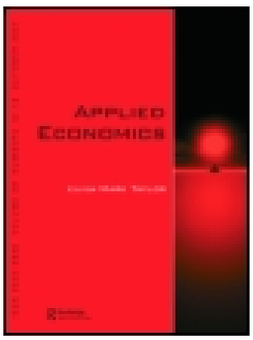


Routledge
Taylor & Francis Group

Applied Economics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

Does the dynamics between government bond and equity markets validate the adaptive market hypothesis? evidence from transfer entropy

Aviral Kumar Tiwari, Sangram Keshari Jena, Emmanuel Joel Aikins Abakah & Seong-Min Yoon

To cite this article: Aviral Kumar Tiwari, Sangram Keshari Jena, Emmanuel Joel Aikins Abakah & Seong-Min Yoon (2023): Does the dynamics between government bond and equity markets validate the adaptive market hypothesis? evidence from transfer entropy, Applied Economics, DOI: 10.1080/00036846.2023.2166896

To link to this article: https://doi.org/10.1080/00036846.2023.2166896

View supplementary material

Published online: 19 Jan 2023.

Submit your article to this journal

View related articles

View Crossmark data

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=raec20

APPLIED ECONOMICS
https://doi.org/10.1080/00036846.2023.2166896

Routledge
Taylor & Francis Group

Check for updates

Does the dynamics between government bond and equity markets validate the adaptive market hypothesis? evidence from transfer entropy

Aviral Kumar Tiwari [a,b], Sangram Keshari Jena [c], Emmanuel Joel Aikins Abakah [d] and Seong-Min Yoon [e]

[a]Indian Institute of Management Bodh Gaya, Bodh Gaya, India; [b]Rajagiri Business School, Kochi, India; [c]International Management Institute, Bhubaneswar, India; [d]University of Ghana Business School, Accra-Ghana; [e]Department of Economics, Pusan National University, Busan, Republic of Korea

ABSTRACT

The study applies the effective transfer entropy (ETE) and Renyi transfer entropy (RTE) to quantify the information flow between government bonds and equity market of G7 countries. The magnitude and direction of information flow between these two markets are dynamic across the state of the markets and time thus confirming their adaptiveness to the evolution of cross-market information flow under different market conditions over time. Although information flow from the equity dominates the flow from the bond market, it is dynamic over the time and state of the markets. However, during the period of market turbulence, the bond dominates the equity market. This study is the first of its kind to validate the adaptive market hypothesis using the novel transfer entropy framework in the bond and equity market.

JEL CLASSIFICATION
C14; C22; G14

KEYWORDS
Transfer entropy; effective transfer entropy; Renyi transfer entropy; government bond market; equity market; G7 countries

1. Introduction

Both bond and equity markets are fundamental to a country's economic development. The government bonds become a safe-haven and a good hedge during downturn of the equity market (Connolly, Stivers and Sun 2005; Baur and Lucey 2010). Further, equilibrium pricing of bond and equity has a bearing on portfolio managers' asset allocation decision, which depends on the efficient functioning of both the markets. Groenewold, Tang and Wu (2003) and Laopodis (2009) argued that improved financial market efficiency leads to less distortion in the economy because capital is properly priced and allocated, investors are rewarded with equilibrium risk-adjusted return and better pricing of risk for portfolio and risk managers. Further, in derivative markets, the parity in option pricing and pricing of futures depends on the dynamics between the bond and the equity markets which is critical for risk management. Now the question arises, how efficient are government bonds and equity markets? It requires quantification of inefficiency of financial market that would help policy makers and regulators to take appropriate policy measures for correcting the inefficiency. It also leads the speculators to exploit the inefficiency and the arbitrageurs to arbitrage out the mispricing based on predictability due to inefficiency (Eom, Oh and Jung 2008).

As far as the efficiency of financial markets is concerned several theories are proposed. The efficient market hypothesis (EMH) of Fama (2012) states that financial market is efficient as it reflects all types of information, such as historical, public, and private. However, the underlying assumption of investor rationality of EMH is challenged by behaviouralist documenting investors as irrational. They challenged the binary view (all or none) of market efficiency by EMH. Campbell et al. (1998) proposes relative market efficiency, where efficiency varies over time. Lo (2004) proposes adaptive market hypothesis, which is a balanced view about market efficiency from the market participants' biological perspective. He states that market efficiency continuously evolves over time and across market and not all or none phenomena. Moreover, factors like market microstructure, noise trading, information technology

CONTACT Seong-Min Yoon smyoon@pusan.ac.kr Department of Economics, Pusan National University, 2, Busandaehak-ro 63beon-gil, Geumjeong-gu, Busan 46241, Korea

Supplemental data for this article can be accessed online at https://doi.org/10.1080/00036846.2023.2166896

© 2023 Informa UK Limited, trading as Taylor & Francis Group

and market regulation, market imperfections and psychological biases may lead the markets departing from their level of efficiency. Government bond and equity markets are different in terms of the above factors, thus affecting their degree of inefficiency.

Perras and Wagner (2020) mentioned about the pricing of equity–bond covariance risk in bond and equity markets. Covariance risk as a pricing factor is more important than their own market risk which is attributed to factors like macro-economic (i.e. inflation), liquidity and uncertainty. Is the pricing of this covariance risk synchronous across bond and equity markets? If the answer is no, the degree of simultaneous mispricing leads to causality and information lead–lag relationship between bond and equity markets. Moreover, this relationship is dynamic as the equity–bond covariance risk is time varying.

The interpretations of the financial market's reaction to the new information by financial experts are found to be ad hoc. In academia, the same information pertaining to one asset/market may have different sign and magnitude of impact on another market. For example, Shiller and Beltratti (1992) argued that the rise in nominal bond yield may lead to either rise or fall or even no change in the stock market depending on how the market participants interpret it. If the rise in bond yield conveys information about higher dividend on stocks, the stock market will rise; however, if it conveys information about higher discount rate, it leads to lowering of stock prices. Alternatively, if the information is about rise in expected inflation, it is unclear whether stock market will change at all; given that, in real terms, future dividends are stable. Therefore, the stock and bond market dynamics seem to be very complex and less understood. Boyd, Hu and Jagannathan (2005) mentions about the different reaction by stock and bond markets to macro-economic news which are fundamental to their pricing particularly during the phases of contraction and expansion the economy. Boyd, Hu and Jagannathan (2005) attributes this to the presence of two extra pricing factors in equity market such as equity risk premium and growth rate of dividend in addition to risk-free rate. Thus, given the state of the business cycle, the same piece of macro-economic news may be good for one market and bad for the another. Thus, the way the markets react to arrival of information may lead to causality between the bond and equity markets.

Therefore, this study investigates the efficiency of the government bonds and equity market using the framework causality in the context of G7 economies. Granger (1969) defines causality in terms of existence of information flow in a linear relationship. It fails to measure the degree of causality in terms amount of information flow between two variables. Amount of information flow drives price formation and market efficiency Liu et al. (2020). If either equity or debt market is efficient according to weak form of EMH, it reflects all the historical information. However, if past information of either of the market drives the other markets, weak form of EMH is violated. The study applies the novel transfer entropy (TE) methodology of Schreiber (2000) which is based on the theory of information. TE is a model free measure of quantifying the information flow in non-linear and non-normal data. It simultaneously segregates information flow between two markets as driving and responding information between markets/assets. Using conditional and TE, Liu et al. (2020) identifies the market regime whether it is driven by return or sentiment based on the pattern of trading activity persists. Liu et al. (2020) states that this change in market regime quantifies the potential change in efficiency in the market. Wang (2022) using entropy family of models finds that efficient markets process more information than inefficient market and efficient markets are net transmitters of the information to the less efficient market. However, TE estimates are biased and noisy due to small sample effect. Moreover, financial time series are often reported for containment of noise. As a solution to overcome the above two limitations of TE, the study estimates effective transfer entropy (ETE) suggested by Marschinski and Kantz (2002). ETE filters out the noise and shows the causality due to information only.

Another dimension of information flow in the financial market is the state of the market. It conveys a different set of information depending upon the state of the market corresponding to

a particular financial and economic environment. In this study, we use Renyi TE (RTE) which shows an excess or lack of information flow across the distribution of one variable by updating the distribution with the known values of another variable. It measures the transfer of information between certain parts of the underlying distribution, which is suitable for both treasury bond yield and equity market that are subject to spikes and jumps (i.e. tail events) affecting their information flow dynamics (Jizba, Kleinert and Shefaat 2012). Unlike TE and ETE, RTE can be positive or negative, where positive (negative) RTE means that the knowledge of historical values of Y improves the informational efficiency (increases the riskiness) of X_{t+1}. Thus, we can differentiate between the transfer of uncertainty or information between equity and bond markets, which will help market participants in their respective spheres of operation.

According to the adaptive market hypothesis, the efficiency of the financial market is evolutionary as the economic and financial environments are dynamic. Therefore, we study how adaptive equity and bond markets are to cross market information flow through time varying RTE using 2000 days[1] moving window.

We find that ETE is greater than TE signifying the presence of noise in the information flow between the bond and equity market. The magnitude and the direction of information flow across state (i.e. low-probable bear and bull markets to high-probable average markets) and time between these two markets are dynamic. Although the information flow is primarily dominated by the equity market, the bond market dominates during the period of market turmoil.

Our contributions to the literature of bond and equity markets are as follows. It is the first study to use TE, a framework information theory and econophysics to test adaptive market hypothesis in government bonds and equity market. Second, this study establishes whether the causality is due to noise or information between the bond and equity markets using the ETE approach. Third, information flow and causality are estimated across the state of the bond and equity markets using RTE. Fourth, the robustness of the causality and the nonlinearity of the flow of information are investigated in a time varying framework of TE using 2000 days moving window method.

The rest of the paper is structured as follows. Section II discusses the literature and the resulting gap, Section II describes the data used for the study, Section III deliberates the methodology used, Section IV presents and interprets the result and, finally, Section V concludes the paper with a discussion of policy implication.

2. Literature

In the literature, initially time-invariant correlation between stock–bond market was reported (Campbell and Ammer 1993; Shiller and Beltratti 1992), which is subsequently rejected with the time-varying correlation between these two important asset classes (Connolly, Stivers and Sun 2005; Aslanidis and Christiansen, 2012; Jammazi et al. 2015). While the negative relationship is attributed to the popular phenomena of flight-to/from quality in case of turbulence in the stock market, positive relationship is associated with the stability of macro-economic environment where both the markets are affected by common factors. For example, Sakemoto (2018) finds decreasing co-movement between equity–bond with increasing market uncertainty measured by VIX in case of 18 advanced and 13 emerging markets. It reveals the demand for cross-market hedging between these two markets. Fang, Yu and Huang (2018) mentioned about the impact of investor sentiment on the bond–equity relationship. The impact of other macro-economic variables on the bond – equity relationship is also reported in the literature such as expected inflation (David and Veronesi 2013), business cycle and monetary policy (Yang, Zhou and Wang 2009). However, some of the studies contradict the impact of macro-economic variables on the bond–equity relation (Shiller and Beltratti 1992; Baele, Bekaert and Inghelbrecht 2010). Additionally, Panchenko and Wu (2009)

[1]Estimates of transfer entropy are biased because of the effect of small sample Marschinski and Kantz (2002).

reported decoupling of bond and equity markets because equity as an asset class is seen a surge in demand. Garcia and Tsafack (2011) also found a time-varying weak dependency between bond and equity.

The time-varying co-movement and impact of macro-economic factors depend on how the information is reflected on the prices of bond and equity. Limited studies are found related to informational dynamics between bond and equity markets, which is critical to the efficient functioning of the financial market. The relative pricing of bond and equity depends on cross-market information transmission, while the transmission of volatility/uncertainty in one market creates instability in another market. As evidenced from the Li et al. (2016) study, the interaction of joint price dynamics and cross-market trading behaviour of heterogeneous agents shapes the feedback relationship between bond–stock market linkage and capital allocation for portfolio optimization between bond and stock. The heterogeneous agent model of Li et al. (2016) consists of one set of agents called fundamentalists who trade on fundamental factors and another set called chartists who follow price patterns. Then, the obvious question is, what does the trading behaviour of heterogeneous agents bring to the market, information, or shock? Hence, the nature of information flow between the bond and equity markets should be revisited for the stability of the financial market being critical for asset allocation and risk management.

Even though informational causality between bond and equity markets is important for their efficiency, literature is inconclusive about the direction of causality (Jammazi et al. 2017). However, in addition to directionality, it is the degree of causality in terms of amount of information flow between these two markets is more crucial. Further, along with direction and degree of causality a question still arises whether the directional causality is due to information or uncertainty/shock? Veronesi's (1999) theoretical argument for increased uncertainty in stock market is related to the timing of news, that is, good news in bad times and bad news in good times. Hence, uncertainty is endogenous in the financial market eco-system. Thus, in case of cross-market hedging and flight-to/from-quality, the asset price of non-shocked market (bond) is influenced by the transfer of shocks from the shocked market (equity). Hence, in addition to the transfer of information, there exists some sort of dynamics related to transfer of uncertainty/shock between equity and bond markets. Therefore, from risk and portfolio management perspective, it is imperative to understand, 'what is the dynamics of uncertainty, along with transfer of information'? Another aspect about the informational causality is related to the state of the market which gets changed as the macro-finance environment changes. For example, the co-movement between bond and equity markets is affected by the changes in investors' confidence (Zhao 2017), in case of high-risk aversion (Valseth 2013) where both markets are affected severely like in a tail event.

This study is perhaps the first to examine the informational (Granger) causality between G-7 equity and treasury bond markets considering above discussed gap in the literature using the novel TE and ETE, a framework of econophysics and information theory. For Gaussian variables, there is equality between Granger causality and TE (Barnett, Barrett and Seth, 2009). Schreiber (2000) first mentions TE as model free measure of quantifying the degree of information flow thereby coping with the limitation of Granger causality of being an indicator of presence or absence of causality only. Further, how granger causality is related to TE is discussed by Amblard and Michel (2012). Since a future value x_{t+1} can be forecasted (quantification of information gain) by TE by relating it to past observations of x_t and y_t, it satisfies the definition of causality given by Granger (1969). TE is an indicator of causality as it quantifies the information being transferred from one variable to another Storhas, De Mello and Singh (2020). It is model independent measure of conditional non-linear causality between two variables Storhas, De Mello and Singh (2020). The standard VAR granger causality measures the linear lag impact, while entropy takes all the useful information up to date by using information filtration Liu et al. (2020). Use of TE and ETE for the detection of granger causality in the literature are found in case of Marschinski and Kantz (2002) between DJIA and DAX, Kwon and Yang (2008), Sensoy et al. (2014) and Dimpfl and Peter (2018). Huynh (2020) investigates the

causality relationship between economic uncertainty and four precious metal using TE. The study finds that precious metal causes uncertainty proxied by the economic policy uncertainty (EPU) and volatility index (VIX). However, even though precious metal is immune from EPU, they are caused by VIX. Similar study of causality using TE done by Huynh, Wang and Vo (2021) finds that global policy uncertainty causes the volatility and volume of Bitcoin using TE. García-Medina and Luu Duc Huynh (2021) studies the predictive power of the determinants of Bitcoin prices using the continuous TE.

We have estimated TE and ETE, which is a non-linear asymmetric measure of direction and degree of causality in terms information flow considering the aspect of uncertainty/shock between equity and treasury bond markets. Further, the study estimates the informational causality considering the state of the bond and equity markets using RTE. Connolly, Stivers and Sun (2005) established time-varying relationship between bond and equity markets, followed by studies to explore the underlying reason for such time-varying relationship. Campbell, Sunderam and Viceira (2009) documented that the sign and magnitude of the co-movement between treasury bonds and equity changes over time, which affects the pricing (risk premium and volatility) where positive (negative) covariance leads to positive (negative) nominal bond risk premia. Therefore, we have estimated the time varying informational causality between the bond and equity markets by estimating the ETE and RTE using 2000 days moving window. This moving window analysis will show how evolutionary is the information causality between these two markets capturing the non-linearity aspect of it.

Our contributions to the literature of bond and equity markets are as follows. First, we have used the entropy method, a framework of econophysics and information theory in investigating the degree and direction of causality between these markets. Second, the novel ETE helps to study the informational causality by removing the impact of uncertainty associated with noise, liquidity, and degree of friction in the market microstructure. Third, RTE is used by the study to estimate the informational causality at different state of the bond and equity markets. Finally, the study estimates RTE using 2000 days moving window to investigate the time-varying causality dynamics over time and across the state of the market, respectively, to understand how confirmative the information flow between bond and equity market to adoptive market hypothesis of Lo (2004) is.

Our study finds the presence of noise in the information flow between the bond and equity market as ETE is greater than TE. Further, the magnitude and the direction of information flow across state (i.e. low-probable bear and bull markets to high-probable average markets) and time between these two markets are dynamic. Although the information flow is primarily dominated by the equity market, the bond market dominates during the period of market turmoil.

3. Empirical methodology

3.1. Transfer entropy

The concept of TE, which is used to enumerate the ability and directivity of the rate at which information is transferred between two interrelated systems, was first mentioned, and popularized by Schreiber (2000). The technique adopted to detect the flow of information between two systems may be used to distinguish between driving and reacting elements. Shannon (1948) described the TE formula as the mean number of bits required to proficiently encode independent draws for an isolated random variable X with probability distribution $p(x_t)$. This is based on the Shannon entropy hypothesis;

$$H_X = -\sum_{X_t} p(x_t) log_2 p(x_t). \tag{1}$$

By description of entropy, we quantify uncertainty, which increases directly with the quantity of bits required to totally translate an order of X realizations. As demonstrated in the consequent steps, log represents the logarithm to the base 2, and this base is chosen to indicate and emphasize the bits measurement of the entropy unit. Shannon entropy is used along with the Kullback – Leibler distance for quantifying the rate of information transfer between two time series under the assumption that the basic processes are Markov processes. Consider a stationary

Markov process X of order k; the probability of observing X in state x_t at time $(t+1)$ is $p(x_{t+1}|x_t,\cdots,x_{t=k+1}) = p(x_{t+1}|x_t,\cdots,x_{t-k})$. The average number of bits required to encode the observation in $(t+1)$ is defined by;

$$h_x(k) = -\sum_{x_t} p\left(x_{t+1,}x_t^{(k)}\right) logp(x_{t+1}|x_t^{(k)}). \quad (2)$$

Equation (2) is analogous to another Markov process, Y, where $x_t^{(k)} = x_t,\cdots,x_{t=k+1}$. According to Schreiber's approach, the rate of information transfer between processes Y and X is quantified in the bivariate case by quantifying the deviation from the generalized Markov property $p(x_{t+1}|x_t^{(k)},y_t^{(l)})$, where l is the order of the Markov process Y. In the absence of information transfer from Y to X, previous observations of Y have no effect on the transition probabilities of X. Schreiber defined Shannon TE as follows;

$$T_{\mathrm{YX}}(k,l) = \sum^{p}\left(x_{t+2},x_t^{(k)},y_t^{(l)}\right)\log\frac{p(x_{t+1}|x_t^{(k)},y_t^{(l)})}{\mathrm{p}(x_{t+1}|x_t^{(l)})}. \quad (3)$$

The flow of information between processes Y and X, quantified by T_{YX}. T_{XY}, which quantifies the information flow between processes X and Y, can be similarly calculated. Because of the asymmetric property of the TE, the difference between T_{YX} and T_{XY} can reveal the predominant direction of the rate of information transfer. Additionally, an unremitting time series data are required to estimate the TE in Equation (3). Meanwhile, the data should be grouped into discretized values as a panel because the TE is calculated based on discrete data. Therefore, all the data points contained within a nonoverlapping partition should be symbolically encoded. Although partitioning the data into numerous bins is an option, we grouped our data into three bins owing to the larger amount of data required for a large number of partitions, which is the most popular symbolic encoding strategy. Given a time series $y(t)$, one can obtain the symbolically encoded series $S(t)$ by partitioning $y(t)$ in the following manner.

$$S(t) = \begin{cases} 1\ for & y(t) \le q_1 \\ 2\ for & q_1 < y(t) < q_2 \\ 3\ for & y(t) \ge q_2 \end{cases}. \quad (4)$$

The bins should be chosen based on the distribution of the data. As tail observations are significant in analysing financial return data, binning should be done such that the empirical quantile being considered should result in segregating the left tail observations from the right. The grouping of the tail observations into three distinct bins, as in this study, and the use of the lower bound of 5% and upper bound of 95% empirical quantiles of the return data for the binning would result in a symbolic encoding with the first (third) bin containing the extreme negative (positive) returns. Specifically, we divide the symbolically encoded series $S(t)$ as follows;

$$S(t) = \begin{cases} 1\ for & y(t) \le q^r_{[0.05]} \\ 2\ for & q^r_{[0.05]} < y(t) < q^r_{[0.95]} \\ 3\ for & y(t) \ge q^r_{[0.95]} \end{cases}. \quad (5)$$

After symbolically encoding the return and realizing the fractions of the joint probabilities using the chain rule to convert the conditional probabilities, the probabilities in Equation (3) can be calculated using the relative frequencies of all possible outcomes. Calculating the TE measures requires determining the block lengths of the Markov process orders k and l in Equation (3), and the choice of block lengths depends on the time series data under consideration. Although large values of k and l adequately capture the rate of information transfer between two time series, they may introduce finite sample effects. When k in $T_{\mathrm{YX}}(k,l)$ is small, however, the information contained in the lagged values of X may be incorrectly presumed to be derived from Y. Dimpfl and Peter's (2013) study showed an appropriate value for k in the TE measure $T_{\mathrm{YX}}(k,l)$, which can be determined by computing the mutual information between the time series and its series with delay k,

$$M_{xx^{(k)}} = \sum_{xx^{(k)}} p(x,)\log\frac{p\left(x,x^{(k)}\right)}{p(x)P(x^{(k)})}, \quad (6)$$

where $x^{(k)}$ is the series x with a delay of k. Thus, the ideal block length k is equal to the value of the first local minimum in Equation (5). To simplify the interpretation of the results, the block lengths k and l must be in the same order. Given that the specific focus is on the financial markets, specifically the stock market, information from the immediate past or just a day before the current day is critical for defining the current day's dynamics. Thus, we equalize the lag orders k and l.

3.2. Effective entropy transfer

Large data sets are required for TE estimation. Owing to the short supply of large data sets, the estimates are always skewed because of the small sample effects. However, Marschinski and Kantz (2002) posited that this bias can be rectified by calculating a TE measure, that is, ETE, which is calculated by subtracting the shuffled TE from the TE of a randomized series in which the elements of the time series are individually drawn randomly so that the dependencies between the series and other series are demolished (shuffling) without distorting the probability distribution of the shuffled series. This can be stated mathematically as;

$$ETE_{YX}(k,l) - TE_{YX}(k,l) - TE_{Y_{shuffled}X}(k,l), \quad (7)$$

where $TE_{Y_{shuffled}X}(k,l)$ indicates the TE with series Y shuffled. The shuffling is conducted by randomly drawing from the distribution of Y and rearranging them to generate a new time series, which indicate that all statistical dependencies between Y and X are destroyed, as well as time series dependencies of Y. Consequently, $TE_{Y_{shuffled}X}(k,l)$ converges to zero with increasing sample size, and any non-zero value of $TE_{Y_{shuffled}X}(k,l)$ is a result of small sample effects. The data are reorganized several times to obtain a dependable estimator. A standard TE estimate over the simulations is also obtained, then deducted from the yet-to-be shuffled TE estimate to obtain a bias-free, ETE estimate.

4. Data

In our study, we have covered debt and equity markets of G7 countries which are developed and liquid. Daily closing prices of 22 years' sovereign 10 years bond yield and major equity index of respective countries[2] are taken from Refinitiv DataStream (https://solutions.refinitiv.com) from 4 January 2000 to 17 August 2022. The log difference between two consecutive closing prices of bond yield and equity index are estimated for the estimation of entropy. The descriptive statistics and the unit root test results are summarized in Table 1. The changes in bond yield and equity market return are asymmetric, where return on equity is negatively skewed and the change in bond yield is positively skewed, except for the United Kingdom and the United States. Further, the Jarque–Bera test of normality is rejected for all series. TE is a non-parametric method suitable for non-Gaussian and highly non-linear data instead of vector autoregression (VAR) Granger causality (Gong, Tang and Wang 2019). The significance of the Ljung–Box statistics is the evidence of lack market efficiency. Therefore, an in-depth study of market efficiency dynamics between stock and bond market is revisited.

The TE is a measure of non-parametric Granger causality and most suitable for highly non-Gaussian or non-linear data (Gong, Tang and Wang 2019). As the BDS test[3] confirms non-linearity of the data, TE will be an effective measure of information transfer (He and Shang 2017). Further, as all series are leptokurtic, indicating that much of the information lies at the tails, we have estimated TE at the quantiles using RTE. The linear correlation between bond and equity markets is positive except Italy, which means that both markets co-move in the same direction.

5. Empirical results and discussion

The results are presented and discussed in two parts. The first part presents the static analysis through TE and ETE and the VAR Granger causality for comparison. The second part presents the

[2]S&P 500, FTSE100, NIKKEI 225, CAC 40, DAX, FTSEMIB and SPTSX for US, UK, Japan, France, Germany, Italy and Canada, respectively.
[3]Results are available upon request.

Table 1. Descriptive statistics.

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP	KPSS	ZA	L-B	L-B^2	ARCH-LM (10)	Obs.	Corr
CA_SPTSX	0.000	0.001	0.113	−0.132	0.011	−0.940*	19.818*	67774.1*	−18.502*	−5872.898*	0.034	−22.523*	74.1*	5588.9*	1535.5*	5680	0.271
CA_BOND	0.000	−0.001	0.35	−0.301	0.024	0.427*	23.162*	96376.6*	−16.624*	−5545.902*	0.125	−25.101*	42.0*	4774.2*	1709.6*	5680	
FR_CAC40	0.000	0.000	0.106	−0.095	0.014	−0.02766926	8.195*	5988.7*	−17.665*	−5005.332*	0.211	−23.937*	53.7*	2542.8*	904.5*	5326	0.008
FR_BOND	−0.001	0.000	3.784	−3.526	0.169	1.080*	223.161*	10757490.9*	−17.768*	−6422.213*	0.017	−21.363*	1082.7*	2115.2*	1480.7*	5326	
GR_DAX	0.000	0.001	0.108	−0.089	0.015	−0.00178428	7.490*	4159.1*	−16.755*	−4832.381*	0.153	−22.006*	25.0*	2637.7*	909.8*	4952	0.107
GR_BOND	0.001	−0.001	1.792	−2.639	0.104	−1.334*	176.965*	6245904.4*	−21.326*	−4529.943*	0.174	−21.635*	554.9*	3163.6*	1234.6*	4952	
IT_FTSEMIB	0.000	0.001	0.109	−0.185	0.015	−0.580*	11.843*	19030.4*	−17.732*	−5931.781*	0.089	−22.817*	22.753	1326.6*	670.2*	5742	−0.192
IT_BOND	0.000	0.000	0.404	−0.335	0.026	0.704*	27.226*	140893.2*	−17.865*	−5508.916*	0.090	−23.147*	38.3*	2806.7*	1448.3*	5742	
JP_NKY	0.000	0.000	0.132	−0.121	0.015	−0.332*	9.244*	8189.0*	−16.352*	−4955.140*	0.378	−21.760*	14.98552	3351.9*	1136.6*	4984	0.099
JP_BOND	0.000	−0.001	2.944	−2.197	0.179	1.515*	78.420*	1183164.4*	−17.643*	−5504.344*	0.009	−24.296*	549.2*	2669.7*	1107.0*	4984	
UK_FTSE100	0.000	0.000	0.094	−0.115	0.012	−0.336*	10.791*	14565.0*	−19.202*	−5555.158*	0.092	−23.793*	67.9*	3461.5*	1179.3*	5716	0.204
UK_BOND	0.000	0.000	0.537	−0.401	0.041	0.865*	31.699*	196873.1*	−19.769*	−5484.090*	0.070	−26.180*	119.9*	5534.7*	1552.0*	5716	
US_SPX	0.000	0.001	0.11	−0.128	0.012	−0.398*	13.483*	26208.2*	−18.191*	−6071.930*	0.340	−23.624*	99.6*	5651.0*	1663.8*	5691	0.386
US_BOND	0.000	−0.001	0.406	−0.341	0.026	0.176*	39.957*	323894.0*	−16.449*	−5634.140*	0.094	−24.036*	153.0*	5863.3*	2758.0*	5691	

Symbol* indicates significance at the 1% level. Std. Dev. means standard deviation. L-B and L-B^2 is Ljung–Box test statistics for serial correlation of returns and squared returns at lag 10, respectively. ARCH-LM is the test statistic for heteroscedasticity at lag 10. Corr is correlation between bond and equity market of the respective countries.

Table 2. VAR Granger causality between government bonds and equity markets of G7 countries based on AIC determined lag structure.

Predictor	Causes	χ^2	*p*-value
CA_SPTSX	CAN_BOND	34.414	0.000***
CAN_BOND	CA_SPTSX	9.910	0.194
CAC40	FR_BOND	32.948	0.000***
FR_BOND	FR_CAC40	2.454	0.930
GR_DAX	GR_BOND	24.168	0.001***
GR_BOND	GR_DAX	1.929	0.964
IT_FTSEMIB	IT_BOND	5.517	0.238
IT_BOND	IT_FTSEMIB	11.678	0.020**
JP_NKY	JP_BOND	2.772	0.250
JP_BOND	JP_NKY	0.794	0.672
UK_FTSE100	UK_BOND	18.483	0.010**
UK_BOND	UK_FTSE100	13.809	0.055*
US_SPX	US_BOND	34.381	0.000***
US_BOND	US_SPX	7.534	0.480

***, ** and * indicate significance level at 1%, 5% and 10%, respectively.

dynamic analysis through RTE and the time varying analysis of RTE using 2000 days moving window.

5.1. Static analysis of information flow between bond and equity markets

Table 2 presents VAR Granger causality. Unidirectional causality from equity to bond (from bond to equity) markets is reported for Canada, France, Germany and the United States (Italy). Bidirectional (no) causality exits in case UK (Japan). However, it shows only the existence of informational causality but does not quantify the causality in terms of the amount of information flow. The further limitation of this estimation is that it is based on the linear assumption in contrast to non-linear complexities of the financial market. Since, linear dynamics between time series quickly disappears (Ferreira, Dionísio and Movahed, 2017), it justifies our study of the non-linear quantification of causality using the novel TE and ETE methodology.

Table 3 presents the Shannon TE and ETE measuring the degree and direction of non-linear causality between government bonds and equity markets of G7 countries. ETE > TE shows information flow contains noise across the all the countries. The degree of information flow from equity to bond is greater than bond to equity as both $TE_{x\to y}$ and $ETE_{x\to y} > TE_{y\to x}$ and $ETE_{y\to x}$. Unidirectional (bi-directional) causality is observed from equity to bond market only in case of Germany and Japan (US). However, VAR causality shows unidirectional (bi-directional) information flow from (between) equity to bond in case of Canada, France, Germany, and US (UK). While TE and ETE shows no information flows for Canada, France, Italy, and Japan, it is only Japan as per the VAR Causality. Thus, it justifies our application of

Table 3. Shannon transfer entropy (TE) and effective transfer entropy (ETE) between government bonds and equity markets of G7 countries.

	Direction	TE	ETE	Standard error	*p*-value
CA_SPTSX → CA_BOND	*X* → *Y*	0.0023	0.0006	0.0007	0.2200
CA_BOND → CA_SPTSX	*Y* → *X*	0.0018	0.0002	0.0007	0.3533
FR_CAC40 → FR_BOND	*X* → *Y*	0.0020	0.0002	0.0007	0.2800
FR_BOND → FR_CAC40	*Y* → *X*	0.0020	0.0002	0.0006	0.32334
GR_DAX → GR_BOND	*X* → *Y*	0.0031	0.0013	0.0007	0.0433**
GR_BOND → GR_DAX	*Y* → *X*	0.0018	0.0000	0.0008	0.5133
IT_FTSEMIB → IT_BOND	*X* → *Y*	0.0027	0.0009	0.0006	0.0533
IT_BOND → IT_FTSEMIB	*Y* → *X*	0.0015	0.0000	0.0007	0.5667
JP_NKY → JP_BOND	*X* → *Y*	0.0037	0.0018	0.0006	0.0100***
JP_BOND → JP_NKY	*Y* → *X*	0.0020	0.0002	0.0007	0.3800
UK_FTSE100 → UK_BOND	*X* → *Y*	0.0021	0.0004	0.0007	0.2700
UK_BOND → UK_FTSE100	*Y* → *X*	0.0010	0.0000	0.0007	0.8467
US_SPX → US_BOND	*X* → *Y*	0.0044	0.0027	0.0006	0.0000***
US_BOND → US_SPX	*Y* → *X*	0.0031	0.0014	0.0006	0.0267**

***, ** and * indicate significance level at 1%, 5% and 10%, respectively. X and Y are equity and bond market, respectively.

non-linear model free methodology like TE and ETE for the detection of causality between bond and equity markets.

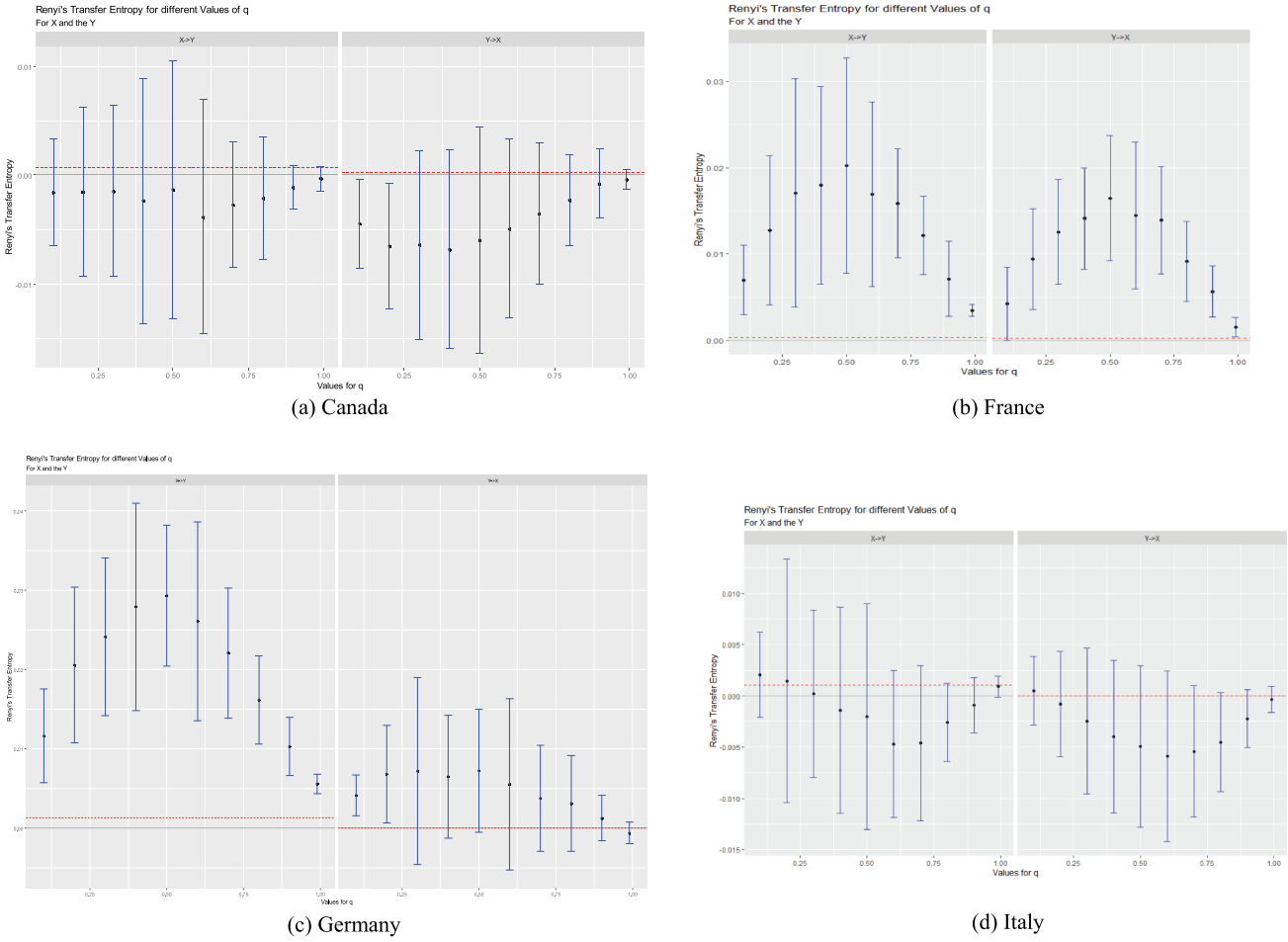
5.2. Dynamic analysis of information transfer between bond and equity markets

First dynamic aspect of information flow between bond and equity markets is presented through RTE. The second dynamic aspect related to evolution of RTE measured in a time varying framework using 2000 days moving average to study the Adaptive Market Hypothesis of Lo (2004).

5.2.1. Renyi transfer entropy (RTE)

RTE is based on the weighting parameter q which emphasizes different areas of distribution in measuring the information flow and causality. For $0 < q < 1$, when q approaches 0 (1), more weights are assigned to lower (higher) probability events i.e. distribution at the tail (centre). When $q \to 1$, RTE converges to Shannon TE, presented through the red dashed line in Figure 1. Although the sign of the RTE could be negative, that does not mean no information flow between the variables. In case of positive (negative) RTE, knowledge of past bond return increases the informational efficiency (increase the riskiness/uncertainty) of the equity market in the next time step and vice versa. Figure 1 presents the RTE between government bonds and equity market across the quantiles q for the G7 economies.

In case of Canada and US, similar pattern of informational causality i.e. bidirectional negative RTE is observed. This pattern of information flow indicates increase of uncertainty (loss of information) in bond and equity market that results from learning the value of equity and bond, respectively.



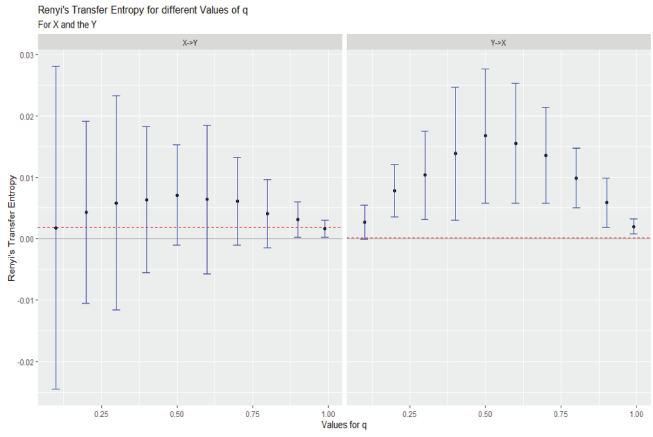
(a) Canada

(b) France

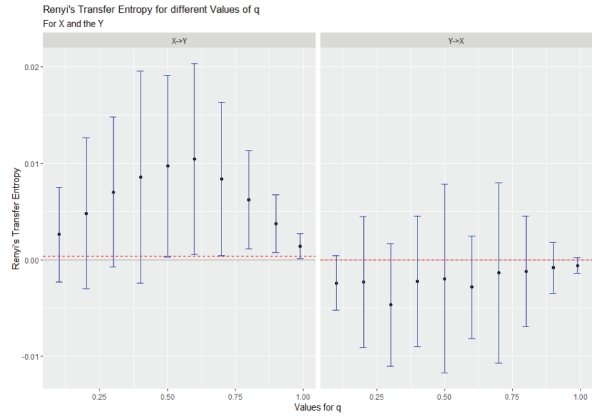
(c) Germany

(d) Italy

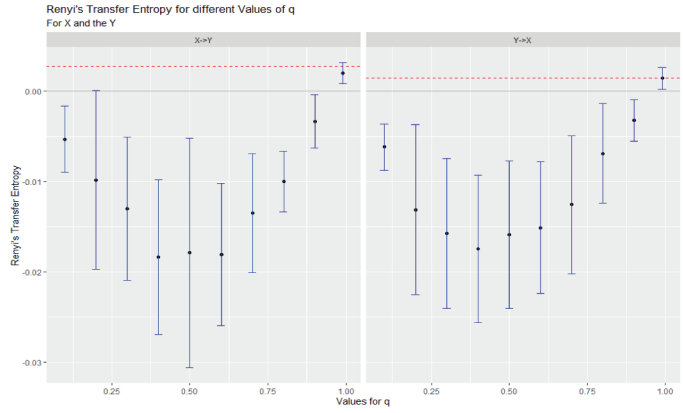
Figure 1. Renyi transfer entropy between stock (X) and bond (Y) markets for different values of q. The red dashed line indicates the Shannon transfer entropy. Vertical axis shows the Renyi transfer entropy for corresponding values of q in the horizontal axis. $X \to Y$ indicates the direction from equity to bond and vice versa.



(e) Japan



(f) UK



(g) US

Figure 1. (continued).

While, in case of Canada, information flow is much stronger from bond to equity, it is equally stronger from either of the market to the other one in case of US. Further the flow of information in either direction is stronger in high probable normal market than low probable tail (i.e. bear and bull) markets in case of US. Similar pattern is observed from bond to equity only in case of Canada. While it is a kind of even flow of information from equity to bond across the values of q for Canada. Our findings are consistent with those by Glasserman and Mamaysky (2019), where unusual negative news (at the lower tail of our study) increases predicted stock market volatility and unusual positive news (at the higher tail of our study) lower the predicted stock market volatility. Also in case US equity market, Ferreira and Dionísio (2016) mention about the presence of long memory violating the EMH. That means inefficient markets process less information than the efficient market and Wang (2022).

Positive RTE from bond to equity across the distribution (i.e. value of q) and vice versa is observed for France, Germany, and Japan. That means informational efficiency of either of the markets improves due to the flow of information from the respective other markets. The concave pattern of information flow across the value of q indicates more information flow in case of high probable average markets relative to the low probable tail markets. As far as the dominance of information flow is concerned, equity (bond) markets dominate the bond (equity) markets in France and Germany (Japan). As entropy reflects new information, the positive TE from the equity to bond markets indicates the efficiency of the equity market

(Glasserman and Mamaysky 2019). Another aspect of entropy is that it denotes the market's risk premium (Backus, Boyarchenko and Chernov 2018). Thus, positive TE reflects the transfer of risk premium between bond and equity markets, and vice versa.

The dynamics of information flow between bond and equity markets is different in case of UK and Italy in comparison to other five markets. In case of UK, RTE is positive from equity to bond market and vice versa. That means information flow from equity (bond) leads to gain of information i.e. reduction of uncertainty (loss of information, i.e., increase of uncertainty) about the bond (equity) market. As far as strength of flow is concerned, it is concave from equity to bond signifying more information flow in high probable average market relative to low probable tail (extreme) market. However, it is more of a straight line from bond to equity indicating a stable and moderate flow of information. In case of Italian bond and equity markets, a concave pattern of information flow across the values of q between these two markets implies positive and negative RTE at the tails and the centre of the return distribution, respectively. The positive RTE at the left tail i.e. below q = 0.30 and right tail above q = 0.80 from equity to bond markets indicates gain of information about the bond markets from past values of equity market. However, in the high probable average market (i.e. at the centre of the distribution) bilateral negative RTE implies knowledge of the either bond or equity market leads to loss of information or increase of uncertainty of the respective other market.

The following are a few important observations about the informational causality between bond and equity markets of the G-7 countries. First, the magnitude and structure of information flow between these two markets are dynamic across the state of the markets raging form low probable tail to high probable average markets. It means that markets are adaptive to the evolution of cross-market information flow under different market conditions, and thus confirming the theory of adaptive market hypothesis. Second, the dominance of the equity market confirms its efficiency over the bond market under both extreme and normal market conditions. Third, surprisingly, both bond and equity markets of the US and Canada do not possess any extra information that contributes to the efficiency of each other.

5.2.2. Time varying RTE for q = 0.30

In this section, how bond and equity markets are adaptive to cross market information flow from each other over time is studied using 2000 days' rolling window RTE considering the most widely used $q = 0.30$.

Figure 2 shows that the RTE for q = 0.30 between bond to equity markets of G-7 economies. It is evident that information flow is time varying both in terms direction (i.e. the sign of RTE) and degree (magnitude). Hence, the bond and equity markets are adaptive to new cross market information flow from each other over time, thus substantiates the adaptive market hypothesis of Lo (2004). Although the dominance of equity over bond market is primarily observed, it is dynamic over the time. That means amount of information transferred from the bond to equity markets, and vice versa, changes and, accordingly, defines the lead market in terms of information transfer at any point of time. Specifically, in case of Canada, Japan and US equity markets dominate and in case of the European markets such as UK, Germany, Italy and France, bond markets dominate in terms of information transfer. During the period of 2008 GFC, 2011–2012 European debt crisis and towards the end of 2017–2018 emerging market crisis, the bond market dominates the equity market in terms of information flow and market efficiency.

The following reasons could be attributed to the time varying RTE between the bond and stock markets, in addition to the dynamic macroeconomic and financial environment of the economy. As argued by Backus, Boyarchenko and Chernov (2018), TE reflects inter- and intra-market transfer of risk premium, and thus time varying RTE reinforces their term structure of risk premium in a cross section of assets. Another related study by Perras and Wagner (2020) mentioned about the pricing of equity–bond covariance risk. Thus, information lead/lag, as evidenced from time-varying RTE and RTE across different states of the market, indicates non-synchronous pricing of bond–equity covariance risk. Glasserman and Mamaysky (2019) finds that new information is

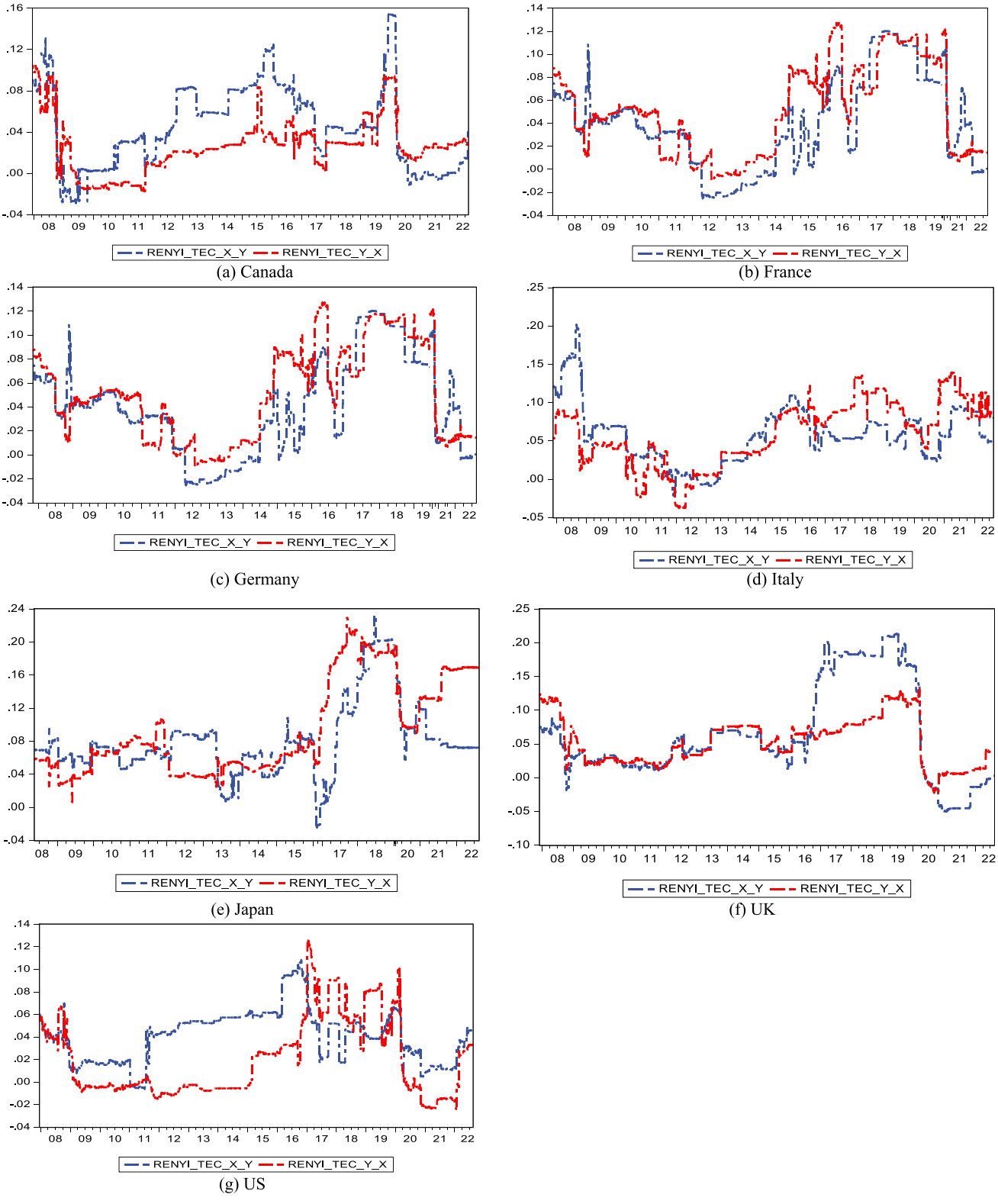


Figure 2. Time-varying Renyi transfer entropy from equity to bond markets in green (RENYI_TEC_X_Y) and from bond to equity market in red (RENYI_TEC_Y_X) Note: It is estimated at $q = 0.30$ using 2000 days' rolling-window framework. Positive and negative RTEs indicate transfer of information and uncertainty, respectively.

first reflected in the of stock market, and in the context of stock market index (at the aggregate level) the reflection of news is gradual.

6. Conclusion and policy implication

Efficient operation of both government bonds and equity markets and their interactions are fundamental to a country's economic development, as it leads to less distortion in the economy due to proper pricing and allocation of capital, better pricing of risk and the resulting equilibrium risk-adjusted return for the investors.

The efficiency of the financial markets is the ability to reflect all types of information, such as historical, public, and private as per EMH of Fama (1970). This binary view (all or none) of market efficiency by EMH is challenged by adaptive market hypothesis (AMH) of Lo (2004). As per the AMH, market efficiency is evolutionary because of factors such as market microstructure, noise trading, information technology and market regulation, market imperfections and psychological biases. The study measures the efficiency of bond and equity market of G-7 countries in terms amount of information flow and causality between these two markets using TE, which is based on theory of information.

The magnitude and direction of information flow between these two markets are dynamic across the state of the markets and time. It means that markets are adaptive to the evolution of cross-market information flow under different market conditions, and thus confirming the theory of adaptive market hypothesis. The study is the first of its kind to validate the AMH in the context of bond and equity markets using the novel TE framework. Although the dominance of equity over bond market is primarily observed, it is dynamic over the time and state of the markets. During the period of turmoil in the markets, the bond market dominates the equity market. The policy implications are as follows. During normal markets, equity markets may be referred for trading and investment decision. At the of market crisis, flight to quality investment decision may be taken by referring to the performance of the bond markets. Since most of the times flow of information from either of the markets enhances uncertainty instead of informational efficiency about the other respective markets, appropriate regulatory measures may be taken to reduce such transfer of uncertainty. Future studies could be conducted in a multivariate context in quantifying the information flow from other sources to bond and equity market.

Data availability statements

The data that support the findings of this study are available from Refinitiv DataStream. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at https://solutions.refinitiv.com with the permission of Refinitiv DataStream.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2020S1A5B8103268).

ORCID

Aviral Kumar Tiwari http://orcid.org/0000-0002-1822-9263
Emmanuel Joel Aikins Abakah http://orcid.org/0000-0003-1472-0722
Seong-Min Yoon http://orcid.org/0000-0003-3011-9486

References

Amblard, P. O., and O. J. Michel. 2012. "The Relation Between Granger Causality and Directed Information Theory: A Review." *Entropy* 15 (1): 113–143. doi:10.3390/e15010113.

Aslanidis, N., and C. Christiansen. 2012. Smooth transition patterns in the realized stock–bond correlation. *Journal of Empirical Finance* 19 (4): 454–464.

Backus, D., N. Boyarchenko, and M. Chernov. 2018. "Term Structures of Asset Prices and Returns." *Journal of Financial Economics* 129 (1): 1–23. doi:10.1016/j.jfineco.2018.04.005.

Baele, L., G. Bekaert, and K. Inghelbrecht. 2010. "The Determinants of Stock and Bond Return Comovements." *The Review of Financial Studies* 23 (6): 2374–2428. doi:10.1093/rfs/hhq014.

Barnett, L., A. B. Barrett, and A. K. Seth. 2009. "Granger Causality and Transfer Entropy are Equivalent for Gaussian Variables." *Physical Review Letters* 103 (23): 238701. doi:10.1103/PhysRevLett.103.238701.

Baur, D. G., and B. M. Lucey. 2010. "Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold." *Financial Review* 45 (2): 217–229. doi:10.1111/j.1540-6288.2010.00244.x.

Boyd, J. H., J. Hu, and R. Jagannathan. 2005. "The Stock Market's Reaction to Unemployment News: Why Bad News is Usually Good for Stocks." *The Journal of Finance* 60 (2): 649–672. doi:10.1111/j.1540-6261.2005.00742.x.

Campbell, J. Y., and J. Ammer. 1993. "What Moves the Stock and Bond Markets? A Variance Decomposition for Long-term Asset Returns." *The Journal of Finance* 48 (1): 3–37. doi:10.1111/j.1540-6261.1993.tb04700.x.

Campbell, J. Y., A. W. Lo, A. C. MacKinlay, and R. F. Whitelaw. 1998. "The Econometrics of Financial Markets." *Macroeconomic Dynamics* 2 (4): 559–562. doi:10.1017/S1365100598009092.

Campbell, J. Y., A. Sunderam, and L. M. Viceira (2009). Inflation Bets or Deflation Hedges? The Changing Risks of Nominal Bonds, NBER Working paper, No. 14701, National Bureau of Economic Research.

Connolly, R., C. Stivers, and L. Sun. 2005. "Stock Market Uncertainty and the Stock-Bond Return Relation." *The Journal of Financial and Quantitative Analysis* 40 (1): 161–194. doi:10.1017/S0022109000001782.

David, A., and P. Veronesi. 2013. "What Ties Return Volatilities to Price Valuations and Fundamentals?" *The Journal of Political Economy* 121 (4): 682–746. doi:10.1086/671799.

Dimpfl, T., and F. J. Peter. 2013. "Using Transfer Entropy to Measure Information Flows Between Financial Markets." *Studies in Non-Linear Dynamics and Econometrics* 17 (1): 85–102. doi:10.1515/snde-2012-0044.

Dimpfl, T., and F. J. Peter. 2018. "Analyzing Volatility Transmission Using Group Transfer Entropy." *Energy Economics* 75: 368–376. doi:10.1016/j.eneco.2018.08.008.

Eom, C., G. Oh, and W. S. Jung. 2008. "Relationship Between Efficiency and Predictability in Stock Price Change." *Physica A: Statistical Mechanics and Its Applications* 387 (22): 5511–5517. doi:10.1016/j.physa.2008.05.059.

Fama, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance* 25 (2): 383–417.

Fang, L., H. Yu, and Y. Huang. 2018. "The Role of Investor Sentiment in the Long-Term Correlation Between US Stock and Bond Markets." *International Review of Economics & Finance* 58: 127–139. doi:10.1016/j.iref.2018.03.005.

Ferreira, P., and A. Dionísio. 2016. "How Long is the Memory of the US Stock Market?" *Physica A: Statistical Mechanics and Its Applications* 451: 502–506. doi:10.1016/j.physa.2016.01.080.

Ferreira, P., A. Dionísio, and S. M. S. Movahed. 2017. "Assessment of 48 Stock Markets Using Adaptive Multifractal Approach." *Physica A: Statistical Mechanics and Its Applications* 486: 730–750. doi:10.1016/j.physa.2017.05.046.

García-Medina, A., and T. Luu Duc Huynh. 2021. "What Drives Bitcoin? An Approach from Continuous Local Transfer Entropy and Deep Learning Classification Models." *Entropy* 23 (12): 1582. doi:10.3390/e23121582.

Garcia, R., and G. Tsafack. 2011. "Dependence Structure and Extreme Comovements in International Equity and Bond Markets." *Journal of Banking & Finance* 35 (8): 1954–1970. doi:10.1016/j.jbankfin.2011.01.003.

Glasserman, P., and H. Mamaysky. 2019. "Does Unusual News Forecast Market Stress?" *The Journal of Financial and Quantitative Analysis* 54 (5): 1937–1974. doi:10.1017/S0022109019000127.

Gong, C., P. Tang, and Y. Wang. 2019. "Measuring the Network Connectedness of Global Stock Markets." *Physica A: Statistical Mechanics and Its Applications* 535: 122351. doi:10.1016/j.physa.2019.122351.

Granger, C. W. 1969. "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods." *Econometrica: Journal of the Econometric Society* 37 (3): 424–438. doi:10.2307/1912791.

Groenewold, N., S. H. K. Tang, and Y. Wu. 2003. "The Efficiency of the Chinese Stock Market and the Role of the Banks." *Journal of Asian Economics* 14 (4): 593–609. doi:10.1016/S1049-0078(03)00097-6.

He, J., and P. Shang. 2017. "Comparison of Transfer Entropy Methods for Financial Time Series." *Physica A: Statistical Mechanics and Its Applications* 482: 772–785. doi:10.1016/j.physa.2017.04.089.

Huynh, T. L. D. 2020. "The Effect of Uncertainty on the Precious Metals Market: New Insights from Transfer Entropy and Neural Network VAR." *Resources Policy* 66: 101623. doi:10.1016/j.resourpol.2020.101623.

Huynh, T. L. D., M. Wang, and V. X. Vo. 2021. "Economic Policy Uncertainty and the Bitcoin Market: An Investigation in the COVID-19 Pandemic with Transfer Entropy." *The Singapore Economic Review* 1–27. doi:10.1142/S0217590821500119.

Jammazi, R., R. Ferrer, F. Jareño, and S. M. Hammoudeh. 2017. "Main Driving Factors of the Interest Rate-Stock Market Granger Causality." *International Review of Financial Analysis* 52: 260–280. doi:10.1016/j.irfa.2017.07.008.

Jammazi, R., A. K. Tiwari, R. Ferrer, and P. Moya. 2015. "Time-Varying Dependence Between Stock and Government Bond Returns: International Evidence with Dynamic Copulas." *The North American Journal of Economics and Finance* 33: 74–93. doi:10.1016/j.najef.2015.03.005.

Jizba, P., H. Kleinert, and M. Shefaat. 2012. "Rényi's Information Transfer Between Financial Time Series." *Physica A: Statistical Mechanics and Its Applications* 391 (10): 2971–2989. doi:10.1016/j.physa.2011.12.064.

Kwon, O., and J. S. Yang. 2008. "Information Flow Between Composite Stock Index and Individual Stocks." *Physica A: Statistical Mechanics and Its Applications* 387 (12): 2851–2856. doi:10.1016/j.physa.2008.01.007.

Laopodis, N. T. 2009. "Fiscal Policy and Stock Market Efficiency: Evidence for the United States." *The Quarterly Review of Economics and Finance* 49 (2): 633–650. doi:10.1016/j.qref.2007.10.004.

Liu, A., J. Chen, S. Y. Yang, and A. G. Hawkes. 2020. "The Flow of Information in Trading: An Entropy Approach to Market Regimes." *Entropy* 22 (9): 1064. doi:10.3390/e22091064.

Li, M., H. Zheng, T. T. L. Chong, and Y. Zhang. 2016. "The Stock–Bond Comovements and Cross-Market Trading." *Journal of Economic Dynamics & Control* 73: 417–438. doi:10.1016/j.jedc.2016.10.007.

Lo, A. W. 2004. "The Adaptive Markets Hypothesis." *The Journal of Portfolio Management* 30 (5): 15–29. doi:10.3905/jpm.2004.442611.

Marschinski, R., and H. Kantz. 2002. "Analysing the Information Flow Between Financial Time Series." *European Physical Journal B-Condensed Matter and Complex Systems* 30 (2): 275–281. doi:10.1140/epjb/e2002-00379-2.

Panchenko, V., and E. Wu. 2009. "Time-Varying Market Integration and Stock and Bond Return Concordance in Emerging Markets." *Journal of Banking & Finance* 33 (6): 1014–1021. doi:10.1016/j.jbankfin.2008.10.016.

Perras, P., and N. Wagner. 2020. "Pricing Equity-Bond Covariance Risk: Between Flight-To-Quality and Fear-Of-Missing-Out." *Journal of Economic Dynamics & Control* 121: 104009. doi:10.1016/j.jedc.2020.104009.

Sakemoto, R. 2018. "Co-Movement Between Equity and Bond Markets." *International Review of Economics & Finance* 53: 25–38. doi:10.1016/j.iref.2017.10.013.

Schreiber, T. 2000. "Measuring Information Transfer." *Physical Review Letters* 85 (2): 461. doi:10.1103/PhysRevLett.85.461.

Sensoy, A., C. Sobaci, S. Sensoy, and F. Alali. 2014. "Effective Transfer Entropy Approach to Information Flow Between Exchange Rates and Stock Markets." *Chaos, Solitons & Fractals* 68: 180–185. doi:10.1016/j.chaos.2014.08.007.

Shannon, C. E. 1948. A mathematical theory of communication. *The Bell system technical journal* 27(3): 379–423.

Shiller, R. J., and A. E. Beltratti. 1992. "Stock Prices and Bond Yields: Can Their Comovements Be Explained in Terms of Present Value Models?" *Journal of Monetary Economics* 30 (1): 25–46. doi:10.1016/0304-3932(92)90042-Z.

Storhas, D. P., L. De Mello, and A. K. Singh. 2020. "Multiscale Lead-Lag Relationships in Oil and Refined Product Return Dynamics: A Symbolic Wavelet Transfer Entropy Approach." *Energy Economics* 92: 104927. doi:10.1016/j.eneco.2020.104927.

Valseth, S. 2013. "Price Discovery in Government Bond Markets." *Journal of Financial Markets* 16 (1): 127–151. doi:10.1016/j.finmar.2012.04.005.

Veronesi, P. 1999. "Stock Market Overreactions to Bad News in Good Times: A Rational Expectations Equilibrium Model." *The Review of Financial Studies* 12 (5): 975–1007. doi:10.1093/rfs/12.5.975.

Wang, X. 2022. "Efficient Markets are More Connected: An Entropy-Based Analysis of the Energy, Industrial Metal and Financial Markets." *Energy Economics* 111: 106067. doi:10.1016/j.eneco.2022.106067.

Yang, J., Y. Zhou, and Z. Wang. 2009. "The Stock–Bond Correlation and Macroeconomic Conditions: One and a Half Centuries of Evidence." *Journal of Banking & Finance* 33 (4): 670–680. doi:10.1016/j.jbankfin.2008.11.010.

Zhao, G. 2017. "Confidence, Bond Risks, and Equity Returns." *Journal of Financial Economics* 126 (3): 668–688. doi:10.1016/j.jfineco.2017.09.007.