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The Relation between Return and Volatility in ETFs Traded in Borsa Istanbul: Is there any Difference between Islamic and Conventional ETFs?

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Abstract

In this study, we aim to analyze the relation between return and volatility in different types of exchange-traded funds (ETFs) traded in the Borsa Istanbul. The types we examine are Islamic stock index, conventional stock index, bond, commodity, and U.S. dollar ETFs. We employ the following battery of causality analysis methods that have different statistical advantages to each other: Toda-Yamamoto (1995); bootstrap based Hatemi-J (2005); volatility spillover, which allows investigating causality in variance; frequency domain, which decomposes causality due to different time frequencies; and asymmetric causality, developed by Hatemi-J, which enables finding causation linkages for different types of shocks in each variable. Although the results obtained from our analyses show that a negative relationship between return and volatility is valid for most ETF types, an asymmetric relation running from negative return shocks to positive volatility shocks is valid for only some conventional stock ETFs and U.S. dollar ETFs. On the other hand, Islamic ETFs and commodity ETFs have an asymmetric relation running from positive return shocks to negative volatility shocks. Our results show that the

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hypotheses investigated in this study vary with the ETF type included in the model.

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JEL Classification: G12, G23, C22.

1. Introduction

The relationship between return and volatility in the price of a stock index has a crucial role in hedging losses in financial markets. In this context, researchers have investigated the interaction between volatility and returns for numerous financial tools to understand the nature of volatility as an indicator of risk and to try to build an early warning system to reduce the risk of loss. One of the warning systems is the use of returns of an index to implicate future volatility. Empirical evidence obtained from studies shows that there is a negative relationship between the return of any kind of financial asset and its volatility. Despite consensus about the type of relation, the debate on how variables affect each other in different shock types is ongoing.

Black (1976) and Christie (1982) are the initial studies explaining the interaction between variables. According to them, a drop in the value of a stock increases financial leverage, which makes the stock riskier and increases volatility (Wu, 2001: 838). To put it more clearly, the leverage hypothesis states that when the value of a firm falls, the value of its equity becomes a smaller percentage of the firm's total value. Since the equity of the firm bears the entire risk of the firm, the volatility of equity should subsequently increase (Hibbert et al., 2008: 2255).

Black (1976) and Christie (1982), French et al. (1987) and Campbell and Hentschel (1992) try to explain the interaction between return and volatility of stock price in the opposite direction. According to them, if volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline (Wu, 2001: 838). The volatility feedback hypothesis states that for firms with high systematic risk, market wide shocks may significantly increase their conditional covariance with the market. The resulting higher required return leads to a volatility feedback effect on the conditional volatility, which would be absent or weaker for firms less sensitive to market level shocks. So, increases in volatility indicate that required future returns will increase and current stock prices will decline (Bashdad, 2013: 239).

Although they agree with both of the hypotheses on the negative relationship mentioned above, later studies criticize them in two ways. The first way deals with asymmetry in the negative relation, while the second way focuses on the time frequency used to explain the interaction. Giot (2005: 98) finds that negative returns for the stock index yield much larger relative changes in the implied volatility than do positive returns, which supports the findings of Campbell and Hentschel (1992: 2). The findings of Giot (2005) are related to risk aversion behavior. According to risk aversion behavior, losses loom larger than gains. This could translate into greater responsiveness of downside price pressure on raising risk relative to the responsiveness of the upside price pressure on lowering risk (Low, 2004: 527-528). The new insight of the asymmetric relation between volatility and return is called the behavioral explanation hypothesis.

Hibbert et al. (2008: 2256) explain the recent hypothesis in terms of representativeness, affect, and extrapolation bias. This explanation sheds light on why a negative asymmetric return-volatility relation can exist, even for short intraday periods (Padungsaksawasdi and Daigler, 2014: 262). According to them, managers and investors judge the risk-return relation for stocks to be negative, as investors view high return and low risk to be representative of good investments. They conclude that such behavior is valid for the whole market and can be interpreted as a market behavior. Related to representativeness is a feature that affects characteristics, where people form emotional associations with activities, with a positive effect label being considered good and a negative effect label being considered bad. The findings of Bekaert and Wu (2000, 38-39) state that negative shocks increase conditional covariance substantially, whereas positive shocks have a mixed impact on conditional variances.

Another area of criticism of the leverage and volatility feedback hypotheses is the time frequency of responsiveness. According to Badshah (2013: 240), the asymmetric relation is a contemporaneous rather than a lagged phenomenon. That is one way conventional hypotheses fail to explain the relation between stock returns and volatility. Because both are based on fundamental explanations, the effect of return volatility should involve a greater lag in lower frequencies than in higher frequencies.

Over the past two decades, investment in ethical equity mutual funds, whether based on social responsibility principles, environmental considerations, good corporate management, engagement in local communities, or adherence to religious beliefs, have grown considerably around the world (Ashraf, 2013: 106; Bin Mahfouz and Hassan, 2012, 2013). In this regard, Islamic financial tools such as Islamic mutual funds, Islamic stock indices, and Sharī‘ah based financial tools have become very popular among Islamic countries.

Basically, the ethical/Islamic investors prefer to satisfy their ethical criteria and are not interested in traditional risk-return trade off (Renneboog, 2008; 308). In the light of behavioral differences between ethical investors and conventional investors, there might be differences between conventional and Islamic financial tools in terms of returns, sentiment, volatility, and so forth. Thus, the possible relation between volatility and return in different kinds of ETFs, including Islamic ones, might be different.

With the rapid growth of Islamic finance, there has been an emergence of Sharīʻah compliant ETFs, which seek to provide investment opportunities beyond the existing pool of investment for Muslim investors and ethical investors as part of its integration process into the international financial system (Alam, 2013: 28). In this regard, ETFs provide numerous benefits such as diversification, lower expense ratio, lower transaction cost, tradability and transparency, but Islamic ETFs also provide conformity to the Sharīʻah principles and practices, which are important to Muslims, Non-Muslims may also wish to invest in such funds based on Sharīʻah principles.

Most of the major index providers offer Sharīʻah-compliant indices created under the guidance of advisory boards comprised of experts in Islamic Law, often representing multiple countries and various schools of Islamic thought. The screening process varies from index to index, but generally Sharīʻah indices exclude businesses with trade activities in the following industries: alcohol, gambling and entertainment, pork, tobacco, and financials, with the exception of Islamic banks, Islamic financial institutions and Islamic insurance companies (Smith, 2013).

Implementing Sharīʻah rules has some advantages. According to Smith (2013), application of financial / leverage screening is one of the major differences. Only those companies that pass certain financial ratios relating leverage (highly indebted companies are excluded) and interest income will be considered Sharīʻah compliant. By excluding companies with high levels of debt, the resultant portfolio has lower financial risk and superior credit fundamentals.

In addition, the removal of tobacco, alcohol and (as is the case with most Sharīʻah indices) defense companies, reduces the political risk, as these industries are often subject to the political whim of politicians (Smith, 2013).

Islamic ETFs are suitable for investors who are searching for a low-cost passive approach to investing in an equity portfolio which comprises Sharīʻah-compliant stocks. Islamic ETFs can either be used for long term investments, as asset – allocation tools, or as a flexible intra – day trading instrument. Islamic ETFs provide an easy way for investors to gain diversified exposure to a portfolio of Islamic stocks through one instrument (SSSC, 2016: 5).

In fact, Islamic ETFs and conventional ETFs share common characteristics. The main difference between a conventional ETF and an Islamic ETF is the benchmark index that the Islamic ETF tracks. An Islamic ETF tracks a benchmark index wholly comprising constituent securities that are Sharīʻah compliant, whereas conventional ETF may track any benchmark index regardless of the Sharīʻah status of its constituents (Alam, 2013: 28). Sharīʻah principles and guidelines are important to manage Islamic ETFs.

In the official website of MyETF, there are four basic features of conventional and Islamic ETFs. While conventional ETFs include any desired index, Islamic ETFs tracks only Sharīʻah compliant index. Sharīʻah governance is absent in conventional ETFs. It also holds securities included in the securities/stocks universe of the index and of the manager. On the other hand, Islamic ETFs only holds Sharīʻah – compliant securities as approved by the Sharīʻah advisor at the company level and regulatory level.

An Islamic ETF is also required to appoint a Sharīʻah adviser/committee to provide expertise and guidance to ensure that its structure, investments and all matters related to the funds' activities comply with the Shairah (SSSC, 2). Sharīʻah committee investigates the Islamic ETF to ensure if the Sharīʻah principles are followed by the issuer of the ETF.

There are a number of studies comparing Islamic and conventional financial tools in the existing literature. They all investigate the connection between two types of financial system tools. Aloui et al. (2016) compare indices in the context of sentiment and both Islamic and conventional equity returns in the U.S. They conclude that Sharia rules have no influence on the connection between sentiment and Islamic equity returns. Hassan and Girard (2011) compare Islamic mutual funds and conventional mutual funds. They conclude that the performance of Islamic mutual funds is better than that of conventional ones. According to Ashraf (2013), this may be a result of long-term investment behavior that induces lower volatility, lower cash flows, and higher investor commitment to the funds. Merdad et al. (2010) investigate the return-performance behavior of Islamic and conventional mutual funds in Saudi Arabia and find no significant difference between the two. Although the total volume of Islamic financial tools has increased, Abderrezak (2008) implies that ethical-based mutual funds underperform compared to conventional funds due to lower diversification and missed investment opportunities.

The comparison between Islamic ETFs and conventional ETFs are made by Diaw et al. (2010) and Alam (2013). Alam (2013) compare them in the context of risk-adjusted performance measures. Findings show that Islamic ETFs beat conventional ETFs and the market benchmark index based on risk – adjusted performance measures. In an early study of Diaw et al. (2010), they compare the conventional and Islamic ETFs in Malaysia. They find that Islamic ETF perform better than conventional one.

In light of the theoretical explanations above, we aim to investigate the validity of three hypotheses to the exchange-traded funds (ETFs) traded in the Borsa Istanbul in order to understand the nature of Islamic/ethical based financial system tool and ETFs based Islamic stock indices. We investigate the relation between stock return and volatility as a risk indicator by employing a battery of causality analysis methods and daily data belonging to five different types of ETFs. These are the Toda-Yamamoto (1995) Granger type causality, bootstrap based Hatemi-J (2005 and 2006) Granger type causality, frequency domain causality, causality in variance, and asymmetric causality analysis methods. While the frequency domain causality method gives a hint about the time frequency of causation linkage, the asymmetric causality test finds an asymmetric relation in different market shocks. Moreover, we compare the causal relationship between causality in mean and in variance by employing volatility spillover, Toda-Yamamoto, and bootstrap based Granger causality analysis methods.

Another purpose of this study is to compare ETFs holding different assets such as commodities, stocks, bonds, U.S. dollar, and Islamic stocks. By doing so, we will be able to examine possible differences in the behavior of investors investing in different ETFs. Do they behave asymmetrically as described in the behavioral explanation hypothesis? Is the relation for all types of ETFs contemporaneous or lagged? By comparing Islamic ETFs to conventional ETFs we will be able to understand the possible differences between them.

In the following section, we summarize the existing literature. In the third section, we describe the data and method used to calculate conditional volatility. We present the econometric methods in the fourth section. Empirical results and conclusions are discussed in the fifth and sixth sections, respectively.

2. Pertinent Literature on Conventional Stock and ETF

The literature related to the relationship between return and volatility is focused mainly on stock indices. Badshah (2013), Low (2004), Hibbert et al. (2008) investigate this relation to test the validity of each hypothesis in stock markets. They find an asymmetric relation, supporting the behavioral explanation hypothesis in stock markets. The number of studies investigating the relation in ETFs is limited.

Analyses investigating this relation in ETFs find a relatively weaker relationship. Daigler et al. (2014: 74) find that the relation between return and volatility in Euro currency exchange traded funds (FXE) can possess either a positive or negative sign, is asymmetric, and is weaker. Padungsaksawasdi and Daigler (2014: 261) employ four different types of commodity exchange traded funds in order to test the validity of an asymmetric relation between return and volatility. They find a positive relation between variables in gold ETFs. Moreover, the relation in Euro, oil, and gold ETFs is weaker than in stock markets. Hassan et el (2013) examine the determinants of a widely discussed derivative instrument Credit Default Swaps (CDS) in recent literature that was blamed for the financial crisis of 2007-2009. Hassan et al (2015) examine the relationships between CDS and sovereign debt markets using a variety of econometric techniques.

3. Data

There are five different types of ETFs traded in the Borsa Istanbul. These are stock index, Islamic, bond, U.S. dollar, and commodity ETFs. In our study, we employ four of these ETF types, namely the commodity ETFs, stock indices ETFs, Islamic ETFs, and U.S. dollar ETFs. The names of ETFs, components, and issue dates are listed in Table 1. It is possible to classify commodity ETFs into two sub-classes according to issuer—Islamic commodity ETFs issued by participation banks and conventional commodity ETFs issued by conventional banks.

All daily data belonging to ETFs are obtained from the Bloomberg database. The daily return of each ETF is calculated by

$$R_t = \ln P_t - \ln P_{t-1} \tag{1}$$

Where P_t is the daily closing price adjusted for any dividends and splits and P_{t-1} is the closing price of the previous day.

The volatility of each ETF is measured based on the range of high and low prices within a given day. This measure is simple to construct and has been shown to be very efficient because it overcomes the market microstructure related biases of a volatility measure that is based on high-frequency intraday returns (Alizadeh et al. 2002). Parkinson (1980) suggests the following range based estimator of daily volatility that Li and Hong (2011) employ,

Table-1
ETFs Traded in Borsa Istanbul

Name of ETF	**Code**	**Type**	**Inception Date**
Down Jones Islamic Market Turkey Index	DJIMTR	Islamic	02.02.2006
Katilim Model Portfoy Index	KATMP	Islamic	09.07.2014
Katilim 30 Index	KAT30	Islamic	06.01.2011
Katilim 50 Index	KAT50	Islamic	09.07.2014
FTSE Istanbul Bond B type	FBIST	Bond	24.10.2007
Dow Jones Istanbul 20 Equity Intensive	DJIST20	Stock Index	14.01.2005
Turkey Large Cap Banks Equity Intensive	BNKTR	Stock Index	09.09.2009
BIST-30 Index Equity Intensive	IST30	Stock Index	07.04.2009
BIST-30 Index Equity Intensive	ISY30	Stock Index	25.05.2007
U.S. treasury bill dollar Intensive	USDTR	U.S. dollar	02.05.2012
Silver participation	SLVRP	Silver/Islamic	21.05.2012
Gold participation	GOLDP	Gold/Islamic	02.08.2010
Gold ETF	GLDTR	Gold	28.09.2006
Silver B type ETF	GMSTR	Silver	02.05.2012

$$\hat{\sigma}_t^2 = \left(\frac{1}{4}\ln 2\right)\left(\ln H_t - \ln L_t\right)^2 \qquad (2)$$

Where H_t and L_t are daily high and low prices, respectively. This measure is static in nature and does not incorporate dynamic evolution of volatility in the financial markets. Following Hsieh (1993) and as used in Li and Hong (2011), we specify the dynamic counterpart of the above specification as,

$$R_t = \sigma e_t \quad e_t \text{ is } i.i.d.(0,1) \qquad (3)$$

$$\ln \hat{\sigma}_t^{\,2} = a + \sum_{i=1}^{m} \beta \hat{\sigma}_{t-1}^{\,2} + \upsilon_t \cdots\cdots \upsilon_t \text{ is } i.i.d.(0, \upsilon_\upsilon^2) \qquad (4)$$

4. Methodology

In this section, we introduce the empirical methods used. In the first step, we introduce a causality test that investigates causality in variance. Then we summarize the causality analyses to investigate causality in the mean. By doing so we will be able to determine whether causality appears in the variance of volatility. The tests to find the causality in means are as follows: Toda-Yamamoto (1995) Granger type causality; bootstrap based Hatemi-J (2005 and 2006) Granger type causality; frequency domain causality developed by Breitung and Candelon (2006) which investigates causality in different time frequencies; and asymmetric causality which finds the causality in different types of shocks. Employing various causality analyses allows us to determine the validity of the leverage and volatility feedback hypotheses for longer time periods. We also test the asymmetries between return and volatility and better understand the existence of affect and representativeness notions in ETF markets by employing the Hatemi-J and Roca (2014) asymmetric causality test.

4.1. Causality-in-Variance (Volatility Spillover) Test

Even though linear and nonlinear causality methods are capable of capturing predictive power from one variable to another variable, they are not able to detect volatility spillover between two variables since volatility corresponds to fluctuations in the variance of data. Therefore, in addition to analyzing causality, it is useful to conduct a causality-in-variance test to better understand transmission mechanisms between variables. In order to determine the volatility spillover, this study adopts the causality-in-variance test recently developed by Hafner and Herwartz (2006). In examining volatility spillover between two series, we use the causality-variance test of Cheung and Ng (1996) and Hong (2001), which is based on cross-correlation functions (CCF) of standardized residuals obtained from univariate general autoregressive conditional heteroscedasticity (GARCH) estimations. It is utilized in the applied literature on commodity prices. However, the CCF based Portmanteau test is likely to suffer from significant oversizing in small and medium samples when the volatility process are leptokurtic (Hafner and Herwartz, 2006).

In addition to this drawback of Cheung and Ng's procedure, the results from CCF based volatility spillover testing are sensitive to the orders of leads and lags which in turn places doubt on the robustness of findings. The volatility spillover test of Hafner and Herwartz (2006), based on the Lagrange multiplier (LM) principle, overcomes the shortfalls of Cheung and Ng's method and is very practical for empirical illustrations. Furthermore, the Monte Carlo experiment carried out in

Hafner and Herwartz (2006) indicates that the LM approach is more robust against leptokurtic innovations in small samples and the gains from carrying out the LM test increase with sample size.

The results further show that an inappropriate lead and lag order choice in the CCF test distorts its performance and thereby leads to the risk of selecting a wrong order of the CCF statistic. In what follows, we briefly explain the details of Hafner and Herwartz (2006) causality-in-variance test.

In the Hafner and Herwartz (2006) approach, testing for causality in variance is based on estimating univariate GARCH models. The null hypothesis of non-causality in variance between two return series is described as follows:

$$H_0 : Var\left(\varepsilon_{it} \middle| F_{t-1}^{(j)}\right) = Var\left(\varepsilon_{it} \middle| F_{t-1}\right) \qquad j = 1,...,N,\ i \neq j \tag{5}$$

where $F_t^{(j)} = F_t \setminus \sigma(\varepsilon_{j\tau}, \tau \leq t)$ and ε_{it} is the residuals from the GARCH model. The following model is considered to test for the null hypothesis:

$$\varepsilon_{it} = \xi_{it} \sqrt{\sigma_{it}^2 g_t}\,, \qquad g_{it} = 1 + z'_{jt}\pi, \quad z_{jt} = \left(\varepsilon_{t-1}^2, \sigma_{t-1}^2\right)' \tag{6}$$

where conditional variance $\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2$ and ξ_{it} denotes the standardized residuals of the GARCH model**.** In equation (6), the sufficient condition is $\pi = 0$ which ensures that the null hypothesis of non-causality in variance $H_0 : \pi = 0$ is tested against the alternative hypothesis $H_1 : \pi \neq 0$. The score of the Gaussian log-likelihood function of ε_{it} is given by $x_{it}\left(\xi_{it-1}^2\right)/2$ where the derivatives $x_{it} = \sigma_{it}^{-2}(\partial \sigma_{it}^2 / \partial \theta_i)$ such that $\theta_i = (\omega_i, \alpha_i, \beta_i)'$. Hafner and Herwartz (2006) propose the following LM test in order to determine the volatility transmission between the series:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z'_{jt}\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)z_{jt}\right) \tag{7}$$

where

$$V(\theta_i) = \frac{\kappa}{4T}\left(\sum_{t=1}^{T} z_{jt} z'_{jt} - \sum_{t=1}^{T} z_{jt} x'_{it}\left(\sum_{t=1}^{T} x_{it} x'_{it}\right)^{-1} \sum_{t=1}^{T} x_{it} z'_{jt}\right), \quad \kappa = \frac{1}{T}\sum_{t=1}^{T}(\xi_{it}^2 - 1)^2$$

The asymptotic distribution of the test statistic in equation (7) will depend on the number of misspecification indicators in z_{jt}. Since there are two misspecification indicators in λ_{LM} , the test has an asymptotic chi-square distribution with two degrees of freedom.

4.2. Toda-Yamamoto (1995) Granger Type Causality Test

Toda and Yamamoto (1995) represent an improvement over the standard Granger causality test by ensuring that the latter's test statistic follows a standard asymptotic distribution (Squalli, 2007). This technique has the advantage of being applicable irrespective of the integration and co-integration properties of the system. In this approach, VAR $(k + d_{\max})$ has to be estimated to use the modified Wald test for linear restrictions on the parameters of a VAR (k) which has an asymptotic distribution. All we need is to determine the maximal order of integration $d_{\max}$ that we suspect might occur in the model and then to over-fit intentionally a level VAR with additional lags (Toda and Yamamoto, 1995). In the first step of the Toda and Yamamoto causality test, the lag length of the variables (k) can be set according to the Akaike Information criterion (AIC) and then to identify integration of variables ($d_{\max}$) stationary tests. In the last step of the test, a modified Wald test is employed to estimate following the VAR system where the null hypothesis of no causality is not rejected when $\beta_{1i} = 0$, $\lambda_{1j} = 0$, and $\delta_{1j} = 0$.

4.3. Hatemi-J (2005) Bootstrap Process-Based Toda-Yamamoto Granger Causality Test

The Granger-type causality test developed by Toda-Yamamoto (1995) is based on the ordinary least squares method, where heteroscedasticity, auto-correlation, and functional problems are taken into account and thus model construction errors are solved. But the method of Toda-Yamamoto (1995) may have biased results that prevent the obtainment of robust results when using small sample sizes and having ARCH effects in error terms. Hatemi-J (2005) has developed a bootstrapped causality test based on Efron (1979). By doing so, the causality method which tests data for normality and the presence of ARCH effects also tests the co-integration order of variables. The optimal lag length has to be chosen according to the minimum criteria for HJC[1]. If the variables are co-integrated in the $VAR(p+d_{\max})$ model, we can write the equation with a simpler expression as follows:

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \ldots + y_{t-p-d_{\max}} + \varepsilon_t , \tag{8}$$

and including

$$Y = (y_1,\ldots,y_T), D = (v, A_1,\ldots,A_p,\ldots,A_{p+d_{\max}}), \delta = (\varepsilon_1,\ldots,\varepsilon_T) \; and \; Z_t = \begin{bmatrix} 1 \\ y_t \\ y_{t-1} \\ . \\ . \\ . \\ y_{t-p-d+1} \end{bmatrix}$$

The equation can be written as,

$$Y = DZ + \delta \tag{9}$$

The null hypothesis claims that there is no Granger causality (causality non-Granger). The modified Wald test (modified WALD) statistics developed by Toda-Yamamoto (1995) are calculated by equation (10). The bootstrap based causality test also employs the same test statistics.

$$MWALD = (C\beta)'\left[C((Z'Z)^{-1} \otimes S_U)C'\right]^{-1}(C\beta) \; \chi_p^2 \tag{10}$$

where $\otimes$ is the Kronecker product, C is a $pxn(1+n(p+d_{\max}))$ selector matrix, S_U is variance-covariance matrix of residuals, and $\beta = vec(D)$ signifies the column-stacking operator. In contrast to Toda-Yamamoto (1995), Hatemi-J (2005) employs critical values obtained from the bootstrap process and gets more robust results.

4.4. Hatemi J and Roca (2014) Asymmetric Causality Test

P_{1t} and P_{2t} are two co-integrated variables (Hatemi J, Roca, 2014; 7)

$$P_{1t} = P_{1t-1} + \varepsilon_{1t} = P_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i} \tag{11}$$

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[1] Please see Hatemi-J (2003) for detailed information about HJC information criteria.

and

$$P_{2t} = P_{2t-1} + \varepsilon_{2t} = P_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i} \tag{12}$$

Where t is t=1,2,…,T; $P_{1,0}$ and $P_{2,0}$ are constant terms; and $\varepsilon_t = (\varepsilon_1, \varepsilon_2)\ is\ iid(0, \sigma^2)$. Positive and negative changes in each variable are $\varepsilon_{1i}^{+} = \max(\varepsilon_{1i}, 0)$, $\varepsilon_{2i}^{+} = \max(\varepsilon_{2i}, 0)$, $\varepsilon_{1i}^{-} = \min(\varepsilon_{1i}, 0)$, and $\varepsilon_{2i}^{-} = \min(\varepsilon_{2i}, 0)$, respectively. We estimate results as $\varepsilon_{1i} = \varepsilon_{1i}^{+} + \varepsilon_{1i}^{-}$ and $\varepsilon_{2i} = \varepsilon_{2i}^{+} + \varepsilon_{2i}^{-}$. So,

$$P_{1t} = P_{1t-1} + \varepsilon_{1t} = P_{1,0} + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-} \tag{13}$$

$$P_{2t} = P_{2t-1} + \varepsilon_{2t} = P_{2,0} + \sum_{i=1}^{t} \varepsilon_{2i}^{+} + \sum_{i=1}^{t} \varepsilon_{2i}^{-} \tag{14}$$

The accumulation of positive and negative shocks in each variable are $P_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1t}^{+}$, $P_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1t}^{-}$, $P_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2t}^{+}$, and $P_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2t}^{-}$, respectively (Hatemi J, Roca, 2014: 8). $P_t^{+} = (P_{1t}^{+}, P_{2t}^{+})$ vector is used in order to test causation linkage between positive shocks. For detailed information about optimal lag length selection and bootstrap processes please see Hatemi-J (2003, 2008) and Hatemi J and Roca (2014), respectively.

4.5. Frequency Domain Causality Test

While conventional time domain causality tests produce a single test statistic for the interaction between the variables of concern, frequency domain methodology generates tests statistics at different frequencies across spectra. The frequency domain approach to causality thereby permits investigation of causality dynamics at different frequencies rather than relying on a single statistic as is the case with conventional time domain analysis (Ciner, 2011). Hence, it seems to be very meaningful to carry out frequency domain causality tests to better understand temporary and permanent linkages between policy rates and credit rates. To test for causality based on frequency domain, Geweke (1982) and Hosoya (1991) define a two-dimensional vector of time series $z_t = [x_t, y_t]'$ where z_t has a finite-order VAR;

$$\Theta(L)z_t = \varepsilon_t \tag{15}$$

where $\Theta(L) = I - \Theta_1 L - ... - \Theta_p L_p$ and lag polynomial with $L^k z_t = z_{t-1}$. Then Granger causality at different frequencies is defined as;

$$M_{y\to x} = \log\left[\frac{2\pi f_x(\omega)}{\left|\psi_{11}(e^{-i\omega})\right|^2}\right] = \left[1 + \frac{\left|\psi_{12}(e^{-i\omega})\right|^2}{\left|\psi_{11}(e^{-i\omega})\right|^2}\right]$$

(16)

if $\left|\psi_{12}(e^{-i\omega})\right|^2 = 0$ that y does not cause x at frequency ω .

Breitung and Candelon (2006), who use a bivariate vector autoregressive model, propose a simple test procedure that is based on a set of linear hypotheses on the autoregressive parameters. The test procedure can be generalized to allow for cointegration relationships and higher-dimensional systems. Breitung and Candelon (2006) assume that ε_t is white noise with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t, \varepsilon_t') = \Sigma$, where Σ is positive definite. We can use this representation for spectral density of x_t;

$$f_x(\omega) = \frac{1}{2\pi}\{|\psi_{11}(e^{-i\omega})|^2 + |\psi_{12}(e^{-i\omega})|^2\} \tag{17}$$

Breitung and Candelon (2006) investigate the causal effect of $M_{y\to x}(\omega) = 0$ if $|\psi_{12}(e^{-i\omega})|^2 = 0$. The null hypothesis is equivalent to a linear restriction on the VAR coefficients. y does not cause x at frequency ω if

$$|\Theta_{12}(e^{-i\omega})| = \left|\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)i\right| = 0 \tag{18}$$

with $\theta_{12,k}$ denoting the (1,2)-element of Θ_k .

5. Empirical Results

Before the presentation of empirical findings, it is prudent to check the statistical properties of the time series employed in the analysis. In Table 3, we summarize descriptive statistics of series belonging to variables included in the model. According to Table 1, the return series of all Islamic stock ETFs are skewed to the left while other series for all Islamic ETFs are skewed to the right. Kurtosis coefficients of variables show that return and risk series are steep. Probability values of the Jarque – Bera hypothesis imply that series are distributed abnormally and the alternative hypothesis is accepted.

Table-2
Descriptive Statistics

	ETFs	Mean	Max.	Min.	Standard Dv.	Skewness	Kurtosis	Jarque-Bera (p-value)
Islamic ETFs	$r_{KATLIMP}$	-0.000116	0.012752	-0.017398	0.004013	-0.693782	5.059371	113.0496 (0.00)
	$\hat{\sigma}^2_{KATLIMP}$	2.98e-06	3.48e-08	2.44e-07	3.55e-06	4.552536	32.51988	32.51988 (0.00)
	$r_{KATLM30}$	-0.000194	0.020855	-0.022755	0.004791	-0.301245	5.401154	338.0909 (0.00)
	$\hat{\sigma}^2_{KATLM30}$	4.34e-06	8.22e-05	1.98e-07	6.52e-06	5.449288	43.91853	98919.6 (0.00)
	$r_{KATLM50}$	-0.000353	0.020066	-0.001780	0.004378	-0.284030	5.073106	84.708847 (0.00)
	$\hat{\sigma}^2_{KATLM50}$	3.42e-06	3.03e-06	2.00e-07	3.87e-06	3.679293	20.71995	6749.336 (0.00)
	r_{DJIMTR}	0.000106	0.046987	-0.037616	0.006253	-0.429850	7.6811624	2777.33 (0.00)
	$\hat{\sigma}^2_{DJIMTR}$	7.47e-06	0.000397	0.00	1.39e-05	11.32911	11.32911	7130804.6 (0.00)
Commodity ETFs	r_{GLDTR}	1.26e-05	0.098986	-0.020048	0.004734	4.555048	89.72159	759095.5 (0.00)
	$\hat{\sigma}^2_{GLDTR}$	4.02e-06	0.000752	5.47e-08	2.06e-05	26.08983	835.8690	69523280.8 (0.00)
	r_{GOLDP}	0.000384	0.100745	-0.044044	0.006901	9.172117	130.9153	994275.9 (0.00)
	$\hat{\sigma}^2_{GOLDP}$	4.77e-06	0.000783	0.00	4.28e-05	16.27025	272.7269	4394858.6 (0.00)
	r_{GMSTR}	0.000161	0.094976	-0.026872	0.0066255	3.995139	60.06633	136136.8 (0.00)
	$\hat{\sigma}^2_{GMSTR}$	6.64e-06	0.000707	6.40e-08	3.22e-05	19.478861	408.2690	9796185.4 (0.00)
	r_{SLVRP}	2.85e-05	0.091190	-0.024882	0.007815	3.485072	38.55230	53158.23 (0.00)
	$\hat{\sigma}^2_{SLVRP}$	1.54e-05	0.002190	0.00	9.23e-05	16.37172	16.37172	4605319.7 (0.00)
Stock ETFs	$r_{DJIST20}$	-0.000115	0.097774	-0.030055	0.006909	3.576216	56.20243	175180.7 (0.00)
	$\hat{\sigma}^2_{DJIST20}$	6.60e-06	0.000779	8.09e-05	2.97e-05	23.81170	23.81170	22685182.4 (0.00)
	r_{BNKTR}	-0.00035	0.096294	-0.047262	0.008513	0.265543	12.08116	9033.498 (0.00)

	ETFs	Mean	Max.	Min.	Standard Dv.	Skewness	Kurtosis	Jarque-Bera (p-value)
	$\hat{\sigma}^2_{BNKTR}$	1.10e-05	0.00076	0.00	2.88e-05	13.84766	13.84766	84736668.1 (0.00)
	r_{IST30}	-0.000171	0.102173	-0.038127	0.007244	2.720637	43.17194	120625.4 (0.00)
	$\hat{\sigma}^2_{IST30}$	7.66e-06	0.000786	1.83e-08	2.89e-05	22.13916	576.2623	24270830.4 (0.00)
	r_{ISY30}	0.000684	0.106219	-0.022132	0.011041	6.198688	54.48402	102240.1 (0.00)
	$\hat{\sigma}^2_{ISY30}$	1.19e-05	0.000849	0.00	7.78e-05	9.635690	94.79581	320755.2 (0.00)
BOND	r_{FBIST}	0.000224	0.098186	-0.008944	0.003206	26.36653	802.1799	56796761 (0.00)
	$\hat{\sigma}^2_{FBIST}$	9.62e-07	0.000726	0.00	2.22e-05	31.69552	1019.796	91896647 (0.00)
USD	r_{USDTR}	0.000239	0.093160	-0.009977	0.003830	14.62876	353.7825	5080078.4 (0.00)
	$\hat{\sigma}^2_{USDTR}$	3.84e-06	0.000723	0.00	4.29e-05	15.74546	251.3527	2569501.6 (0.00)

Conventional stock ETFs, commodity ETFs, bond ETFs, and U.S. dollar ETFs have similar statistical properties. They are skewed to the right. The Kurtosis coefficients show that all time series are steep. The null hypothesis claiming series are distributed normally is rejected in light of Jarque-Bera hypothesis p-values.

Prior to employing VAR based causality analysis, it is important to identify stationarity of variables in order to prevent the spurious regression problem. With this aim, we employ unit root tests developed by Dickey-Fuller (1979, 1981) (hereafter ADF) and Phillips-Perron (1988) (hereafter PP). According to both unit root test results in Table 3, it is possible to conclude that all variables belonging to each type of ETFs are stationary in level. Therefore, it is possible to use time series in level values.

In Table 4, the results of both Toda – Yamamoto (1995) and bootstrap based Hatemi-J (2005 and 2006) Granger causality analyses are presented in a combined version. According to both test results, there is a uni-directional causation linkage running from return to volatility in all Islamic stock ETFs. On the other hand, the uni-directional causality in the same direction is valid for two of the four commodity based ETFs. These are GLDTR and SLVRP.

For U.S. dollar based ETFs, the causality running from return to volatility on a daily basis exists at the 1% significance level. Lastly, uni-directional causality running from returns to volatility is valid for DJIST, BNKTR, and IST30. Neither the Toda-Yamamoto nor the Hatemi-J Granger causality test supports the validity of such a relationship in FBIST, bond ETFs, ISY30, and conventional stock ETFs. In light of these results, the leverage hypothesis may be valid in all Islamic ETFs, two of the commodity ETFs, three of the conventional stock ETFs, and U.S. dollar ETFs. Results indicating causality running from returns to volatility in each ETF type also give some hints about the validity of the behavioral explanation hypothesis.

Table-3
ADF (1979, 1981) and PP (1988) Unit Root Test Results in Level

Model	Group	*Variables*	ADF	PP	*Variables*	ADF	PP
Constant	Islamic ETFs	$r_{KATLIMP}$	-21.62 (0) [0.00]***	-21.62 (2) [0.00] ***	$r_{KATLM30}$	-38.43 (0) [0.00] ***	-38.42 (2) [0.00] ***
		$\hat{\sigma}^2_{KATLIMP}$	-17.39 (0) [0.00] ***	-18.27 (9) [0.00] ***	$\hat{\sigma}^2_{KATLM30}$	-12.46 (2) [0.00] ***	-24.40 (17) [0.00] ***
		$r_{KATLM50}$	-21.36 (0) [0.00] ***	-21.39 (6) [0.00] ***	r_{DJIMTR}	-51.84 (0) [0.00] ***	-51.81 (17) [0.00] ***
		$\hat{\sigma}^2_{KATLM50}$	-9.08 (2) [0.00] ***	-18.93 (10) [0.00] ***	$\hat{\sigma}^2_{DJIMTR}$	-14.94 (5) [0.00] ***	-53.45 (30) [0.00] ***
	Commodity	r_{GLDTR}	-49.46 (0) [0.00] ***	-49.61 (14) [0.00] ***	r_{GOLDP}	-23.24 (1) [0.00] ***	-38.45 (17) [0.00] ***
		$\hat{\sigma}^2_{GLDTR}$	-30.02 (1) [0.00] ***	-33.13 (7) [0.00] ***	$\hat{\sigma}^2_{GOLDP}$	-6.44 (14) [0.00] ***	-39.73 (19) [0.00] ***
		r_{GMSTR}	-33.72 (0) [0.00] ***	-33.63 (7) [0.00] ***	r_{SLVRP}	-27.30 (0) [0.00] ***	-27.88 (11) [0.00] ***
		$\hat{\sigma}^2_{GMSTR}$	-31.21 (0) [0.00] ***	-31.21 (2) [0.00] ***	$\hat{\sigma}^2_{SLVRP}$	-7.74 (6) [0.00] ***	-30.74 (15) [0.00] ***
	Stock ETFs	$r_{DJIST20}$	-37.70 (0) [0.00] ***	-37.71 (5) [0.00] ***	r_{BNKTR}	-46.53 (0) [0.00] ***	-46.75 (11) [0.00] ***
		$\hat{\sigma}^2_{DJIST20}$	-37.31 (0) [0.00] ***	-37.37 (7) [0.00] ***	$\hat{\sigma}^2_{BNKTR}$	-21.35 (3) [0.00] ***	-50.66 (24) [0.00] ***
		r_{IST30}	-42.12 (0) [0.00] ***	-42.17 (11) [0.00] ***	r_{ISY30}	-14.04 (2) [0.00] ***	-27.70 (12) [0.00] ***
		$\hat{\sigma}^2_{IST30}$	-40.68 (0) [0.00] ***	-40.88 (10) [0.00] ***	$\hat{\sigma}^2_{ISY30}$	-2.82 (20) [0.05]*	-27.98 (15) [0.00] ***
	BOND	r_{FBIST}	-45.17 (0) [0.00] ***	-45.17 (2) [0.00] ***			
		$\hat{\sigma}^2_{FBIST}$	-46.137 (0) [0.00] ***	-46.13 (2) [0.00] ***			
	USD	r_{USDTR}	-30.51 (0) [0.00] ***	-30.53 (5) [0.00] ***			
		$\hat{\sigma}^2_{USDTR}$	-7.44 (8) [0.00] ***	-23.40 (6) [0.00] ***			
Constant +Trend	Islamic ETFs	$r_{KATLIMP}$	-21.61 (0) [0.00] ***	-21.61 (2) [0.00] ***	$r_{KATLM30}$	-38.46 (0) [0.00] ***	-38.43 (3) [0.00] ***
		$\hat{\sigma}^2_{KATLIMP}$	-17.83 (0) [0.00] ***	-18.37 (8) [0.00] ***	$\hat{\sigma}^2_{KATLM30}$	-12.55 (2) [0.00] ***	-24.40 (17) [0.00] ***
		$r_{KATLM50}$	-21.41 (0) [0.00] ***	-21.43 (6) [0.00] ***	r_{DJIMTR}	-51.83 (0) [0.00] ***	-51.804 (17) [0.00] ***
		$\hat{\sigma}^2_{KATLM50}$	-9.17 (2) [0.00] ***	-18.95 (10) [0.00] ***	$\hat{\sigma}^2_{DJIMTR}$	-18.91 (3) [0.00] ***	-52.46 (29) [0.00] ***
	Commodity	r_{GLDTR}	-49.48 (0) [0.00] ***	-49.61 (14) [0.00] ***	r_{GOLDP}	-23.32 (1) [0.00] ***	-38.36 (16) [0.00] ***
		$\hat{\sigma}^2_{GLDTR}$	-30.02 (1) [0.00] ***	-33.12 (7) [0.00] ***	$\hat{\sigma}^2_{GOLDP}$	-6.72 (14) [0.00] ***	-39.45 (18) [0.00] ***
		r_{GMSTR}	-33.74 (0) [0.00] ***	-33.66 (6) [0.00] ***	r_{SLVRP}	-27.49 (0) [0.00] ***	-27.87 (10) [0.00] ***
		$\hat{\sigma}^2_{GMSTR}$	-31.43 (0) [0.00] ***	-31.43 (6) [0.00] ***	$\hat{\sigma}^2_{SLVRP}$	-8.23 (6) [0.00] ***	-30.53 (14) [0.00] ***
	Stock ETFs	$r_{DJIST20}$	-37.70 (0) [0.00] ***	-37.71 (5) [0.00] ***	r_{BNKTR}	-46.52 (0) [0.00] ***	-46.74 (11) [0.00] ***
		$\hat{\sigma}^2_{DJIST20}$	-37.38 (0) [0.00] ***	-37.42 (6) [0.00] ***	$\hat{\sigma}^2_{BNKTR}$	-21.42 (3) [0.00] ***	-50.59 (24) [0.00] ***
		r_{IST30}	-42.11 (0) [0.00] ***	-42.16 (11) [0.00] ***	r_{ISY30}	-14.40 (2) [0.00] ***	-27.75 (10) [0.00] ***
		$\hat{\sigma}^2_{IST30}$	-40.67 (0) [0.00] ***	-40.87 (10) [0.00] ***	$\hat{\sigma}^2_{ISY30}$	-3.08 (20) [0.109]	-27.80 (14) [0.00] ***
	BOND	r_{FBIST}	-45.22 (0) [0.00] ***	-45.22 (1) [0.00] ***			
		$\hat{\sigma}^2_{FBIST}$	-46.25 (0) [0.00] ***	-46.25 (5) [0.00] ***			
	USD	r_{USDTR}	-30.51 (0) [0.00] ***	-30.53 (5) [0.00] ***			
		$\hat{\sigma}^2_{USDTR}$	-8.15 (9) [0.00] ***	-23.66 (9) [0.00] ***			

Notes: The figures in parentheses denote the lag length selected by the Schwarz criterion. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Values within the brackets show the probability ratios. For the ADF test: The results of the Dickey Fuller test are in the case of zero lag length and lag length chosen due to SIC criteria. For both models the Mac Kinnon(1996) critical values are -.3.485 and -2.885 at the 1% and 5% levels respectively. For the PP test: Values in the parentheses show bandwidths obtained according to Newey-West using Bartlett Kernel criteria. The Mac Kinnon (1996) critical values for the first model are -3.483 and -2.884 at the 1% and 5% levels respectively and for the second model are -4.033 and -3.446 at the 1% and 5% levels respectively.

Table-4
Toda-Yamamoto (1995) and Bootstrap Based Hacker-Hatemi J (2005, 2006) Granger Causality Test Results

ETFs	Hypothesis	$k+d_{max}$	MWALD	%1 Bootstrap CV	%5 Bootstrap CV	%10 Bootstrap CV	Hypothesis	$k+d_{max}$	MWALD	%1 Bootstrap CV	%5 Bootstrap CV	%10 Bootstrap CV
Islamic ETFs	$r_{KATLIMP} \nRightarrow \hat{\sigma}^2_{KATLIMP}$	6	12.700 (0.026)**	17.444	12.936	10.877*	$\hat{\sigma}^2_{KATLIMP} \nRightarrow r_{KATLIMP}$	6	6.950 (0.224)	17.309	12.364	10.314
	$r_{KATLM30} \nRightarrow \hat{\sigma}^2_{KATLM30}$	4	19.025 (0.00)***	12.604***	10.042**	7.716*	$\hat{\sigma}^2_{KATLM30} \nRightarrow r_{KATLM30}$	4	6.703 (0.081)*	12.746	9.131	6.650*
	$r_{KATLM50} \nRightarrow \hat{\sigma}^2_{KATLM50}$	3	10.627 (0.00)***	11.790	6.190**	4.851*	$\hat{\sigma}^2_{KATLM50} \nRightarrow r_{KATLM50}$	3	0.447 (0.799)	7.371	4.688	3.779
	$r_{DJIMTR} \nRightarrow \hat{\sigma}^2_{DJIMTR}$	19	80.110 (0.00)***	37.274***	31.163**	28.154*	$\hat{\sigma}^2_{DJIMTR} \nRightarrow r_{DJIMTR}$	19	42.697 (0.00)***	41.499***	30.184**	27.422*
Commodity ETFs	$r_{GLDTR} \nRightarrow \hat{\sigma}^2_{GLDTR}$	3	8.043 (0.045)**	12.246	7.633**	4.979*	$\hat{\sigma}^2_{GLDTR} \nRightarrow r_{GLDTR}$	3	6.108 (0.106)	12.396	4.741**	4.074*
	$r_{GOLDP} \nRightarrow \hat{\sigma}^2_{GOLDP}$	8	6.567 (0.475)	72.260	27.823	19.055	$\hat{\sigma}^2_{GOLDP} \nRightarrow r_{GOLDP}$	8	28.402 (0.00)***	67.022	29.560	19.957*
	$r_{GMSTR} \nRightarrow \hat{\sigma}^2_{GMSTR}$	2	0.382 (0.825)	44.571	4.234	4.439	$\hat{\sigma}^2_{GMSTR} \nRightarrow r_{GMSTR}$	2	2.593 (0.273)	15.543	6.599	3.698
	$r_{SLVRP} \nRightarrow \hat{\sigma}^2_{SLVRP}$	7	21.171 (0.00)***	52.504	17.867**	11.505*	$\hat{\sigma}^2_{SLVRP} \nRightarrow r_{SLVRP}$	7	3.131 (0.792)	37.836	16.280	10.561
Stock ETFs	$r_{DJIST20} \nRightarrow \hat{\sigma}^2_{DJIST20}$	5	24.700 (0.00)***	94.614	10.210**	7.935*	$\hat{\sigma}^2_{DJIST20} \nRightarrow r_{DJIST20}$	5	2.395 (0.66)	65.261	9.753	8.008
	$r_{BNKTR} \nRightarrow \hat{\sigma}^2_{BNKTR}$	4	25.567 (0.00)***	17.27***	11.70**	9.465*	$\hat{\sigma}^2_{BNKTR} \nRightarrow r_{BNKTR}$	4	14.579 (0.00)***	18.29	12.177**	9.729*
	$r_{IST30} \nRightarrow \hat{\sigma}^2_{IST30}$	2	8.014 (0.00)***	13.404	4.686**	1.980*	$\hat{\sigma}^2_{IST30} \nRightarrow r_{IST30}$	2	0.987 (0.320)	13.282	3.839	2.531
	$r_{ISY30} \nRightarrow \hat{\sigma}^2_{ISY30}$	7	7.311 (0.293)	52.175	25.487	16.492	$\hat{\sigma}^2_{ISY30} \nRightarrow r_{ISY30}$	7	17.267 (0.00)***	55.108	18.862	14.899*
BOND	$r_{FBIST} \nRightarrow \hat{\sigma}^2_{FBIST}$	4	0.3967 (0.94)	8.711	3.505	1.780	$\hat{\sigma}^2_{FBIST} \nRightarrow r_{FBIST}$	4	6.205 (0.102)	8.922	4.302**	3.244*
USD	$r_{USDTR} \nRightarrow \hat{\sigma}^2_{USDTR}$	10	211.406 (0.00)***	121.135***	31.500**	15.606*	$\hat{\sigma}^2_{USDTR} \nRightarrow r_{USDTR}$	10	7.918 (0.542)	192.964	22.797	16.448

Note: ***, **, and * denote the existence of causation linkage between variables at significance levels 1%, 5%, and 10%, respectively. $k+d_{max}$ value shows the total amount of stationary level and optimal lag length chosen due to the AIC information criterion. Values in parentheses show asymptotically distributed probability value.

Table-5
Frequency Domain Causality Results

ETFs	ω_i	Long Term		Med Term		Short Term		ω_i	Long Term		Med Term		Short Term	
		0.01	**0.05**	**1.00**	**1.50**	**2.00**	**2.50**		**0.01**	**0.05**	**1.00**	**1.50**	**2.00**	**2.50**
Islamic ETFs	$r_{KATLIMP} \nRightarrow \hat{\sigma}^2_{KATLIMP}$	8.75*	8.68*	0.29	0.29	6.84*	8.27*	$\hat{\sigma}^2_{KATLIMP} \nRightarrow r_{KATLIMP}$	6.46*	6.45*	0.92	2.10	3.00*	3.34*
	$r_{KATLM30} \nRightarrow \hat{\sigma}^2_{KATLM30}$	24.47*	24.36*	1.54	0.59	2.46	6.65*	$\hat{\sigma}^2_{KATLM30} \nRightarrow r_{KATLM30}$	8.92*	8.96*	1.48	10.85*	0.27	2.67
	$r_{KATLM50} \nRightarrow \hat{\sigma}^2_{KATLM50}$	8.80*	8.69*	0.27	2.77	5.36*	0.64	$\hat{\sigma}^2_{KATLM50} \nRightarrow r_{KATLM50}$	6.19*	6.27*	3.47*	0.66	1.41	3.53*
	$r_{DJIMTR} \nRightarrow \hat{\sigma}^2_{DJIMTR}$	81.55*	81.20*	9.66*	7.74*	3.45*	0.47	$\hat{\sigma}^2_{DJIMTR} \nRightarrow r_{DJIMTR}$	13.90*	13.60*	1.01	4.04*	4.96*	4.90*
Commodity ETFs	$r_{GLDTR} \nRightarrow \hat{\sigma}^2_{GLDTR}$	2.53	2.52	0.60	0.00	2.73	2.71	$\hat{\sigma}^2_{GLDTR} \nRightarrow r_{GLDTR}$	1.83	1.82	0.99	2.55	0.08	13.03*
	$r_{GOLDP} \nRightarrow \hat{\sigma}^2_{GOLDP}$	4.35*	4.35*	2.60	1.86	8.68*	0.69	$\hat{\sigma}^2_{GOLDP} \nRightarrow r_{GOLDP}$	11.72*	11.74*	12.59*	17.59*	1.45	7.47*
	$r_{GMSTR} \nRightarrow \hat{\sigma}^2_{GMSTR}$	0.35	0.35	1.61	0.42	0.14	0.35	$\hat{\sigma}^2_{GMSTR} \nRightarrow r_{GMSTR}$	0.00	0.00	3.01*	0.55	0.49	0.92
	$r_{SLVRP} \nRightarrow \hat{\sigma}^2_{SLVRP}$	5.71*	5.64*	19.41*	2.43	1.76	1.31	$\hat{\sigma}^2_{SLVRP} \nRightarrow r_{SLVRP}$	0.31	0.34	2.17	0.13	2.88	3.27*
Conventional ETFs	$r_{DJIST20} \nRightarrow \hat{\sigma}^2_{DJIST20}$	18.87*	18.91*	2.70	0.82	2.49	2.09	$\hat{\sigma}^2_{DJIST20} \nRightarrow r_{DJIST20}$	0.52	0.51	0.71	0.49	3.04*	1.76
	$r_{BNKTR} \nRightarrow \hat{\sigma}^2_{BNKTR}$	18.55*	18.46*	0.79	0.25	3.39*	4.47*	$\hat{\sigma}^2_{BNKTR} \nRightarrow r_{BNKTR}$	0.98	1.03	15.81*	0.06	5.56*	6.64*
	$r_{IST30} \nRightarrow \hat{\sigma}^2_{IST30}$	19.84*	19.73*	4.14*	1.16	1.77	4.56*	$\hat{\sigma}^2_{IST30} \nRightarrow r_{IST30}$	0.03	0.03	5.83*	0.44	4.30*	2.72
	$r_{ISY30} \nRightarrow \hat{\sigma}^2_{ISY30}$	4.22*	4.21*	2.32	5.54*	0.51	0.66	$\hat{\sigma}^2_{ISY30} \nRightarrow r_{ISY30}$	7.25*	7.26*	0.30	8.25*	0.40	1.07
BOND	$r_{FBIST} \nRightarrow \hat{\sigma}^2_{FBIST}$	0.23	0.23	0.99	2.36	1.41	0.66	$\hat{\sigma}^2_{FBIST} \nRightarrow r_{FBIST}$	3.26*	3.21*	3.10*	5.05*	2.06	3.42*
USD	$r_{USDTR} \nRightarrow \hat{\sigma}^2_{USDTR}$	29.39*	28.86*	20.42*	47.52*	0.74	86.96*	$\hat{\sigma}^2_{USDTR} \nRightarrow r_{USDTR}$	3.49*	3.48*	1.29	0.51	1.02	1.83

Notes: The lag lengths for the VAR models are determined by SIC. F- distribution with (2, T-2p) degrees of freedom equals about 2.99. For every ω_i (frequency) between 0 and π, $\omega \in (0, \pi)$.

According to the Toda-Yamamoto and Hatemi-J causality analyses results, the uni-directional causality running from volatility to returns is found in a small number of ETFs. It is valid in two of the Islamic stock ETFs (KATLM30 and DJIMTR), two of the commodity ETFs (GLDTR and GOLDP), and two of conventional stock ETFs (BNKTR and ISY30). On the other hand, there is no causality running from volatility to returns in U.S. dollar ETFs and bond ETFs. Results indicate that the volatility feedback hypothesis does not exist in all ETFs.

In order to better understand the validity of the behavioral explanation, leverage, and volatility feedback hypotheses we apply frequency domain tests which allow for the investigation of interactions between variables in different time frequencies. The test results imply causation linkages running from return to volatility in both short- and long-run for all Islamic ETFs. Similar to Toda-Yamamoto (1995) and bootstrapped Hatemi-J (2005 and 2006) test results, uni-directional causality is valid for U.S. dollar ETFs in both short- and long-run. Return affects volatility in all conventional stock ETFs. The interaction is valid in the short- and long-run for all conventional stock ETFs but not for DJIST in the short-run. The results of our analysis imply that our hypotheses are valid for GOLDP and SLVRP commodity ETFs. Analysis results show that there is no causation linkage between variables in any time period for bond ETFs. Frequency domain causality analysis reports that causality between variables may occur in both long- and short-run. This means the leverage and volatility hypotheses in the longer periods and behavioral explanation hypothesis in the shorter periods are valid for most ETFs.

Results of the causality-in-variance test, which analyzes the existence of causality between variables in variance (as opposed to conventional causality analyses which test the causality in mean), are presented in Table 6. According to our test results, the causation linkage running from volatility to return exists in only two Islamic stock ETFs. These are KATLM30 and DJIMTR, which matches the results of Toda-Yamamoto and Hatemi-J Granger causality tests. These results indicate that variance of volatility induces volatility in returns for KATLM30 and DJIMTR. Consequently, the volatility feedback hypothesis is valid for two Islamic ETFs, while the leverage hypothesis is not valid for any kind of ETF. Despite two empirical methods supporting each other for two Islamic ETFs, results differ for other ETF types.

Unlike the causality tests employed above, the Hatemi-J and Roca (2014) test allows for investigation of the causation linkage between variables in different types of shocks. In this regard, testing the relation between return and volatility of an ETF helps to better understand the validity of the hypotheses explained above.

In Table 7, each type of ETF result is grouped. In order to save space we report only asymmetric causality results. According to the results of our analysis on Islamic stock ETFs, there is uni-directional causality from increase in returns to decrease in volatility. Increasing returns in Islamic ETFs will reduce volatility. This is consistent with the leverage hypothesis. On the other hand, the results imply that a reduction in returns will not increase volatility. Return of an Islamic stock ETF affects volatility of the ETF only in the case of positive return shock.

On the other hand, an increase in volatility will reduce the return of Islamic ETFs, except for KATLMP. However, a decrease in volatility will not affect the return in the same way. This means there is no relationship between negative shocks in volatility and positive shocks in returns. DJIMTR is the only exception.

To sum up, our results are consistent with the leverage hypothesis and the volatility feedback hypothesis, with exceptions. Moreover, our results differ from the behavioral explanation hypothesis. Contrary to the suggestions of Badshah (2013) implying that negative returns have a greater impact on the volatility index than do positive returns, our results show that there is a causation linkage running from positive returns to negative volatility. This indicates that an increase in returns will reduce volatility in Islamic stock ETFs.

In the second part of Table 7, results of the asymmetric causality test are presented for commodity ETFs. According to our results, there is uni-directional causality running from positive returns to negative volatility in all commodity ETFs. On the other hand, there is no causality between variables in the case of negative shocks in returns. These results support the leverage hypothesis but not the behavioral explanation hypothesis as implied by Badshah (2013).

The effect of volatility on returns is asymmetric in all commodity ETFs. A positive volatility shock will reduce returns. Moreover a negative shock in volatility will increase returns in commodity ETFs except for GOLDP. These results support the volatility feedback hypothesis in commodity ETFs.

In the third part of Table 7, asymmetric causality test results for conventional stock ETFs are presented. According to our results, a positive shock in returns will reduce volatility in all stock based ETFs. Contrary to other types of ETFs, a negative shock in returns of BNKTR and ISY30 ETFs will increase volatility. These results support the leverage hypothesis and the behavioral explanation hypothesis. In this type of ETF, an increase in volatility will reduce returns. DJIST is the only exception.

These results imply that the volatility feedback hypothesis is valid for three of four conventional stock ETFs. For bond ETFs, results show that there is no causation linkage in any case, just like in other causality test results.

Table-6
Results of Causality-in-Variance Analysis

ETFs		**Statistic (p-value)**		**Statistic (p-value)**
Islamic ETFs	$r_{KATLIMP} \nRightarrow \hat{\sigma}^2_{KATLIMP}$	0.141 (0.931)	$\hat{\sigma}^2_{KATLIMP}\ r_{KATLIMP}$	4.481 (0.106)
	$r_{KATLM30} \nRightarrow \hat{\sigma}^2_{KATLM30}$	0.147 (0.928)	$\hat{\sigma}^2_{KATLM30}\ r_{KATLM30}$	21.922 (0.00)***
	$r_{KATLM50} \nRightarrow \hat{\sigma}^2_{KATLM50}$	0.712 (0.700)	$\hat{\sigma}^2_{KATLM50}\ r_{KATLM50}$	1.240 (0.537)
	$r_{DJIMTR} \nRightarrow \hat{\sigma}^2_{DJIMTR}$	0.156 (0.924)	$\hat{\sigma}^2_{DJIMTR}\ r_{DJIMTR}$	12.91 (0.00)***
Commodity ETFs	$r_{GLDTR} \nRightarrow \hat{\sigma}^2_{GLDTR}$	0.031 (0.984)	$\hat{\sigma}^2_{GLDTR}\ r_{GLDTR}$	0.108 (0.947)
	$r_{GOLDP} \nRightarrow \hat{\sigma}^2_{GOLDP}$	0.265 (0.875)	$\hat{\sigma}^2_{GOLDP}\ r_{GOLDP}$	0.738 (0.691)
	$r_{GMSTR} \nRightarrow \hat{\sigma}^2_{GMSTR}$	0.027 (0.986)	$\hat{\sigma}^2_{GMSTR}\ r_{GMSTR}$	2.461 (0.292)
	$r_{SLVRP} \nRightarrow \hat{\sigma}^2_{SLVRP}$	0.050 (0.975)	$\hat{\sigma}^2_{SLVRP}\ r_{SLVRP}$	0.257 (0.879)
Stock ETFs	$r_{DJIST20} \nRightarrow \hat{\sigma}^2_{DJIST20}$	0.009 (0.995)	$\hat{\sigma}^2_{DJIST20}\ r_{DJIST20}$	0.789 (0.673)
	$r_{BNKTR} \nRightarrow \hat{\sigma}^2_{BNKTR}$	0.032 (0.983)	$\hat{\sigma}^2_{BNKTR}\ r_{BNKTR}$	1.071 (0.585)
	$r_{IST30} \nRightarrow \hat{\sigma}^2_{IST30}$	0.034 (0.982)	$\hat{\sigma}^2_{IST30}\ r_{IST30}$	0.062 (0.969)
	$r_{ISY30} \nRightarrow \hat{\sigma}^2_{ISY30}$	0.154 (0.925)	$\hat{\sigma}^2_{ISY30}\ r_{ISY30}$	0.781 (0.676)
BOND	$r_{FBIST} \nRightarrow \hat{\sigma}^2_{FBIST}$	0.005 (0.997)	$\hat{\sigma}^2_{FBIST}\ r_{FBIST}$	0.011 (0.994)
USD	$r_{USDTR} \nRightarrow \hat{\sigma}^2_{USDTR}$	0.042 (0.979)	$\hat{\sigma}^2_{USDTR}\ r_{USDTR}$	0.320 (0.851)

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level of significance, respectively.

Finally, the results of the asymmetric causality analysis for U.S. dollar based ETFs are presented at the end of Table 7. According to our results, a positive shock in returns will reduce volatility. On the other hand, a negative shock in returns will increase volatility. Our results support the leverage and behavioral explanation hypotheses, implying an asymmetric relation between returns and volatility. But contrary to the implication of Badshah (2013), the power of negative shocks in returns is not supported by the test results. A positive (negative) shock in volatility will induce a negative (positive) change in returns for this type of ETF. This result also supports the volatility feedback hypothesis.

6. Concluding Remarks

In this study, we analyze the probable interactions between return and volatility in different types of ETFs traded in the Borsa Istanbul by employing various recently developed causality analysis methods, namely Toda-Yamamoto (1995) Granger, bootstrap based Hatemi-J (2005 and 2006) Granger, causality-in-variance, frequency domain developed by Breitung and Candelon (2006), and Hatemi-J and Roca (2014) asymmetric causality.

First, interactions between our variables are valid in both short- and long-run. Contrary to the conclusions of earlier research that the relation exists only in the short-run and can be explained by the behavioral explanation hypothesis, we find that the relation exists in the long-run and can therefore be explained via the leverage hypothesis. Moreover, the volatility feedback hypothesis is valid in the longer periods. Thus, the negative relation between return and volatility exists and the results are consistent with the literature.

Moreover, our asymmetric causality analysis results also support the negative relation. However, the asymmetric causality relation implied by Low (2004), Hibbert et al. (2008), and Badshah (2013) is not valid for every type of ETF. While the authors claim that negative return shocks are more impactful than positive ones on volatility, such a relation is valid for only two of the conventional stock ETFs. Most of the asymmetric relation exists in the case of positive return shocks, contrary to Badshah’s (2013) implications. Negative return shocks effect volatility for just two stock ETFs and U.S. dollar ETFs. The same results are found in the case of commodity ETFs. These results imply that a positive return shock induces a decrease in volatility, but negative shocks do not induce positive volatility in Islamıc stock ETFs.

In the case of bond ETFs, there is no negative or asymmetric causality. None of the hypotheses are valid for bond ETFs. On the other hand, the behavioral explanation hypothesis may be valid for U.S. dollar ETFs. There is a uni-directional causality running from negative returns to positive volatility as well as reverse causality.

As can be seen, our results differ with the type of ETF examined. It is clear that a negative relation between return and volatility is valid for all type of ETFs except bond ETFs. However, the validity of asymmetric causality explained by Low (2004) and Hibbert (2008) is somewhat complicated. Although we find some evidence implying that the behavioral explanation hypothesis may be valid for U.S. dollar ETFs and some conventional stock ETFs, other evidence does not fit well into this hypothesis, implying that negative return shocks are more impactful than positive ones on volatility.

The disparity between the existing literature about the behavioral explanation hypothesis and our findings may arise from the disparity in the financial tools examined. Padungsaksawasdi and Daigler (2014) and Daigler et al. (2014) claim that the asymmetric relation is weaker in ETFs compared to stock indices. Moreover we employ different ETF types. Consequently, the relation between return and volatility for ETFs may be hypothesized separately from stock indices.

When we compare Islamic stock ETFs to other/conventional stock ETFs, we find that the causality between returns and volatility is stronger in conventional stock ETFs than in Islamic stock ETFs. This means that conventional hypotheses are better suited to explaining conventional ETFs than Islamic ones. This is also consistent with the findings of Abderrezak (2008) regarding the performance of Islamic mutual funds. Moreover, our findings on the frequency domain support Ashraf (2013), who claims that ethical financial tools perform better in the longer periods. As a consequence of this study, we find that Islamic ETFs perform quite differently from conventional tools. This feature of the Islamic ETFs may provide advantage for not only Muslim investors, but also for investors who look for long term investment opportunities. This will lead to more financial inclusion by bringing more investors in the capital market, and will contribute to economic growth.

Table-7
Hatemi J-Roca (2014) Asymmetric Causality Test Results

Islamic ETFs									
Hypothesis	**MWALD**	**%1 BCV**	**%5 BCV**	**%10 BCV**	**Hypothesis**	**MWALD**	**%1 BCV**	**%5 BCV**	**%10 BCV**
$(r_{KATLIMP})^{+} \not\Rightarrow (\hat{\sigma}^{2}_{KATLIMP})^{-}$	6.783 (0.034)**	12.028	6.386**	4.546*	$(\hat{\sigma}^{2}_{KATLIMP})^{+} \not\Rightarrow (r_{KATLIMP})^{-}$	3.116 (0.211)	12.106	6.752	4.883
$(r_{KATLIMP})^{-} \not\Rightarrow (\hat{\sigma}^{2}_{KATLIMP})^{+}$	1.027 (0.587)	11.847	6.885	4.917	$(\hat{\sigma}^{2}_{KATLIMP})^{-} \not\Rightarrow (r_{KATLIMP})^{+}$	1.434 (0.488)	11.929	6.927	4.832
$(r_{KATLM30})^{+} \not\Rightarrow (\hat{\sigma}^{2}_{KATLM30})^{-}$	122.169 (0.00)***	15.435***	8.632**	6.201*	$(\hat{\sigma}^{2}_{KATLM30})^{+} \not\Rightarrow (r_{KATLM30})^{-}$	66.647 (0.00)***	12.074***	6.569**	4.498*
$(r_{KATLM30})^{-} \not\Rightarrow (\hat{\sigma}^{2}_{KATLM30})^{+}$	0.771 (0.856)	11.931	7.756	6.357	$(\hat{\sigma}^{2}_{KATLM30})^{-} \not\Rightarrow (r_{KATLM30})^{+}$	4.208 (0.122)	11.028	5.745	4.251
$(r_{KATLM50})^{+} \not\Rightarrow (\hat{\sigma}^{2}_{KATLM50})^{-}$	14.571 (0.00)***	12.820***	6.624**	4.952*	$(\hat{\sigma}^{2}_{KATLM50})^{+} \not\Rightarrow (r_{KATLM50})^{-}$	6.256 (0.044)**	11.623	6.616	4.697*
$(r_{KATLM50})^{-} \not\Rightarrow (\hat{\sigma}^{2}_{KATLM50})^{+}$	2.688 (0.261)	11.412	6.334	4.807	$(\hat{\sigma}^{2}_{KATLM50})^{-} \not\Rightarrow (r_{KATLM50})^{+}$	3.274 (0.195)	11.504	6.073	4.697
$(r_{DJIMTR})^{+} \not\Rightarrow (\hat{\sigma}^{2}_{DJIMTR})^{-}$	80.224 (0.00)***	17.111***	7.882**	6.050*	$(\hat{\sigma}^{2}_{DJIMTR})^{+} \not\Rightarrow (r_{DJIMTR})^{-}$	38.321 (0.00)***	14.637***	8.595**	6.104*
$(r_{DJIMTR})^{-} \not\Rightarrow (\hat{\sigma}^{2}_{DJIMTR})^{+}$	2.388 (0.496)	13.784	8.153	6.486	$(\hat{\sigma}^{2}_{DJIMTR})^{-} \not\Rightarrow (r_{DJIMTR})^{+}$	65.830 (0.00)***	15.476***	7.672**	5.618**
Commodity ETFs									
Hypothesis	**MWALD**	**%1 BCV**	**%5 BCV**	**%10 BCV**	**Hypothesis**	**MWALD**	**%1 BCV**	**%5 BCV**	**%10 BCV**

$(r_{GLDTR})^{+} \not\Rightarrow (\hat{\sigma}^2_{GLDTR})^{-}$	238.816 (0.00)***	18.253	9.437**	6.584*	$(\hat{\sigma}^2_{GLDTR})^{+} \not\Rightarrow (r_{GLDTR})^{-}$	155.981 (0.00)***	17.381***	8.379**	6.250*
$(r_{GLDTR})^{-} \not\Rightarrow (\hat{\sigma}^2_{GLDTR})^{+}$	1.034 (0.793)	14.483	8.866	6.398	$(\hat{\sigma}^2_{GLDTR})^{-} \not\Rightarrow (r_{GLDTR})^{+}$	37.174 (0.00)***	17.194***	8.752**	5.847**
$(r_{GOLDP})^{+} \not\Rightarrow (\hat{\sigma}^2_{GOLDP})^{-}$	357.285 (0.00)***	16.657***	9.489**	6.611*	$(\hat{\sigma}^2_{GOLDP})^{+} \not\Rightarrow (r_{GOLDP})^{-}$	379.811 (0.00)***	18.808***	8.526**	5.742*
$(r_{GOLDP})^{-} \not\Rightarrow (\hat{\sigma}^2_{GOLDP})^{+}$	5.455 (0.141)	14.869	8.246	5.844	$(\hat{\sigma}^2_{GOLDP})^{-} \not\Rightarrow (r_{GOLDP})^{+}$	1.107 (0.775)	14.891	7.305	5.763
$(r_{GMSTR})^{+} \not\Rightarrow (\hat{\sigma}^2_{GMSTR})^{-}$	79.239 (0.00)***	9.420***	5.928**	4.597*	$(\hat{\sigma}^2_{GMSTR})^{+} \not\Rightarrow (r_{GMSTR})^{-}$	37.402 (0.00)***	8.878***	5.951**	4.564*
$(r_{GMSTR})^{-} \not\Rightarrow (\hat{\sigma}^2_{GMSTR})^{+}$	3.248 (0.197)	8.936	5.848	4.508	$(\hat{\sigma}^2_{GMSTR})^{-} \not\Rightarrow (r_{GMSTR})^{+}$	14.554 (0.00)***	9.830***	6.263**	4.556*
$(r_{SLVRP})^{+} \not\Rightarrow (\hat{\sigma}^2_{SLVRP})^{-}$	58.930 (0.00)***	11.151***	6.398**	4.708*	$(\hat{\sigma}^2_{SLVRP})^{+} \not\Rightarrow (r_{SLVRP})^{-}$	29.182 (0.00)***	9.346***	6.223**	4.662**
$(r_{SLVRP})^{-} \not\Rightarrow (\hat{\sigma}^2_{SLVRP})^{+}$	3.150 (0.207)	9.940	6.306	4.314	$(\hat{\sigma}^2_{SLVRP})^{-} \not\Rightarrow (r_{SLVRP})^{+}$	18.884 (0.00)***	10.719***	5.703**	4.275*
Conventional Stock ETFs									
Hypothesis	**MWALD**	**%1 BCV**	**%5 BCV**	**%10 BCV**	**Hypothesis**	**MWALD**	**%1 BCV**	**%5 BCV**	**%10 BCV**
$(r_{DJIST20})^{+} \not\Rightarrow (\hat{\sigma}^2_{DJIST20})^{-}$	74.957 (0.00)***	13.049***	8.232**	6.124*	$(\hat{\sigma}^2_{DJIST20})^{+} \not\Rightarrow (r_{DJIST20})^{-}$	69.062 (0.00)	15.481	8.400	6.342
$(r_{DJIST20})^{-} \not\Rightarrow (\hat{\sigma}^2_{DJIST20})^{+}$	1.583 (0.663)	11.266	7.842	6.095	$(\hat{\sigma}^2_{DJIST20})^{-} \not\Rightarrow (r_{DJIST20})^{+}$	14.460 (0.00)	15.475	7.530	6.017
$(r_{BNKTR})^{+} \not\Rightarrow (\hat{\sigma}^2_{BNKTR})^{-}$	24.524 (0.00)***	12.344***	6.348**	4.464*	$(\hat{\sigma}^2_{BNKTR})^{+} \not\Rightarrow (r_{BNKTR})^{-}$	11.629 (0.00)***	13.038	5.529**	4.272*
$(r_{BNKTR})^{-} \not\Rightarrow (\hat{\sigma}^2_{BNKTR})^{+}$	9.587 (0.00)***	11.739	6.400**	4.560*	$(\hat{\sigma}^2_{BNKTR})^{-} \not\Rightarrow (r_{BNKTR})^{+}$	0.892 (0.64)	12.683	6.720	4.575

$(r_{IST30})^{+} \not\Rightarrow (\hat{\sigma}^2_{IST30})^{-}$	29.670 (0.00)***	11.494***	6.298**	4.935*	$(\hat{\sigma}^2_{IST30})^{+} \not\Rightarrow (r_{IST30})^{-}$	27.806 (0.00)***	10.295***	5.800**	4.352*
$(r_{IST30})^{-} \not\Rightarrow (\hat{\sigma}^2_{IST30})^{+}$	2.582 (0.275)	11.863	6.592	4.667	$(\hat{\sigma}^2_{IST30})^{-} \not\Rightarrow (r_{IST30})^{+}$	2.452 (0.294)	13.279	7.058	4.293
$(r_{ISY30})^{+} \not\Rightarrow (\hat{\sigma}^2_{ISY30})^{-}$	65.800 (0.00)***	15.184***	10.100**	7.943*	$(\hat{\sigma}^2_{ISY30})^{+} \not\Rightarrow (r_{ISY30})^{-}$	46.771 (0.00)***	15.481***	10.703**	8.359*
$(r_{ISY30})^{-} \not\Rightarrow (\hat{\sigma}^2_{ISY30})^{+}$	8.246 (0.083)*	16.133	10.907	8.171*	$(\hat{\sigma}^2_{ISY30})^{-} \not\Rightarrow (r_{ISY30})^{+}$	7.593 (0.108)	16.441	10.035	7.904

Bond ETF

Hypothesis	MWALD	%1 BCV	%5 BCV	%10 BCV	Hypothesis	MWALD	%1 BCV	%5 BCV	%10 BCV
$(r_{FBIST})^{+} \not\Rightarrow (\hat{\sigma}^2_{FBIST})^{-}$	0.381 (0.826)	13.727	6.695	4.288	$(\hat{\sigma}^2_{FBIST})^{+} \not\Rightarrow (r_{FBIST})^{-}$	0.307 (0.858)	17.502	7.414	4.361
$(r_{FBIST})^{-} \not\Rightarrow (\hat{\sigma}^2_{FBIST})^{+}$	0.523 (0.770)	19.092	8.808	4.277	$(\hat{\sigma}^2_{FBIST})^{-} \not\Rightarrow (r_{FBIST})^{+}$	0.258 (0.879)	17.583	7.664	4.510

USD ETF

Hypothesis	MWALD	%1 BCV	%5 BCV	%10 BCV	Hypothesis	MWALD	%1 BCV	%5 BCV	%10 BCV
$(r_{USDTR})^{+} \not\Rightarrow (\hat{\sigma}^2_{USDTR})^{-}$	157.927 (0.00)***	19.432***	8.833**	6.325*	$(\hat{\sigma}^2_{USDTR})^{+} \not\Rightarrow (r_{USDTR})^{-}$	70.075 (0.00)***	14.402***	8.464**	6.363*
$(r_{USDTR})^{-} \not\Rightarrow (\hat{\sigma}^2_{USDTR})^{+}$	26.624 (0.00)***	14.021***	8.587**	6.596*	$(\hat{\sigma}^2_{USDTR})^{-} \not\Rightarrow (r_{USDTR})^{+}$	54.286 (0.00)***	15.501***	9.216**	6.213*

Note: $\not\Rightarrow$ denotes the null hypothesis claiming there is no causality. Values in parentheses show asymptotically probability. ***,**, and * denote significance level of causality between variables at 1%, 5%, and 10%, respectively. The number of bootstraps is 10,000.

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