Causal coupling between European and UK markets triggered by announcements of monetary policy decisions

Vittoria Volta[1] **and Tomaso Aste**[1,2,3]

[1]Department of Computer Science, University College London, Gower Street, London, UK
[2]UCL Centre for Blockchain Technologies, UCL, London, UK
[3]Systemic Risk Centre, London School of Economics and Political Sciences, London, UK.

ABSTRACT

We investigate high-frequency reactions in the Eurozone stock market and the UK stock market during the time period surrounding European Central Bank (ECB) and the Bank of England (BoE)'s interest rate decisions assessing how these two markets react and co-move influencing each-other. The dynamic multiscale interaction between these markets and the spillover effect on monetary policy announcement days are quantified by measuring linear and non-linear transfer entropy combined with a Bivariate Empirical Mode Decomposition (BEMD) from a dataset of 1-minute prices for the Euro Stoxx 50 and the FTSE 100 stock indices. We draw the following conclusions. First, central banks' interest rate decisions induce an upsurge in intraday volatility that is more pronounced on ECB announcement days. Second, there is a clear and significant information flow between the markets surrounding the time interest rates are released with prevalent direction going from the market where the announcement is made towards the other. Third, the coupling between the two markets describing the spillover effects is sufficiently well modeled with the linear approach to transfer entropy.
Keywords: Eurozone stock market; UK stock market; Spillover effect; Bivariate Empirical Mode Decomposition; Granger causality test; Transfer entropy.

1 Introduction

The key role of central banks has been to conduct monetary policy to achieve price stability (low and stable inflation) and help manage economic fluctuations. However, the policy frameworks within which central banks operate have been subject to major changes over the recent decade. In the aftermath of the 2008 Financial Crisis and the current COVID-19 pandemic, central banks have upgraded their financial stability functions and developed new instruments in order to promote credit flows and keep economies afloat. Some of these programmes fall into the category of serving as 'market-maker-of-last-resort'[1], a type of intervention that barely existed before 2007.

Not only central banks have gained more power on the financial markets, but also the progressively more interconnected global environment have influenced the degree to which cross-border asset prices react to monetary policy decisions. According to[2], capital flow volatility and the cross-border correlation of asset price movements and credit growth have increased in recent years, in connection with unconventional monetary policies put in place and with the intensifying search for a yield in a low interest rate environment. This has revived the debate over the risks posed by international spillovers of monetary policies across countries, not only to financial stability but also to monetary policy autonomy.

Given the considerable sway that central banks nowadays hold over the financial markets and the increasing global financial integration, the knowledge of how financial markets interact dynamically to the release of monetary policy decisions is of fundamental interest. It is a key input for policy makers who need to evaluate the impact of policy measures and monitor its transmission across different financial markets. It is also of particular benefit for market participants who are involved in intraday trading and need to assess the market risk of their positions induced by both foreign and domestic monetary policy announcements.

In this paper, we aim to explore how financial markets - specifically the Eurozone market and the UK market - react, co-move and might cause each-other movements surrounding interest rate decisions made by the European Central Bank (ECB) and the Bank of England (BoE). To the best of our knowledge, this study represents the first attempt to investigate the dynamic interdependence between markets surrounding monetary policy decisions and quantify spillover effects in a high-frequency and non-parametrical way.

This paper contributes to the existing literature in multiple aspects. From the content perspective, traditionally, papers studying the effects of monetary policy announcements on asset prices have mainly relied on the *level* effects on financial markets (see, for example,[3],[4],[5] and[6]). However, equity returns merely inform about an increase/decrease of an asset in reaction to announcements. We believe that more information could be gained by looking at the *volatility* which measures the markets' sensitivity - that is, whether markets are getting more nervous (volatility increase) or calmer (volatility decrease) - and therefore, it mirrors the immediate reaction on financial markets during an announcement day. This paper explicitly measures the linear and non-linear interrelations between the European and UK stock markets volatilities surrounding ECB and BoE announcement days, which to our knowledge not has been addressed in earlier research.

This paper introduces a novel methodology to investigate potential interactions between the two stock markets volatilities by using a data-driven approach which consists of two steps[1]. First, a Bivariate Empirical Mode Decomposition (BEMD) technique is used to decompose the European and UK stock markets volatilities into several pairs of intrinsic mode functions (IMFs) and residual functions with different timescales. Specifically, we use the BEMD algorithm developed by[8], which is an extension of the traditional Empirical Mode Decomposition (EMD) and is data-driven, hence, it has obvious advantages in processing non-stationary and non-linear data[9]. Second, the linear and non-linear transfer entropy are applied to inspect the causality [2] between the residues and the IMFs of each pair. To investigate linear relations, we use a generalization of the Granger–Geweke causality test, which assumes linearity and employs vector auto-regressive techniques to detect the impact of past values of a variable X_t on future values of another variable Y_t. In fact, it has been shown[10] that, for multivariate Gaussian variables, Granger-causality and transfer entropy are equivalent. To detect non-linear relations, we adopt the measure formalized by Schreiber[11], known as transfer entropy, which offers a natural way to model statistical causality between variables in multivariate distributions. Specifically, it quantifies the reduction in uncertainty about the dependent time series provided by the past values of the driving signal, conditioning on the past values of the dependent variable itself[12]. This method is model-free, able to capture the time-directed transfer of information between stochastic variables also in the non-linear case.

Only a fewer papers to date have investigated the response of stock index prices to monetary policy actions using high frequency data. One of the primary obstacles of working with intraday data has been the accessibility to high-quality, high-frequency prices over a relatively long calendar time period [3]. Among the earlier papers based on intraday observations,[15] reports a significant effect of policy shocks on the level and volatility of US stock returns.[16] examines bond and stock market volatility reactions in the euro area and the US following their respective economies' monetary policy decisions. He found a strong upsurge in intraday volatility at the time of the release of the monetary policy announcements by the two central banks.[17] explore the impact of Federal Open Market Committee (FOMC) announcements on the intraday volatility dynamics of the S&P 500 index. Their analysis show elevated intraday volatility through the market close, with a spike at the time of the announcement. This paper contributes to the existing high frequency empirical literature by examining a unique dataset of historical 1-minute prices for the Euro Stoxx 50 stock index and the FTSE 100 stock index from December 2015 to December 2019. The use of intraday data allows for better isolation of the response of stock index prices to the minutes release, since no other economic news is systematically released within such a narrow (one-minute) window around the monetary announcements.

This paper uncovers four main findings. First, both central banks' interest rate decisions induce an upsurge in intraday volatility, however, the reaction of the markets appears to be more pronounced following ECB decisions than following BoE decisions. Second, there is a clear information flow between markets surrounding the press releases on announcement days. Such information flow spans across time-scales and it is statistically significant for the majority of the intrinsic mode functions. Fourth, we found that the non-linear transfer entropy results are consistent with the linear ones and do not seem to add any extra element. We therefore believe the linear approach to transfer entropy is sufficient in detecting the spillover effects between the Eurozone stock market and the UK stock market.

The rest of the paper is organized as follows. In Section 2, we review the related literature on the impact of central banks' decisions on intraday stock market volatility. In Section 3, we provide a brief background on the Bivariate Empirical Mode Decomposition (BEMD) and the linear and non-linear transfer entropy. In Section 4, we describe in details the methodology used to quantify and validate the linear and non-linear causality measures. Results for real, one-minute intraday data are reported in Section 5. Section 6 reports conclusions and financial implications.

2 Data

Our data consists of 1-min intraday prices for the Euro Stoxx 50 stock market index and the FTSE 100 stock market index from December 2015 to December 2019. The data is from FirstRate Data[4]. From the original dataset, we select the following

[1] A similar method has been previously used by[7] to investigate the relationship between China's stock market and the international oil market. However, our approach to detect non-linear causality is based on information-theoretic measures rather than a non-parametric test statistics.

[2] In this paper, we consider a statistical form of causality, which can be observed in co-dependent time series where a response in the dependent series is more likely to follow after some change in the driving series. If the response of the dependent series scales as a linear multiple of the driving signal, the relationship is defined as a linear coupling. If, instead, the response follows some other functions of the driving series, the relationship is non-linear.

[3] See, for example,[13] and[14]

[4] The original dataset can be found at the homepage: https://firstratedata.com/.

fields: Date, Time (recorded in local time zone) and Close Price. To study the statistical causality surrounding the European Central Bank and Bank of England's monetary policy decisions, we further reduce the original dataset by selecting only trading days in which monetary policy announcements were made. Both central banks' interest rate decisions are typically released on Thursday every six weeks. Hence, the size of our sample amounts to 32 and 35 trading days for ECB and BoE announcement days, respectively, with 510 prices per trading day.

Data on ECB and BoE's monetary policy decisions have been collected internally from the historical archives of the official ECB and BoE websites and from Trading Economics, a provider of an economic calendar, time series statistics, business news, long term forecasts and short term predictions [5]. As regards the timing, the BoE's interest rate decisions are usually released at 12:00 (GMT), and the ECB's interest rate decisions at 13:45 (CET). It should be noted that BoE's interest decisions, are also accompanied by a quarterly Monetary Policy Report that sets out the economic analysis and inflation projections that the Monetary Policy Committee (MPC) uses to make its interest rate decisions. This implies that, particularly for the Bank of England, there are two potential sources of new information released at the same time. In contrast to the BoE, the ECB's interest rate decisions and statements are announced to the public at separate times. The actual outcome of monetary policy decisions are released at 13:45 (CET), however, details about the economic and monetary analyses underlying each interest rate decision are instead conveyed in the Introductory Statement read by the ECB President 45 minutes later.

For each day t, we compute the continuously compounded intraday returns, $r_{t+i\Delta}$, from 8:00 to 16:30 (GMT) using the following equation, which leads to 509 returns per trading day:

$$r_{t+i\Delta} = \ln(p_{t+i\Delta}) - \ln(p_{t+(i-1)\Delta}), \tag{1}$$

where p denotes the price and Δ is the sampling interval which in this case is one minute. In order to minimize the impact that other news releases may have on the statistical causality between the two indices, we select a window size of one hour surrounding the monetary policy announcements, hence, our analysis is performed over 60 returns per trading day. Specifically, we select the time period 13:30 to 14:30 (CET) for ECB announcement days and the time period 11:45 to 12:45 for BoE announcement days.

From the logarithmic returns, we estimate the intraday volatility using a non-parametric estimator, the annualized *realized volatility*, constructed as the square root of the averaged squared returns multiplied by an annualizing factor, which is:

$$\sigma_{t+i\Delta} = \sqrt{252n}\sqrt{\frac{1}{5}\sum_{k=1}^{5} r^2_{t+(i-k)\Delta}}. \tag{2}$$

The first two terms in the equation 2 is the annualizing factor, which assumes 252 trading days per year, whereas $n = 509$ is the number of returns per trading day. The rest is a running average across the last $k = 1,\ldots,5$ intraday squared returns.

According to[18], a good sampling frequency Δ that reduces the bias but maintains the accuracy of the realized volatility measurement is extremely important to avoid any distortions caused by market micro-structure frictions. Authors such as[19] and[20] use 5-minute sampling frequency. In this study, we decide to use all data at our disposal, maintaining a sampling frequency Δ of 1 minute. We however reduce microstructural noise by useing of the moving average of 5 minutes in equation 2, that smooths out irregularities and improves the accuracy of the realized volatility estimation.

From equation 2, we average the realized volatility values over the monetary policy announcement days. In this way, we obtain two couples of averaged realized volatility series - one sampled around the ECB announcements and the other around the BoE announcements - which are used as input signals for the causality investigation described in Section 3.

3 Methods

In order to investigate the interrelation between the Eurozone stock market and the UK stock market, we use linear and non-linear causality measures combined with the Bivariate Empirical Mode Decomposition (BEMD) technique originally proposed by[8]. The framework of the method is presented in Fig.1.

The model includes two steps. First, the BEMD decomposes the time series into pairs of bands at different time scales. Second, two different approaches to transfer entropy are applied to the pairs of the IMFs and residues. The first approach is linear and involves the application of the Granger-Geweke causality test, which uses vector auto-regressive techniques to measure the predictability of the time series. The second approach is non-linear and requires the estimation of the transfer entropy, which employs conditional mutual information to detect the statistical causality between the series.

[5] The web page of the economic calendar can be found at: https://tradingeconomics.com/calendar

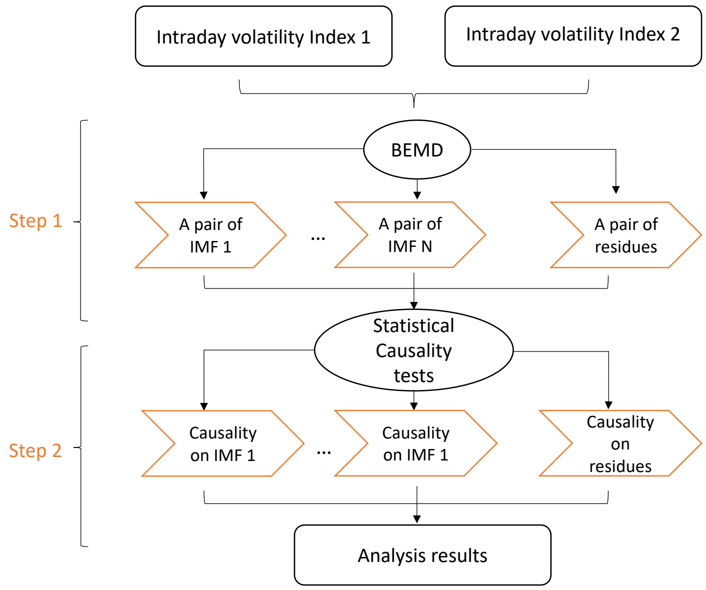


Figure 1. Diagram of the study. The methodology includes two steps, the Bivariate Empirical Mode Decomposition (BEMD) and the linear and non-linear statistical causality tests.

We implement the Bivariate EMD using the Rlibeemd package [6] in R, while we use the PyCausality package[12] [7] in Python to compute linear and non-linear transfer entropy.

3.1 Bivariate Empirical Mode Decomposition

The Bivariate Empirical Mode Decomposition (BEMD) approach is an extended Empirical Mode Decomposition (EMD) method used to process bivariate time series. It is similar to the EMD in that it decomposes the time series into a finite set of components with different and independent time scales. The EMD bivariate extension however differs in extrema detection and envelope definition. This paper builds upon the approach proposed by[8] to perform BEMD. Let us here, for completeness, briefly recall the BEMD methodology. Given two signals, $x_1(t)$ and $x_2(t)$, the bivariate time series is treated as complex-valued time series $x(t) = x_1(t) + ix_2(t)$, where $i = \sqrt{-1}$ is the imaginary number. The decomposition process is as follows.

1. Determine the set of N directions, w_k, in the complex space, with each direction vector defined based on equidistant points along a unit circle in 2D:

$$w_k = \exp(-i\varphi_k) \ \text{ with } \ \varphi_k = \frac{2k\pi}{N}, \tag{3}$$

   where $1 \leq k \leq N$.

2. for $k = 1$ to N, do:

   (a) Project the two-dimensional complex signal $x(t)$ onto the uniformly spaced direction w_k:

$$p_{\varphi_k}(t) = \mathscr{R}(\exp(-i\varphi_k)x(t)) \tag{4}$$

   where $\mathscr{R}(\cdot)$ denotes the real part of a complex number.

   (b) Extract all partial maximum points of $p_{\varphi_k}(t)$: $\{(t_j^k, p_j^k)\}$, where j indexes each individual maxima.

[6] The description of the package is available at: https://rdrr.io/cran/Rlibeemd/.
[7] The repository is available at: https://github.com/ZacKeskin/PyCausality.

(c) Interpolate the set of points $\{(t_j^k, p_j^k \exp(i\varphi_k))\}$ by cubic spline interpolation to obtain the partial complex-valued envelope curve, $e_{\varphi_k}(t)$, in direction φ_k.

3. Calculate the mean of all the complex-valued envelope curves:

$$m(t) = \frac{1}{N}\sum_{k=1}^{N} e_{\varphi_k}(t). \tag{5}$$

4. Similar to the EMD decomposition process, the residual component is calculated as:

$$S(t) = x(t) - m(t). \tag{6}$$

5. Determine whether the $S(t)$ meets the following conditions for a bivariate intrinsic mode function (BIMF):

   (a) the number of extrema and the number of zero crossings are identical or differ at most by one;

   (b) the mean value between the upper and the lower envelope is equal to zero at anytime.

   If satisfied, proceed, if not, repeat steps (1- 5) until $S(t)$ satisfies the requirements of a BIMF.

6. Record the resulting BIMF as $c_1(t)$ and remove it from the original signal $x(t)$ to get the residual component as:

$$r_1(t) = x(t) - c_1(t). \tag{7}$$

7. Repeat the above steps to get all the BIMFs. The original signal can be expressed as:

$$x(t) = \sum_{k=1}^{K} c_k(t) + r_K(t), \tag{8}$$

   where $c_k(t)$ denotes the kth complex-valued BIMF and K is the total number of BIMFs.

3.2 Linear Approach to Transfer Entropy

In the context of statistical causality, the objective is to test the null hypothesis of completely independent processes Y_t and X_t such that future realizations of Y_t are better explainable by using also past values X_{t-k} and than using only past values of Y_{t-k}. In the linear approach, Granger's proposed test can be implemented by fitting the sample data to a linear autoregressive model as follows:

$$Y_t = \sum_{k=1}^{m} \beta_k^{(Y)} Y_{t-k} + \varepsilon_t, \tag{9}$$

where Y_t represents the value of a time series Y at time t, m is the number of distinct lagged series, $\beta_k^{(Y)}$ is a general coefficient term and ε_t is the residual term.

To detect whether the time series X_{t-k} can help to predict future values of Y_t, we can compare equation 9 with the following:

$$Y_t = \sum_{k=1}^{m} \beta_k^{\prime(Y)} Y_{t-k} + \sum_{k=1}^{m} \beta_k^{\prime(X)} X_{t-k} + \varepsilon_t^{\prime}. \tag{10}$$

We can say that Y is Granger-caused by X if the residual $\varepsilon_t^{\prime}$ in equation 10 is significantly smaller than the residual ε_t in equation 9. If such condition holds, then there must be some information transfer from X to Y, which we measure as Granger causality.

The magnitude of such Granger causality interaction can be estimated by the F-statistic[21] as follows:

$$F_{X\to Y} = \log\left(\frac{var(\varepsilon_t)}{var(\varepsilon_t^{\prime})}\right). \tag{11}$$

According to[10], the Granger causality test is equivalent to transfer entropy if the processes are normally distributed. Specifically, within a linear approach, the transfer entropy and Granger causality are related through:

$$TE_{X\to Y} = \frac{1}{2} F_{X\to Y}. \tag{12}$$

3.3 Non-linear Approach to Transfer Entropy

In line with[12], we quantify nonlinear statistical causality by applying the information-theoretic notion of transfer entropy formulated by[11]. In contrast to Granger-causality, transfer entropy is not framed in terms of prediction but in terms of *resolution of uncertainty*[10].

In this approach, considering three random variables X, Y and Z, and denoting with $H(X|Z)$ the entropy of X conditioned to Z and $H(X|Y,Z)$ the entropy of X conditioned to Z and Y, one can define the conditional mutual information between X and Y conditioned to Z as

$$I(X;Y|Z) = H(X|Z) - H(X|Y,Z). \tag{13}$$

This is the amount of information shared by X and Y when conditioned to Z.

In terms of the conditional mutual information one can describe the the information transfer from X to Y, at a lag of k as follows:

$$TE^{(k)}_{X\to Y} = I(Y_t;X_{t-k}|Y_{t-k}) = H(Y_t|Y_{t-k}) - H(Y_t|X_{t-k},Y_{t-k}). \tag{14}$$

To compute this, we can use the chain rule for entropy and coerce the terms into joint entropies as:

$$H(Y_t|Y_{t-k}) = H(Y_t,Y_{t-k}) - H(Y_{t-k}). \tag{15}$$

and

$$H(Y_t|Y_{t-k},X_{t-k}) = H(Y_t,Y_{t-k},X_{t-k}) - H(Y_{t-k},X_{t-k}) \tag{16}$$

Therefore, it is possible to represent the transfer entropy, for a single lag k, in terms of four separate joint entropy terms, using equations 15 and 16:

$$TE^{(k)}_{X\to Y} = H(Y_t,Y_{t-k}) - H(Y_{t-k}) - H(Y_t,Y_{t-k},X_{t-k}) + H(Y_{t-k},X_{t-k}) \tag{17}$$

Equation 17 represents the reduction of uncertainty in Y when considering the past values of both Y and X, discounted by the information already provided by the past values of Y.

To calculate the joint entropy terms in equation 17 and detect non-linear transfer entropy, we perform non-parametric estimation of the probability density distributions using a histogram approach. The method is relatively simple, however, the choice of optimal bin selection requires a trade-off between bias and variance and impacts the value of the calculated transfer entropy[12]. A large number of bins generally results in larger transfer entropy values over the same data, since more information is introduced; this effect amplifies both signal and noise. By contrast, a small number of bins can hide important details about the information transfer.

The computation of the transfer entropy involves three variables and therefore the problem is three-dimensional. Intuitively, one wants to populate bins with at least one observation each. Accordingly, an estimate of the maximum number of bins is provided by the cube root of the total number of observations. In our case, a number between three and five bins per dimension ensures in average more than one observation per bin and provides a sufficient resolution to capture the information transfer. By testing number of bins between three and five, we find that the results are comparable in each case. We report results using histogram of four bins, a partition size which leads to good and meaningful results, that are consistent with the linear transfer entropy results.

In this paper, we partition the sample space using quantile binning, such that each marginal bin contains roughly equal numbers of data points[12]. This partitioning method has been proven to be superior over the equal-sized bins for the calculation of the transfer entropy. Indeed, histograms of equal-width bins give different results depending on the number of bins selected. In contrast, quantile bins appear to be more robust in varying coarseness and both even-numbered and odd-numbered bins provide similar results.

3.4 Non-parametric statistical validation

In order to validate results, we use the p-value and Z-score as statistical measures of significance. Following[12], we adopt a non-parametric approach comparing results with null-hypothesis non-causal transfer entropy values, $TE_s^{shuffle}$, obtained from time series where the time entries are shuffled independently and therefore and therefore any statistical causality based on time-dependence is eliminated. We estimate the significance by computing $N_{shuffles} = 1,000$ shuffled values and calculating the p-value defined as the proportion of shuffled series which have larger transfer entropy values than the original result,

$$p := \frac{1}{N_{shuffles}} \sum_{s=1}^{N_{shuffles}} O(TE_s^{shuffle} - TE). \tag{18}$$

Where $O(\cdot)$ is the step function.

The Z-score is instead measured as the distance between the computed transfer entropy (TE) and the average transfer entropy computed from shuffled data ($\mu_{shuffle}$), standardised by the shuffled standard deviation ($\sigma_{shuffle}$)

$$Z := \frac{TE - \mu_{shuffle}}{\sigma_{shuffle}}. \tag{19}$$

We compute the p-value and Z-score in equation 18 and 19 for both the linear and non-linear case.

4 Results

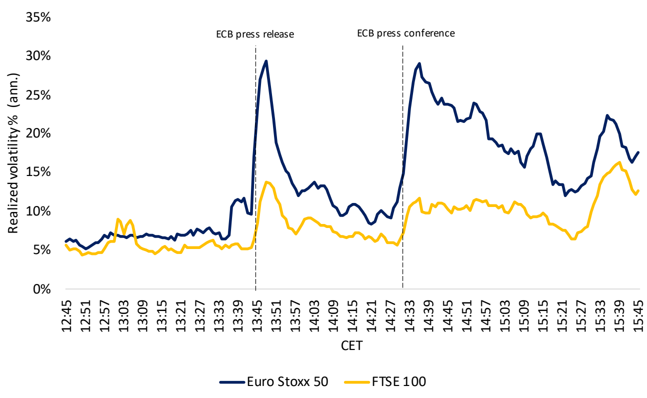
In order to investigate the impact of central banks' interest rate decisions on the stock markets, we examine the average realized volatility profile on announcement days and the excess volatility profile, measured as a ratio between the average volatility on announcement days over the average volatility on non-announcement days. A ratio above one can be interpreted as the monetary policy decisions inducing "higher than normal" volatility[16]. These are reported in Figure 2.

Three interesting features can be observed from Figure 2. First, both ECB and BoE's interest rate decisions induce an upsurge in intraday volatility in their respective domestic and foreign markets (Figure 2a-2b). Such volatility appears to be "higher than normal" on the stock markets surrounding the time of the press release (Figure 2c and 2d), and is particularly pronounced on ECB announcement days, where the average excess volatility is nearly 4.5 on the Euro Stoxx 50 and 2.5 on the FTSE 100. Second, some volatility persistence can be observed on both markets and can be noted up to more than one hour after the central banks' decisions have taken place (Figure 2c and 2d). Third, the Introductory Statement read by the ECB President induces "higher than normal" volatility on the euro area.

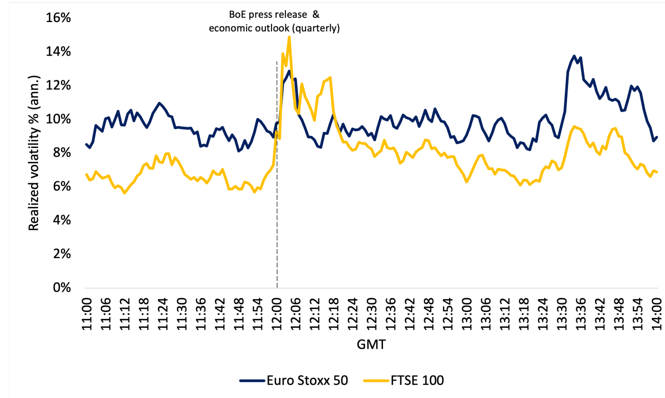
Any interpretation on the basis of Figure 2 could be spurious if important macro announcements were systematically released on the same days and at the same time as the ECB and BoE's monetary policy decisions. Therefore, we collected a significant number of US and euro area macro announcements to examine whether the interest rate decisions coincide with the release time of these macro statistics. The results of this examination suggest that none of the announcements under consideration occurred at the same time as the European Central Bank and Bank of England decisions, therefore, we believe that the observed upsurge in volatility is determined by the actual decisions and does not reflect market reactions to other macro news. By contrast, the ECB press conference is usually held at times of important US macro announcements, making the excess volatility measure difficult to interpret[16]. However, the ECB press conference is outside of the scope of this paper, which purely focus on the market reaction to the release of central banks' interest rate decisions.

In order to minimize the impact that news releases may have on the statistical causality of the two stock market volatilities, we carry out the transfer entropy analysis on a one-hour window surrounding the interest rate announcements. Specifically, we select the time period 13:30 to 14:30 (CET) for ECB announcement days and the time period 11:45 to 12:45 for BoE announcement days. To investigate the interrelation between the Eurozone market and the UK market and examine potential spillovers effects, we apply the methodology described in Section 3 to the average volatility time series. We decompose the Euro Stoxx 50 and the FTSE 100 average volatility series sampled around ECB and BoE announcement days and quantify linear and non-linear causality relations both between the original signals and between the intrinsic mode functions (IMFs) originated from the bivariate decomposition.

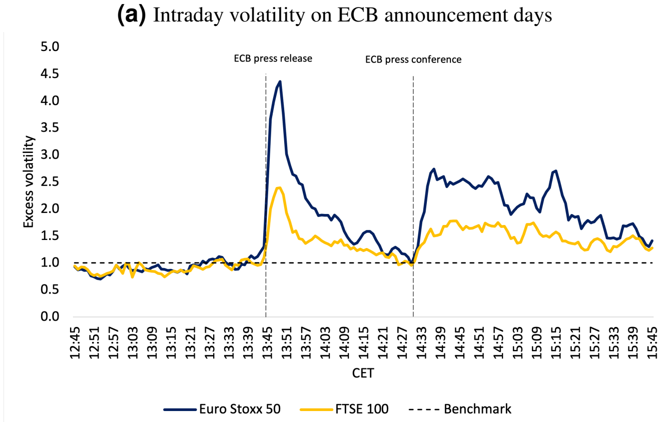
Figure 3 shows the bivariate Empirical Mode Decomposition (BEMD). From the signal decomposition, we get 4 pairs of IMFs and one pair of residual functions. We interpret the results in conjunction with Table 1 which reports the average oscillating period for each BEMD component. The first mode function captures the volatility jumps that take place around the time of the press release, indicating that such fluctuations of the markets due to the release of monetary policy decisions are primarily short-term. However, it is interesting to note that the high volatility in proximity to the announcements is partly transferred to lower-frequency components such as IMF2. This suggests that the volatility fluctuations driven by short-term factors spans between 1 minute to 4 minutes after the central banks' monetary policy decisions. The IMF3 instead captures the medium-term fluctuations of the volatility that ranges between 6 to about 8 minutes. Little information is instead conveyed by the last IMF and the residual. The IMF4, particularly on ECB announcement days, is on a large timescale of about 20-30 minutes and represents the long-term trends in the two markets.



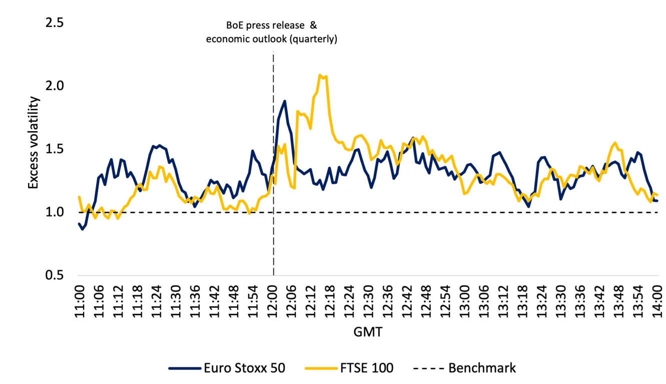
(a) Intraday volatility on ECB announcement days



(b) Intraday volatility on BoE announcement days

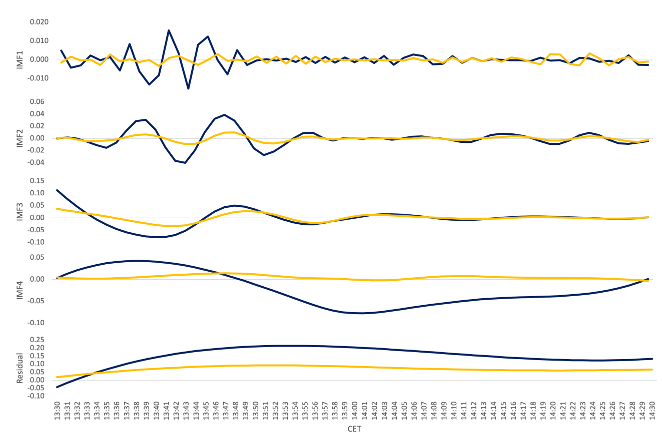


(c) Excess volatility on ECB announcement days

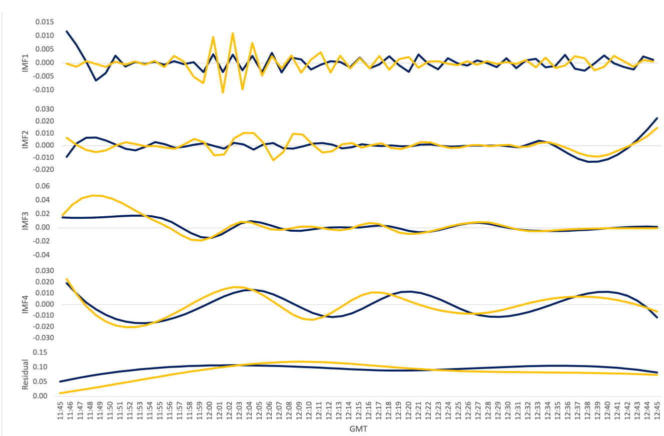


(d) Excess volatility on BOE announcement days

Figure 2. Average intraday volatility and average excess volatility on central banks' announcement days.. The sub-figures above (a,b) display the Euro Stoxx 50 (blue line) and FTSE 100 (yellow line) average intraday volatility across a 3-hour window on ECB and BoE announcement days. The volatility has been calculated using the equation 2. The sub-figures below (c,d) show the average excess volatility, which is defined as the ratio between the average realized volatility on announcement days and the average realized volatility on non-announcement days.



(a) Volatility decomposition on ECB announcement days



(b) Volatility decomposition on BoE announcement days

Figure 3. Decomposition of average realized volatilites via BEMD. The average realized volatilities on ECB and BoE announcement days are used to create complex signals, where the real part (blue line) is represented by the Euro Stoxx 50 average volatility and the imaginary part (yellow line) corresponds to the FTSE 100 average volatility. The complex value signals are then decomposed into IMFs and residual functions, according to the Bivariate Empirical Mode Decomposition approach described in 3.1.

The results of the linear and non-linear causality investigation are shown in Table 2-3, where transfer entropy values,

Mode	Timescale (minutes)			
	ECB announcement days		BoE announcement days	
	Euro Stoxx 50	FTSE 100	Euro Stoxx 50	FTSE 100
IMF1	1.48	1.32	1.45	1.29
IMF2	3.38	3.58	2.65	2.77
IMF3	7.62	7.62	7.62	6.77
IMF4	30.50	20.33	8.71	8.71
Residue	-	-	-	-

Table 1. **Average oscillating periods (minutes)**. This table shows the average oscillating periods for the Euro Stoxx 50 volatility series and the FTSE 100 volatility series measured in minutes for the extracted modes. The residue is a constant or a monotonic slope, therefore, it is the non-oscillating drift of the data.

p-values, z-scores and information flow values are provided. In general, it is expected that causal links should be strongest at time-lags closest to the true signal lag, and gradually decay as the time-lag considered is increased[12]. Therefore, in order to correctly identify causality, we perform the transfer entropy analysis over lags from 1 to 10, and pick the time-lag corresponding to the highest z-score.

Based on the data in Table 2 and 3, the following observations can be made regarding ECB announcement days. The original signal and both short-term and medium-term intrinsic mode functions show a consistent, clear direction of information flow from the Euro Stoxx 50 to the FTSE 100, suggesting that there is a spillover of volatility that is transferred from the Eurozone market to the UK market on ECB announcement days. With respect to the long-term scale (residual function), linear and non-linear transfer entropy reveal opposite results. However, in absolute terms, we can observe that there is a greater net information transfer from the Euro Stoxx 50 to the FTSE 100 (0.16) in Table 2, than from the FTSE 100 to the Euro Stoxx 50 (0.08) in Table 3. The significance of these results can be validated with the z-score and p-value. At the significance level of $\alpha = 5\%$, the linear transfer entropies are significant in both directions, for the original signal and all extracted modes. The non-linear transfer entropy results instead are statistically significant only in one direction for the majority of the intrinsic mode functions. This seems to suggest that the non-linear approach to transfer entropy is less sensitive in detecting statistical causality between the two volatility time series on ECB announcement days.

Mode	**Lag**	$TE_{X\rightarrow Y}$	**p-value**	**z-score**	$TE_{Y\rightarrow X}$	**p-value**	**z-score**	**Information flow**		**Validation**
Original	2	0.34	0.00	26.31	0.18	0.00	13.12	0.16	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF1	1	0.08	0.00	5.90	0.05	0.01	3.46	0.02	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF2	1	0.35	0.00	29.13	0.24	0.00	17.09	0.10	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF3	5	0.72	0.00	53.38	0.46	0.00	31.83	0.25	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF4	10	0.49	0.00	24.50	0.39	0.00	18.41	0.10	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
Residual	1	0.89	0.00	70.96	0.73	0.00	55.27	0.16	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE

Table 2. **Multi-scale linear transfer entropy surrounding ECB announcement days**. This table shows the linear transfer entropy, p-value, z-score for the original signal and all the extracted modes on ECB announcement days. The variable X denotes the Euro Stoxx 50 average realized volatility, whereas the variable Y indicates the FTSE 100 average realized volatility. The information flow is the net transfer entropy, precisely the difference between $TE_{X\rightarrow Y}$ and $TE_{Y\rightarrow X}$. In the validation column, the symbol "$\rightarrow$" indicates unidirectional statistical significance, "$\leftrightarrow$" denotes a bidirectional statistical significance and "*" means no statistical significance. The significance level is 5%.

Mode	**Lag**	$TE_{X\rightarrow Y}$	**p-value**	**z-score**	$TE_{Y\rightarrow X}$	**p-value**	**z-score**	**Information flow**		**Validation**
Original	3	0.23	0.00	7.70	0.07	0.04	2.01	0.15	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF1	1	0.08	0.03	2.43	0.00	0.79	-0.79	0.08	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF2	1	0.27	0.00	9.28	0.08	0.04	2.17	0.19	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF3	2	0.22	0.00	7.28	0.02	0.34	0.06	0.19	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF4	7	0.12	0.02	2.74	0.08	0.08	1.41	0.04	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
Residual	10	0.09	0.10	1.32	0.17	0.01	3.51	-0.08	$\leftarrow$	Euro Stoxx $\leftarrow$ FTSE

Table 3. **Multi-scale non-linear transfer entropy surrounding ECB announcement days**. Notation and symbols are the same as in Table 2.

With respect to BoE announcement days, we report the results in Table 4 and 5. We observe that the linear net transfer entropy (information flow) is positive for the original signals and all extracted modes, indicating a linear spillover effect from the FTSE 100 to the Euro Stoxx 50 on BoE announcement days. The direction of the non-linear information flow is instead less obvious, with IMF1 and residual function that show opposite directions. However, similarly to Table 2 and 3, it can be noted that for IMF1 and residual function, the non-linear net transfer entropy in Table 5 is smaller in absolute values than the linear net transfer entropy in Table 4. Moreover, except for IMF2, the linear transfer entropy values are significant in both directions, while the non-linear transfer entropy values is significant only in the direction from FTSE 100 to the Euro Stoxx 50 for the first intrinsic mode function and instead in both directions for the second. Similarly to ECB announcement days, we conclude that the linear approach to transfer entropy performs better than the non-linear approach in capturing the statistical causality between the volatility time series on BoE announcement days.

Mode	Lag	$TE_{X\rightarrow Y}$	p-value	z-score	$TE_{Y\rightarrow X}$	p-value	z-score	Information flow		Validation
Original	9	0.17	0.00	8.53	0.10	0.00	5.38	0.06	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF1	2	0.16	0.00	11.35	0.05	0.02	3.15	0.11	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF2	1	0.04	0.01	3.36	0.03	0.06	1.63	0.01	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF3	3	0.45	0.00	32.19	0.11	0.00	7.51	0.33	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF4	3	0.44	0.00	31.78	0.34	0.00	24.53	0.09	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
Residual	1	0.18	0.00	14.33	0.07	0.00	4.76	0.10	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE

Table 4. Multi-scale linear transfer entropy surrounding BoE announcement days. This table shows the linear transfer entropy, p-value, z-score for the original signal and all the extracted modes on BoE announcement days. The variable X denotes the FTSE 100 average realized volatility, whereas the variable Y indicates the Euro Stoxx 50 average realized volatility. The information flow is the net transfer entropy, precisely the difference between $TE_{X\rightarrow Y}$ and $TE_{Y\rightarrow X}$. In the validation column, the symbol "$\rightarrow$" indicates unidirectional statistical significance, "$\leftrightarrow$" denotes a bidirectional statistical significance and "*" means no statistical significance. The significance level is 5%.

Mode	Lag	$TE_{X\rightarrow Y}$	p-value	z-score	$TE_{Y\rightarrow X}$	p-value	z-score	Information flow		Validation
Original	9	0.19	0.00	4.39	0.01	0.72	-0.70	0.18	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF1	2	0.11	0.00	3.79	0.14	0.00	4.60	-0.03	$\leftarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF2	9	0.04	0.28	0.32	0.02	0.53	-0.38	0.02	$\rightarrow$	Euro Stoxx * FTSE
IMF3	1	0.22	0.00	7.57	0.00	0.75	-0.75	0.21	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF4	3	0.40	0.00	12.05	0.13	0.00	3.82	0.26	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
Residual	10	0.12	0.04	2.23	0.18	0.00	3.71	-0.06	$\leftarrow$	Euro Stoxx $\leftrightarrow$ FTSE

Table 5. Multi-scale non-linear transfer entropy surrounding BoE announcement days. Notation and symbols are the same as in Table 4.

Before drawing final conclusions, on the results for the announcement days it is important to investigate the statistical causality between the Euro Stoxx 50 volatility and the FTSE 100 volatility in the same time windows but on non-announcement days. The results are reported in Tables 6-9 in Appendix. We observe that, on days in which interest rates announcements are not released, there is a lack of consistency in the direction of information flow across the IMFs for both the linear and non-linear case. Moreover, the non-linear transfer entropy results appear to be non-statistically significant for some of the intrinsic mode functions (Table 7 and 9), revealing a certain degree of disconnection between the Eurozone and the UK stock markets. In our view, this is a strong evidence that the announcements have a significant effects on the markets and their causal coupling. The lack of an obvious direction of causality on non-announcement days is instead an indication that the interaction between the two markets is more complex and hidden and unstable when no external driving factors are at play.

5 Conclusions and Financial Implications

In this paper, we use a high-frequency, data-driven approach to investigate how the Euro Stoxx 50 and the FTSE 100 stock market volatilities react, co-move and influence each-other surrounding central banks' interest rate decisions. According to the above analysis, several interesting conclusions have emerged.

First, both the ECB and the BoE decisions induce an upsurge in intraday volatility. The reaction on the markets following the ECB's decisions are more pronounced compared to the reaction following BoE's decisions. We believe the two best possible explanations are as follows. Firstly, over the past 10 years the Bank of England has shown much greater flexibility and willingness to pursue quantitative easing, increase the money supply and cut interest rates where necessary. Indeed, as it is shown in Table 10 in the Appendix, BoE has cut interest rates twice as often as ECB did [8]. Such accommodating monetary policy where central banks are trapped in a "do whatever it takes" mindset, gripping markets tighter rather than releasing control, may inadvertently prolong a low volatility environment. Secondly, while the European Central Bank is responsible for

[8] This is partly attributable to their inflation target: BoE has a target of CPI = 2% +/- 1, whereas the ECB has an inflation target of below, but close to, 2%. Therefore, the ECB is less tolerant of inflation going above the inflation target.

the inflation rate in the whole Europe, the Bank of England has to consider the inflation only in the UK economy. Therefore, while the ECB's actual monetary policy decisions may be hard to predict, one could expect that BoE's decisions can be better anticipated by market participants. As the surprise effect following BoE's decisions is lower, also the volatility spike and the spillover effect on other markets may be less pronounced.

Second, there is a clear direction of information flow surrounding central banks' interest rate decisions. Specifically, the spillover of volatility is transferred from the Eurozone market to the UK market on ECB announcement days and from the UK market to the Eurozone market on BoE announcement days. Despite a very few exceptions, these directions are consistent across the majority of the intrinsic mode functions at different timescales and are detected by both the linear and non-linear methodologies. Such a clear directionality is instead not detected for days in which no interest rate decisions are released from central banks.

Third, the spillover effects surrounding central banks' interest rate releases are robust, consistent and statistically significant. Therefore, the FTSE 100 market pricing may be affected by the Euro Stoxx 50 market on ECB announcement days and viceversa on BoE announcement days.

Fourth, the majority of the non-linear transfer entropy results turned out to be statistically significant only in one direction. Therefore, in this context the non-linear approach is less efficient in detecting the spillover effects between the volatility time series and the linear-approach is instead sufficient in investigating the causality between the Eurozone stock market and the UK stock market. This indicate that the kind of coupling between the markets is prevalently linear.

From the above conclusions, some implications for the related stakeholders and market regulators can be derived. For investors, central banks' interest rate release affects pragmatic investment and risk mitigation decisions. Monetary policy announcements are often a catalyst for big directional stock movements, either up or down. Market participants could eliminate the investment risk and take advantage of big moves in the markets by using derivatives products such as options to design hedging strategies. For the market regulators, since the interest rate decisions have a significant impact on the asset prices, they need to be concerned about a potential shock from the stock markets and formulate responding strategies.

Building on this study, a key direction for future research would be to find further evidence of spillover effects following interest rate decisions by the Federal Reserve. It has been widely reported that the asset price sensitivity to US news is stronger compared with euro area news, partly owing to the fact that the US is considered among investors as the main engine of global growth[16]. However, little is still known on the volatility transmission of Fed decisions across foreign markets. Given that a break in trading may mitigate the impact of spillover effects, we believe that more information could be gained by carrying out the analysis on the futures markets, which operates nearly 24 hours a day.

6 Acknowledgements

TA acknowledges partial support from ESRC (ES/K002309/1), EPSRC (EP/P031730/1) and EC (H2020-ICT-2018-2 825215).

7 Bibliography

References

1. Buiter, W. & Sibert, A. The central bank as the market-maker of last resort: from lender of last resort to market-maker of last resort. *The First Glob. Financial Crisis 21st Century* **171** (2008).
2. Signorini, L. 'financial integration and inclusive development - a view from the mediterranean countries'. *OECD conference: Panel on 'Central banks, financial integration capital flows'* (2019).
3. Haitsma, U. D. d. H. J., R. The impact of the ecb's conventional and unconventional monetary policies on stock markets. *J. Macroecon.* **48**, 101–116 (2016).
4. Fausch, S. M., J. The impact of ecb monetary policy surprises on the german stock market. *J. Macroecon.* **55**, 46–63 (2018).
5. Fratzscher, D. M. L. S. R., M. Ecb unconventional monetary policy: Market impact and international spillovers. *IMF Econ. Rev.* **64**, 36–74 (2016).
6. Georgiadis, G. & Grab, J. Global financial market impact of the announcement of the ecb's asset purchase programme. *J. Financial Stab.* **26**, 257–265 (2016).
7. Peng, C. W. W. P., Y. & Yu, G. Spillover effect and granger causality investigation between china's stock market and international oil market: A dynamic multiscale approach. *J. Comput. Appl. Math.* **367** (2020).
8. Rilling, F. P. G. P., G. & Lilly, J. Bivariate empirical mode decomposition. *IEEE Signal Process. Lett.* **14** (2008).

9. Xu, W. X. X. X., G. On analysis of bi-dimensional component decomposition via bemd. *Pattern Recognit.* **45**, 1617–1626 (2012).
10. Barnett, B. A., L & Seth, A. Granger causality and transfer entropy are equivalent for gaussian variables. *Phys. review letters* **103** (2009).
11. Schreiber, T. Measuring information transfer. *Phys. Rev. Lett.* **85** (2000).
12. Keskin, A. T., Z. Information-theoretic measures for nonlinear causality detection: application to social media sentiment and cryptocurrency prices. *The Royal Soc.* **7** (2020).
13. Heston, K. R., S. & Sadka, R. Intraday patterns in the cross-section of stock returns. *J. Finance* **65**, 1369–1407 (2010).
14. Wang, W. Y., Y.H. Intraday volatility patterns in the Taiwan stock market and the impact on volatility forecasting. *Asia-Pacific J. Financial Stud.* **39**, 70–89 (2010).
15. Farka, M. The effect of monetary policy shocks on stock prices accounting for endogeneity and omitted variable biases. *Rev. Financial Econ.* **18**, 47–55 (2009).
16. Andersson, M. Using intraday data to gauge financial market responses to federal reserve and ecb monetary policy decisions. *Int. J. Cent. Bank.* **21**, 117–146 (2010).
17. Lunde, Z. A., A. Intraday volatility responses to monetary policy events. *Financial Mark. Portfolio Manag.* **23**, 383–399 (2009).
18. Zheng, Q. Z. T. T. S. H., Z. & Li, B. Realized volatility and absolute return volatility: A comparison indicating market risk. *PLoS ONE* **9** (2014).
19. Andersen, B. T. D. F., T. & Labys, P. The distribution of exchange rate volatility. *J. Am. Stat. Assoc.* **96** (2001).
20. Bandi, F. & Russell, J. Microstructure noise, realized variance and optimal sampling. *The Rev. Econ. Stud.* **75** (2008).
21. Geweke, J. The measurement of linear-dependence and feedback between multiple time-series - rejoinder. *J. Am. Stat. Assoc.* **77**, 323–324 (1982).

8 Appendix Section

Mode	Lag	$TE_{X\to Y}$	p-value	z-score	$TE_{Y\to X}$	p-value	z-score	Information flow		Validation
Original	1	0.05	0.01	3.44	0.00	0.55	-0.43	0.05	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF1	4	0.04	0.02	2.76	0.00	0.60	-0.52	0.04	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF2	6	0.12	0.00	7.10	0.12	0.00	8.01	-0.00	$\leftarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF3	7	0.02	0.13	0.93	0.12	0.00	6.28	-0.09	$\leftarrow$	Euro Stoxx $\leftarrow$ FTSE
IMF4	1	0.18	0.00	13.41	0.16	0.00	11.20	0.02	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
Residual	1	0.62	0.00	49.99	0.18	0.00	13.68	0.44	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE

Table 6. **Multi-scale linear transfer entropy on non-announcement days between 13:30-14:30 CET**. Notation and symbols are the same as in Table 2.

Mode	Lag	$TE_{X\to Y}$	p-value	z-score	$TE_{Y\to X}$	p-value	z-score	Information flow		Validation
Original	1	0.06	0.07	1.64	0.05	0.11	1.26	0.01	$\rightarrow$	Euro Stoxx * FTSE
IMF1	1	0.07	0.04	2.03	0.03	0.26	0.33	0.03	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF2	9	0.09	0.06	1.63	0.01	0.58	-0.47	0.07	$\rightarrow$	Euro Stoxx * FTSE
IMF3	4	0.08	0.03	2.28	0.05	0.16	0.86	0.03	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF4	7	0.07	0.09	1.33	0.08	0.09	1.34	-0.00	$\leftarrow$	Euro Stoxx * FTSE
Residual	10	0.03	0.35	0.00	0.32	0.00	7.59	-0.29	$\leftarrow$	Euro Stoxx $\leftarrow$ FTSE

Table 7. **Multi-scale non-linear transfer entropy on non-announcement days between 13:30-14:30 CET**. Notation and symbols are the same as in Table 2.

Mode	Lag	$TE_{X\rightarrow Y}$	p-value	z-score	$TE_{Y\rightarrow X}$	p-value	z-score	Information flow		Validation
Original	1	0.03	0.04	2.21	0.23	0.00	19.49	-0.19	$\leftarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF1	5	0.16	0.00	10.16	0.03	0.06	1.58	0.13	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF2	1	0.31	0.00	22.65	0.42	0.00	31.94	-0.11	$\leftarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF3	6	0.07	0.01	4.09	0.04	0.04	2.00	0.03	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE
IMF4	1	0.47	0.00	35.80	0.87	0.00	65.93	-0.39	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
Residual	2	1.51	0.00	116.91	0.51	0.00	38.30	1.00	$\rightarrow$	Euro Stoxx $\leftrightarrow$ FTSE

Table 8. **Multi-scale linear transfer entropy on non-announcement days between 11:45-12:45 GMT**.Notation and symbols are the same as in Table 4.

Mode	Lag	$TE_{X\rightarrow Y}$	p-value	z-score	$TE_{Y\rightarrow X}$	p-value	z-score	Information flow		Validation
Original	10	0.18	0.01	2.97	0.05	0.28	0.25	0.13	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF1	4	0.18	0.00	5.25	0.04	0.18	0.69	0.14	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF2	8	0.10	0.04	2.18	0.05	0.17	0.76	0.05	$\rightarrow$	Euro Stoxx $\rightarrow$ FTSE
IMF3	6	0.04	0.23	0.43	0.11	0.03	2.40	-0.06	$\leftarrow$	Euro Stoxx $\leftarrow$ FTSE
IMF4	5	0.17	0.00	4.74	0.49	0.00	16.91	-0.32	$\leftarrow$	Euro Stoxx $\leftrightarrow$ FTSE
Residual	6	0.00	0.99	-0.94	0.00	1.00	-0.99	-0.00	$\leftarrow$	Euro Stoxx * FTSE

Table 9. **Multi-scale non-linear transfer entropy on non-announcement days between 11:45-12:45 GMT**. Notation and symbols are the same as in Table 4.

	ECB	BoE
Total number of events	63	79
of which interest rates were changed	5	8
N. of increases, 10bp	2	0
N. of increases, 25bp	0	2
N. of increases, 50bp	0	0
N. of reductions, 10bp	0	5
N. of reductions, 25bp	3	1
N. of reductions, 50bp	0	0

Table 10. **Central banks' monetary policy decisions**. This table shows the ECB and BoE monetary policy decisions from the period Jan 2013 to Dec 2019.