oriented model, stock-oriented model or both. As such, our findings tie together seemingly incoherent results from static tests in the extant literature. This outcome has important policy and strategic implications. As a possible future line of research, it could be worthwhile investigating country-specific factors triggering the switch in the evidence, direction as well as overall nature of the causality between the exchange rate and stock price returns across time.

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Tables

Table 1: Descriptive statistics

Country	United Kingdom		India		South Africa	
Sample	1791:02 - 2017:07		1920:08 - 2017:07		1910:02 - 2017:07	
Variable	*ex*	*st*	*ex*	*st*	*ex*	*st*
Obs	2718	2718	1164	1164	1290	1290
Mean	-0.046	0.194	0.273	0.427	0.268	0.614
Stdev	2.583	3.723	2.521	5.165	2.844	4.482
Skewness	-0.415	1.162	8.535	-1.517	2.532	-0.690
Kurtosis	234.500	30.562	136.094	30.294	34.244	7.378
JB	6069401^a	86640.81^a	873270.5^a	36577.33^a	53847.48^a	1132.612^a
ADF	-52.99^a	-43.96^a	-31.53^a	-26.04^a	-28.63^a	-28.08^a

Notes: ^{a}, ^{b}, ^{c} mean $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively; *st*: stock returns; *ex*: exchange rate returns; Obs: observations; Stdev: standard deviation; JB: Jarque-Bera; ADF: Augmented Dickey-Fuller.

Table 2: Static Granger causality tests: United Kingdom

Panel A: Granger (1969)

H_0	F-stat
$st \not\rightarrow ex$	0.62
$ex \not\rightarrow st$	0.54

Panel B: Transfer Entropy

Density estimation	Conclusion
Box Kernel	$st \rightarrow ex$ $ex \rightarrow st$
Kraskov estimator	$st \not\rightarrow ex$ $ex \not\rightarrow st$

Panel C: Diks and Panchenko (2006)

H_0	t-stat
$st \not\rightarrow ex$	2.97^a
$ex \not\rightarrow st$	3.08^a

Notes: st: stock returns; ex: exchange rate returns; $\not\rightarrow$: "do not Granger-cause"; $\rightarrow$: "Granger-cause"; ^{a}, ^{b}, ^{c} mean $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 3: Estimated break dates using Bai and Perron (2003) test: United Kingdom

ex	st
1857:08	1825:02
1861:07	1859:06
1899:01	1897:07
1933:08	1932:08
1968:02	1975:03

Notes: Tests on individual equations from a VAR(1) model; Dates are in the format "Year:Month".

Table 4: Static Granger causality tests: India and South Africa

	India	**South Africa**
Panel A: Granger (1969)		
H_0	F-stat	F-stat
$st \not\rightarrow ex$	0.29	3.41^c
$ex \not\rightarrow st$	1.21	0.21
Panel B: Transfer Entropy		
Density estimation	Conclusion	Conclusion
Box Kernel	$st \rightarrow ex$ $ex \not\rightarrow st$	$st \rightarrow ex$ $ex \rightarrow st$
Kraskov estimator	$st \not\rightarrow ex$ $ex \not\rightarrow st$	$st \not\rightarrow ex$ $ex \not\rightarrow st$
Panel C: Diks and Panchenko (2006)		
H_0	t-stat	t-stat
$st \not\rightarrow ex$	2.16^b	3.14^a
$ex \not\rightarrow st$	0.10	3.02^a

Notes: st: stock returns; ex: exchange rate returns; $\not\rightarrow$: "do not Granger-cause"; $\rightarrow$: "Granger-cause"; ^{a}, ^{b}, ^{c} mean $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

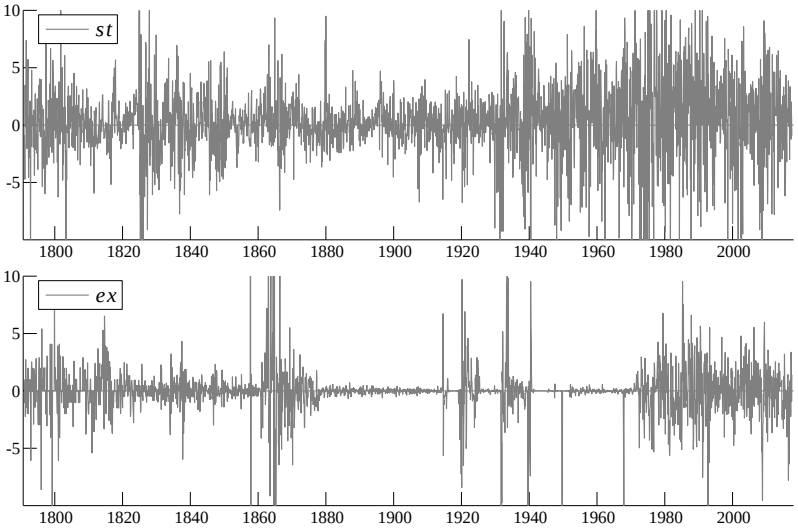
Table 5: Estimated break dates using Bai-Perron tests: India and South Africa

India		South Africa	
ex	*st*	*ex*	*st*
1935:03	1935:03	1926:05	1929:02
1949:09	1949:09	1943:01	1945:03
1966:08	1964:03	1959:02	1961:05
1981:02	1978:09	1975:09	1977:07
1996:03	1993:03	1998:08	1994:12

Notes: Tests on individual equations from a VAR(1) model; Dates are in the format "Year:Month".

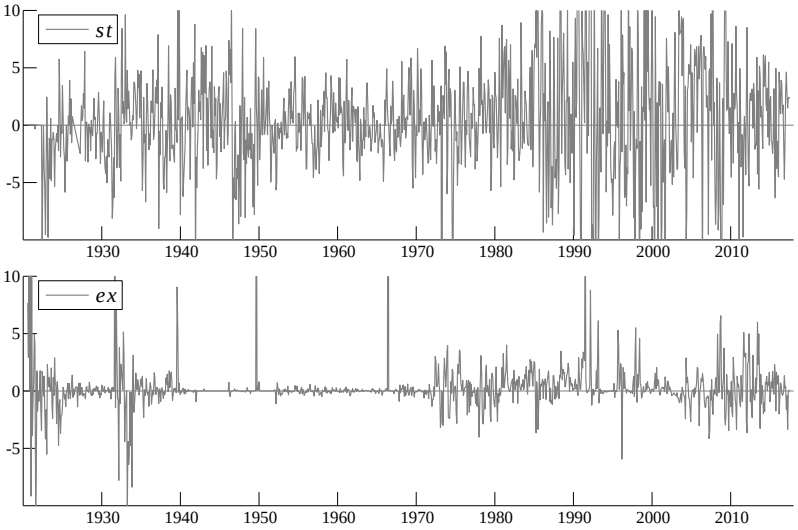
Figures

Figure 1: Time series for stock and exchange rates returns: the United Kingdom



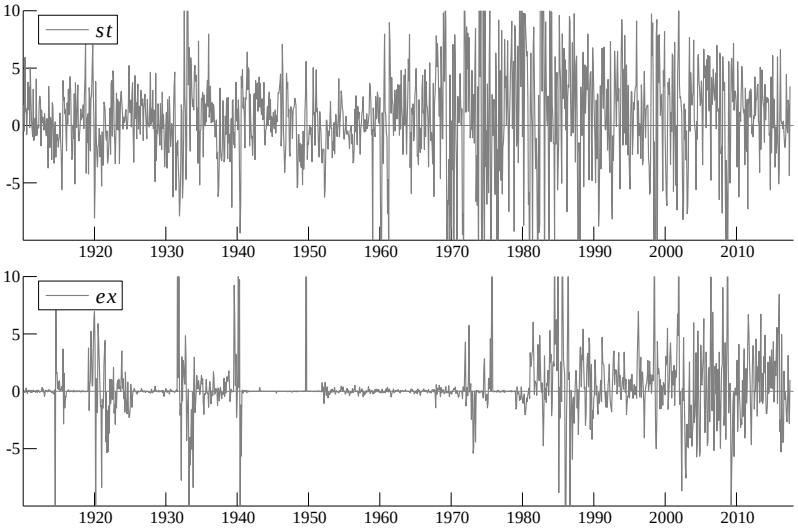
Source: Global Financial Database & own calculations.
Note: *st*: stock returns; *ex*: exchange rate returns.

Figure 2: Time series for stock and exchange rates returns: India



Source: Global Financial Database & own calculations.
Note: *st*: stock returns; *ex*: exchange rate returns.

Figure 3: Time series for stock and exchange rates returns: South Africa



Source: Global Financial Database & own calculations.
Note: *st*: stock returns; *ex*: exchange rate returns.

Figure 4: Entropy causality test (Box Kernel): United Kingdom

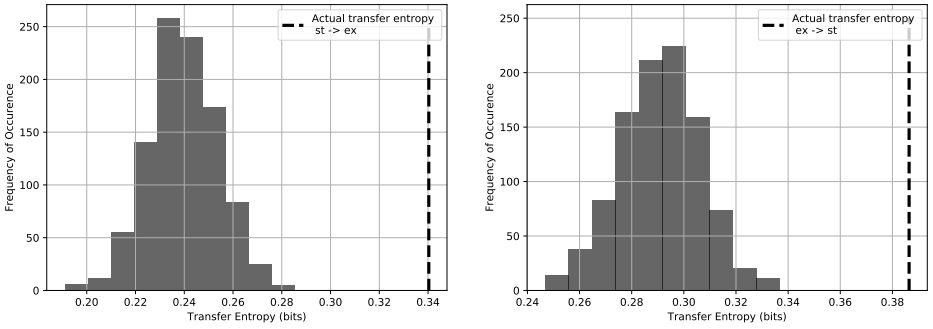


Figure 5: Entropy causality test (Kraskov estimator): United Kingdom

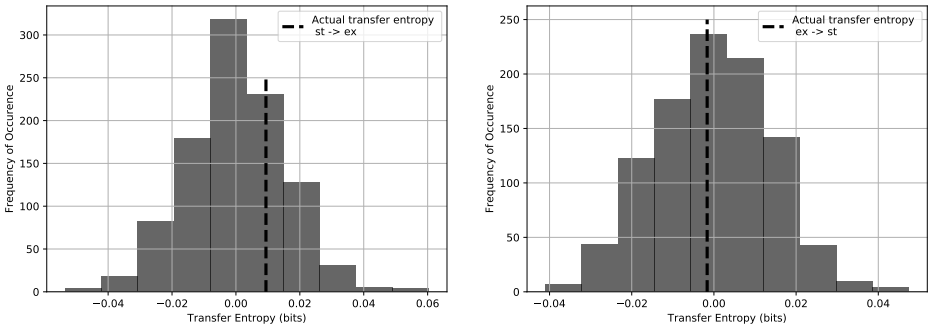
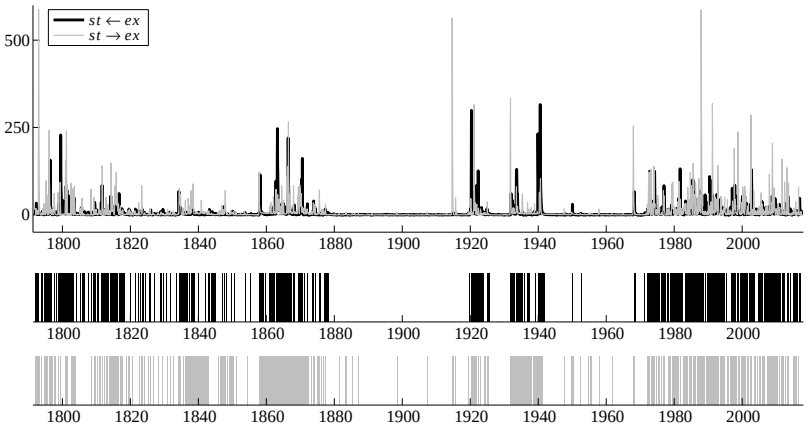
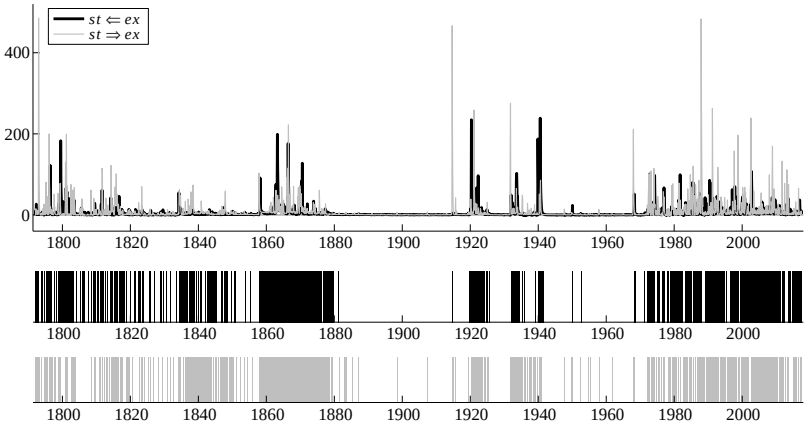


Figure 6: Unidirectional causality test: United Kingdom



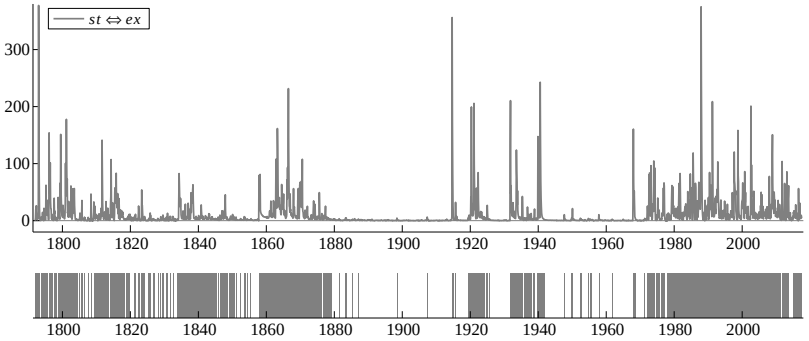
Notes: (1) Jan. 1792 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 7: Instantaneous causality test: United Kingdom



Notes: (1) Jan. 1792 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 8: Bidirectional causality test: United Kingdom



Notes: (1) Jan. 1792 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 9: Entropy causality test (Box Kernel): India

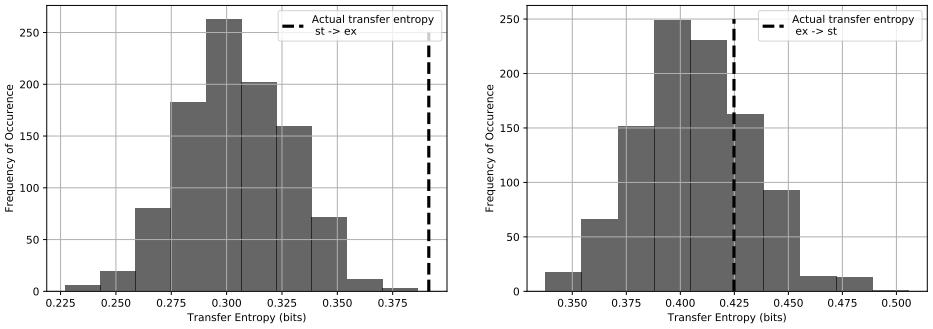


Figure 10: Entropy causality test (Box Kernel): South Africa

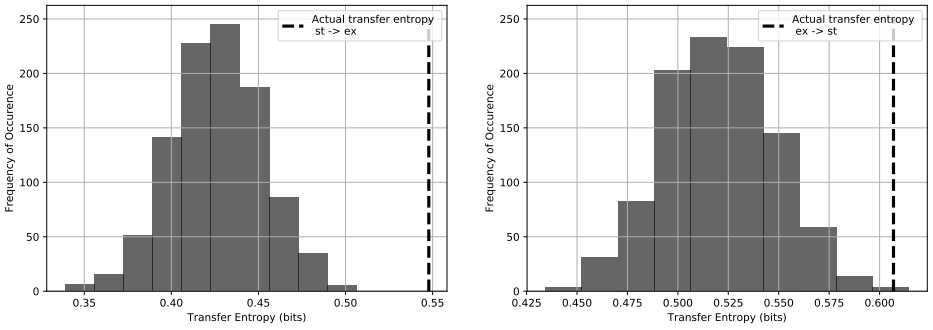


Figure 11: Entropy causality test (Kraskov estimator): India

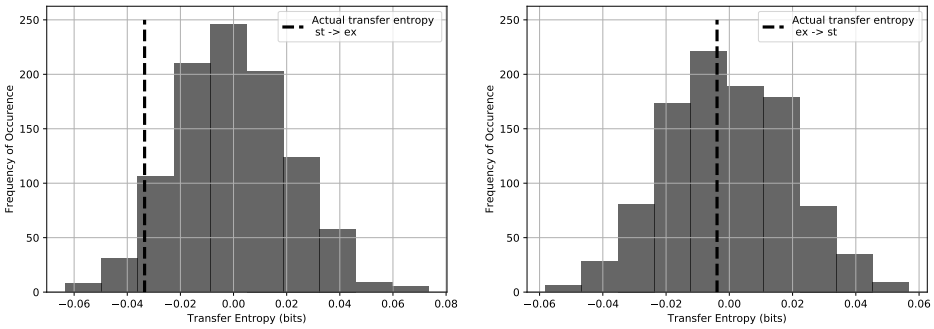


Figure 12: Entropy causality test (Kraskov estimator): South Africa

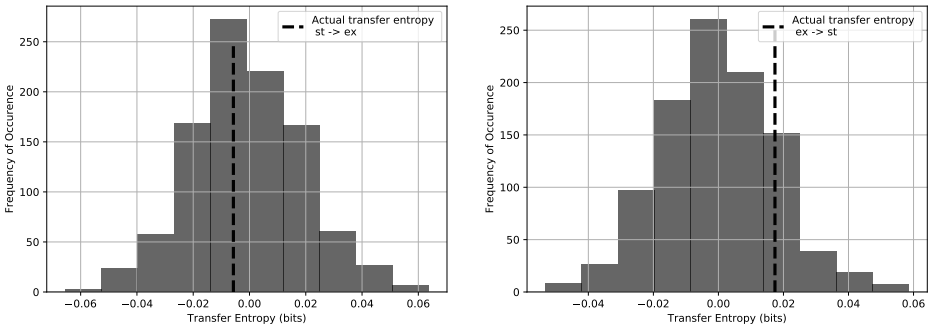
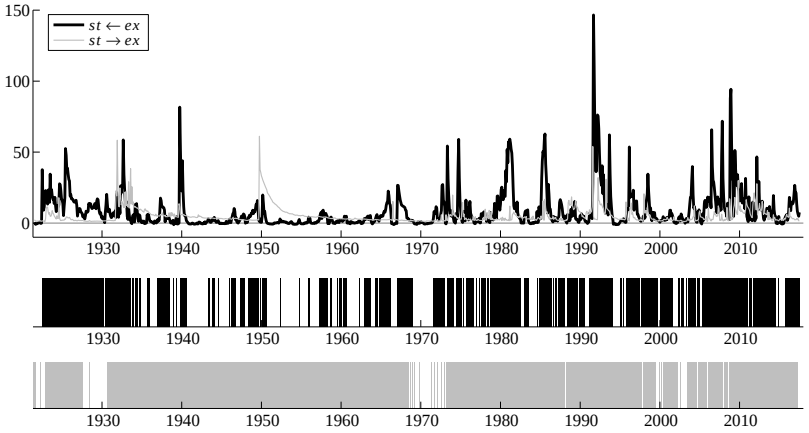
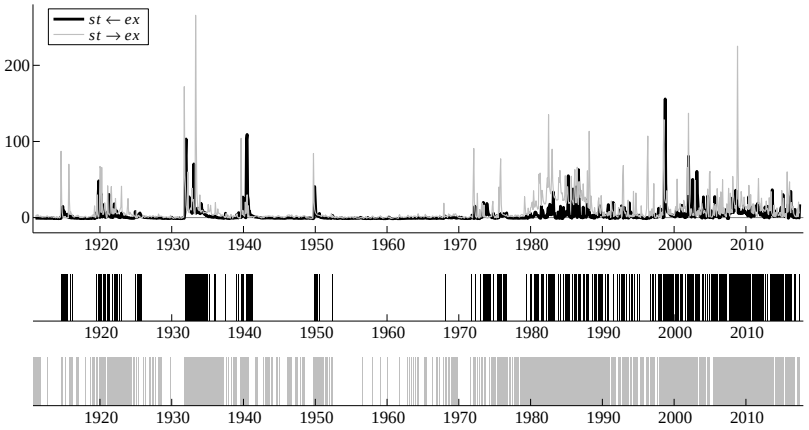


Figure 13: Unidirectional causality test: India



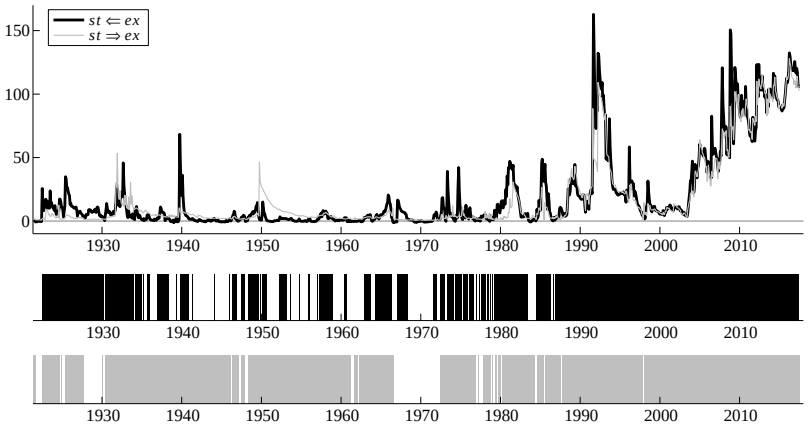
Notes: (1) Jul. 1921 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 14: Unidirectional causality test: South Africa



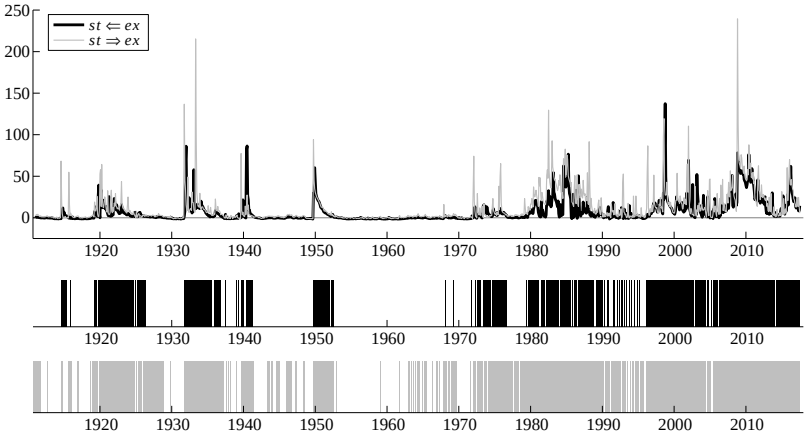
Notes: (1) Jan. 1911 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 15: Instantaneous causality test: India



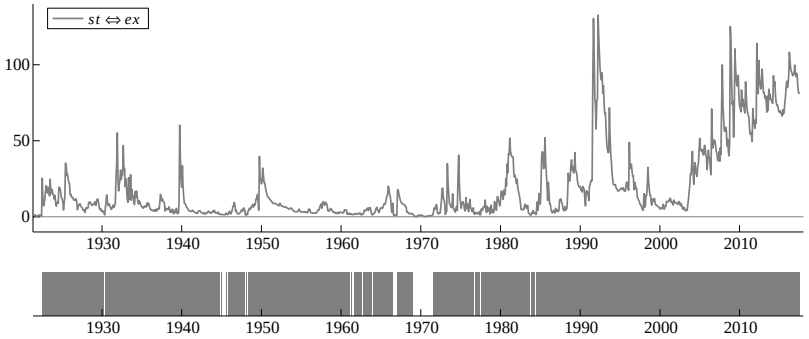
Notes: (1) Jul. 1921 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 16: Instantaneous causality test: South Africa



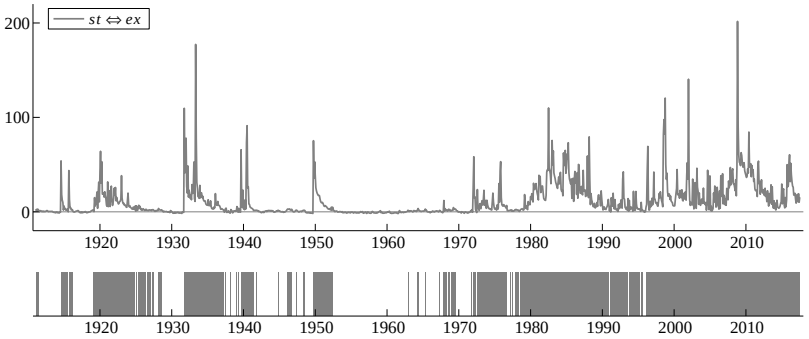
Notes: (1) Jan. 1911 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 17: Bidirectional causality test: India



Notes: (1) Jul. 1921 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.

Figure 18: Bidirectional causality test: South Africa



Notes: (1) Jan. 1911 - Jul. 2017; (2) The top panel shows the time-varying DCC-MGARCH Hong test statistic. The shaded region below shows the month during which the test is statistically significant at the 5% level.