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Determinants of financial stability and risk transmission in dual financial system: Evidence from the COVID pandemic

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ABSTRACT

Existing literature on spillovers and connectedness between Islamic and conventional financial markets overlooked the fundamental role played by money markets in volatility spillovers and risk transmission across markets. That being so, this paper aims at investigating the dynamic co-movements and volatility spillovers across Islamic and conventional financial markets in a dual financial system over the period from January 3, 2007 to June 30, 2021. To this end, the DECO-GJR-GARCH model and the volatility spillover approach were applied. Furthermore, the ARDL model was utilised to explore the key determinants of co-movements and risk transmission across Islamic and conventional financial markets. This not only allowed us to study the interconnectedness and volatility spillovers between financial sectors under different market conditions but also enabled us to highlight the key role played by the money markets. Empirical results show that markets have significant responses to any new relevant information. While both conventional stock and money market are the main transmitters of shocks to other markets, the Islamic money market is a net recipient. Furthermore, the volatility spillovers across conventional and Islamic financial markets became stronger during the COVID-19 epidemic. The study also finds that global uncertainties have a significant and negative impact on the dynamic co-movements, but not on volatility connectedness among the underlying markets. These findings have important implications for many stakeholders including portfolio managers, investors, and policymakers in terms of diversifying their portfolios and enhancement of financial stability during times of black swan events and negative shocks such as the COVID-19 pandemic.

1. Introduction

A large body of literature examines the transmission of shocks across different asset classes such as stock, bonds, money markets, currencies, and commodities both within an economy and across countries (see e. g., Ahmed and Elsayed 2019; Ajmi et al., 2014; Bernanke and Kuttner 2005; Ehrmann et al., 2011; Ehrmann and Fratzscher, 2004; Frank and Hesse, 2009; Mensi et al., 2021; McIver and Kang, 2020; Steeley 2006). The transmission of risks between different markets have important implications both at the macro and micro levels. At the macro level, the transmission of volatility from one market to another can cause systemic risks within an economy and also transmit the risks to other economies. For example, Ehrmann et al. (2011) finds that shocks in domestic asset prices not only

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affected the price volatilities of other financial assets within the US market but also transmitted to different asset classes in the Euro zone during the Global Financial Crisis (GFC) of 2007. Similarly, Frank and Hesse (2009) conclude that the impact of the GFC on the credit, bond and equity markets of emerging markets were highly correlated during the downturns of US markets.

Existing literature also highlighted the fact that financial markets tend to be correlated especially during stress periods (see for example, Elsayed & Helmi, 2021; Forbes and Rigobon, 2002; Maghyereh et al., 2015; Nishimura & Sun, 2018; Yarovaya et al., 2021, among many others). These comovemnets and interlinkages between different financial markets have important implications for trading strategies, diversification and regulations (Elsayed, 2016; Mensi et al., 2019). At the macro level, higher correlations of volatilities between different markets can exacerbate the impact of a negative shock in different sectors while at the micro level spillovers can affect the risk-return performances of investors' portfolios. The co-movements of the volatilities of assets can adversely impact the performance of portfolios during market turbulence. Contagion and volatility among different markets are important for investors as this could be an important factor in determining diversification of assets (Jung and Maderitsch 2014). A diversified portfolio with assets whose prices are either negatively correlated or uncorrelated would be insulated from shocks arising in a specific market. Specifically, a diversified portfolio with safe haven assets such as gold that is uncorrelated to movements in key asset classes can improve the overall risk-return performance in times of turbulence (Flavin et al. 2014).

One category of a new asset class is Islamic financial assets. These have grown significantly in many countries. Islamic finance is governed by Sharia principles which prohibit interest (*riba*), excessive risk taking (*gharar*) and engaging in certain sectors such as those dealing in alcohol, gambling, pornography, etc. (Ayub 2007, Usmani 1999). Islamic commercial law links financial transactions to the real economy, attaches risk-bearing to ownership of assets, and promotes risk-sharing in financial contracts. Given the unique features of Islamic finance, it is considered not only as an alternative ethical asset but also a potential safe haven asset class that investors can use to diversify risks (Foglie and Panetta 2020, Hkiri et al. 2017). Some studies show that Islamic finance provides a hedge during times of market turmoil. For example, Hkiri et al. (2017) find that while the volatilities of conventional and Islamic stock indices are correlated, the transmission is weak during periods of financial crisis. The implication is that Islamic financial assets can be used as an alternative safe asset to bring about stability at the macro level and diversify risks at the micro level as well.

There is a plethora of empirical research examining the relationship between Islamic financial assets/markets and their conventional counterparts. Comparative studies on transmissions between the two sectors include those examining interactions between Islamic stocks and conventional stocks (Abderrezak, 2008, Ajmi et al. 2014, Dewandaru et al. 2014, Hkiri et al. 2017, Hoepner et al. 2011, Hassan and Girard 2010, Rizvi et al. 2015, Shahzad et al. 2017 and Yilmaz et al. 2015), sukuk (Islamic bonds) and conventional bonds (Cakir and Raei 2007, El Mosaid and Boutti 2014) and those including both Islamic and conventional stocks and sukuk/bonds (Ahmed and Elsayed 2019, Maghyereh and Awartani 2016, Akhtar and Jahromi 2017).

An important asset class that is missing in the comparative spillover studies between Islamic and conventional assets is money markets. Money markets constitute an important component of the financial sector and can provide useful insights on originating and transmitting shocks across different sectors. A key source of shock in the financial sector has origins in monetary policy whereby changes in benchmark interest rates affect money markets directly and also influence bonds and capital markets indirectly (Wang et al. 2019). While bond prices are inversely related to benchmark rates, interest rate changes affect the cost of capital of corporations and their stock prices. Some studies find a strong relationship between short-term interest rates and stock markets (Bernanke and Kuttner 2005, Ehrmann and Fratzscher 2004) while others confirm transmissions across money, bond and equity markets (Ehrmann et al. 2011, Frank and Hesse 2009, Steeley 2006).

Even though studies exploring the interrelationship between the money market and other asset classes provide important insights to the sources and directions of contagion in a financial system, to the best of our knowledge no prior research examines the dynamic co-movements and risk transmission among assets which include Islamic money markets. This is partly because Islamic money markets are in the initial stages of development in most countries except Malaysia, a country at the forefront of Islamic finance development. Against this backdrop, this paper aims at filling this gap in the literature by investigating the role that Islamic and conventional money markets play in the transmission of shocks along with the stocks and sukuk/bonds markets in an economy with dual financial sectors. Given the relatively large Islamic stocks, sukuk and money markets in Malaysia that operate along with their conventional counterparts, the paper investigates the dynamic co-movements and risk spillovers among these markets for the period of January 2007 to June 2021.

Doing so allows us to explore the dynamic correlations and risk transmissions across different Islamic and conventional financial sectors within a framework where they operate under the same macroeconomic environment and legal and regulatory regimes. The paper applied the DECO-GJR-GARCH model developed following Engle and Kelly (2012) to jointly model multivariate conditional volatility and the time-varying correlations among markets under consideration. This econometric technique is particularly well-suited as it overcomes the computational requirements and complex interpretation of other techniques such as the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model (Aboura and Chevallier, 2014; Elsayed et al., 2021). Furthermore, patterns of volatility spillovers and risk transmission across markets are examined using the spillover approach proposed by Diebold and Yilmaz (2012, 2014), based on forecasting error variance decompositions from a generalized VAR specification to investigate the direction and strength of the volatility spillover effects between markets attributable to various shocks in the VAR model.

Other than being the first paper to examine the transmissions between the Islamic and conventional stock, bonds/sukuk and money markets, the paper contributes to the literature in a number of important ways. First, the sample period considered in the study covers the COVID-19 pandemic period. This enables us to study how the financial sectors interacted during extreme market conditions due to a negative shock arising from the real economy. Since Islamic financial products are tied to the real economy, it would be interesting to see how different Islamic financial sectors reacted to the COVID-19 shock relative to the conventional financial sectors. Second, using the Error Correction form of an Autoregressive Distributed Lag (ARDL) model, we analysed the determinants of the dynamic co-movements and shock contagion between Islamic and conventional financial markets in both the short run and long run by examining the impact of macroeconomic and global risk factors on co-movements and volatility transmissions.

The paper is organized as follows. Section 2 outlines spillover and contagion between financial markets, the features of Islamic financial contracts governing Shariah-compliant capital market products (stocks, sukuk and money market instruments), provides an overview of the theoretical literature of transmission of shocks and implications for Islamic financial markets, and presents the empirical literature on the linkages between Islamic and conventional financial markets. Section 3 presents the methodology. Section 4 reports the data sources and discusses the empirical results. Section 5 concludes the paper.

2. Spillovers among asset classes and Islamic Finance: Literature review and framework

2.1. Spillover and contagion between financial markets

Contagion or the spread of distrubances across markets can result from fundamental economic linkages or changes in investors behaviours (Dornbusch et al 2000). While the fundamental economic linkages relate to financial and trade links, the investors' behaviour can cause volatilities to spill over across interdependent global financial markets due to reactions of investors to risks and shocks. The volatility of asset prices within a country can be affected by uncertainties that arise from different macroeconomic factors such as changes in output, inflation, exchange rate, etc. With high levels of integration and capital flows across different countries and regions, increased risks in markets of one country can also spillover and affect capital flows in other markets (Fratzscher 2004). Theoretical literature on interconnectedness and contagion between different markets identifies two key explanations for spillovers.

First transmission channel relates to information related factors. The information perspective associates volatility to new information that leads to adjustments of prices to new equilibrium and thus creating fluctuations. Investors have access to different sets of information and infer valuable information from prices and their dynamics in different markets (King and Wadhwani 1990). Changes in prices in one market thus affects prices in other markets through arbitrage and realignment of investments due to new information. An implication of the information perspective is that incomplete information can affect the intensity of contagion (Allen and Gale 2000).

Fleming et al. (1998) provides a theoretical perspective on the linkages of prices of different asset classes. Volatility linkages can be explained by two types of information that link different markets. First, there is the common information on macroeconomic variables such as inflation that affects all markets. Second, the information on a specific market that spills over to other markets due to cross-market hedging. For example, information on stocks that change their prices and demand adversely can also affect the demand for bonds even when there are no changes in the interest rates. The increase in the demand of bonds can result due to the rebalancing of portfolios to hedge against risks. While expected volatility in the stock prices leads to moving assets to bonds to mitigate risks, the extent to which this is done depends on the correlation of the volatility of stocks and bonds.

Another channel of volatility spillovers and contagion among different assets and markets is through liquidity shocksThe simple liquidity perspective to contagion is that when one market is hit by a negative shock investors facing liquidity contraints decide to liquidate assets from multiple markets to obtain cash (Dornbusch et al 2000, Fratzscher 2004). A source of risk and its transmissions arises from money market shocks that create liquidity constraints. Allen and Gale (2000) show how contagion can arise in the banking system through liquidity shocks. Since banks provide liquidity in the economy and have overlapping claims through the interbank market, a small liquidity shock in banks of one region can affect the value of claims of banks in other regions thus creating spillovers that can spread to other sectors.

Other than adversely affecting market liquidity and funding liquidity, shocks can decrease the trading of financial assets and limit price discovery which can increase volatility (Brunnermeier and Pedersen 2009, Frank et al. 2008). The volatility arising from liquidity shocks in the money market can affect liquidity and prices in other financial markets. For example, Brunnermeier and Pedersen (2009) find that the money market played a critical role in transmitting liquidity shocks during the Global Financial Crisis of 2007. Similarly, Lu et al. (2018) find that liquidity shocks in the money market are transmitted to the banking sector and stock markets in China during turbulent periods.

Kodres and Pritsker (2002) develop a multiple asset rational expectations model to explain financial market contagion using both information and liquidy. They decompose the liquidation value of a market index into one representing investors' private information and remaining determined by macroeconomic risk factors. They model contagion through cross-market rebalancing in which investors adjust their portfolios in different markets in response to a shock in one market. The interactions of macroeconomic risks vary across different jurisdictions and information asymmetry determines the nature of financial contagion. There is a plethora of empirical research on spillovers and contagion amongdifferent markets across borders and markets or assets within an economy. Example of studies across borders include Jung and Maderitsch (2014) who find volatility transmission and contagion between stock markets in Hong Kong, Europe and the United States over the period 2000–2011 during the financial crisis of 2007. Similarly, Cheung et al (2009) examine the impact of the US market on stock markets in Australia, China, Hong Kong, Japan, Russia and UK and Bekiros (2014) examines the volatility spillovers among US, EU and BRIC markets. Studies examining spillovers in markets within an economy include Dungey and Martin (2007) studying the linkages of currency and stock markets in four Asian countries, Australia and US during the Asian crisis and Alkan and Cocek (2020) who find the spillovers among between the Turkish stocks and bonds markets.

2.2. Islamic Contracts, capital market products and transmission of shocks

Understanding the differences/similarities between transmission of shocks in Islamic and conventional financial markets would require examining how prices are transmitted across assets and whether the underlying features of Islamic financial products affect them. A key factor that can affect the inter-linkages between sectors is the underlying contractual structures of different financial products (Ahmed and Elsayed 2019, Maghyereh and Awartani 2016). Islamic law prohibits interest (*riba*) in financing and excessive uncertainty (*gharar*) in transactions. Since interest is prohibited, Islamic finance uses other permissible contracts to structure financial products which include sale (*murabahah, salam, istisna*), leasing (*ijarah*), partnership (*musharakah* and *mudarabah*) and agency (*wakalah*) contracts.[1]

Shariah-compliant stocks are a sub-set of the universe of all stocks and are identified by applying two layers of screening. The first screening is a qualitative business activity-based screening that excludes companies that are involved in prohibited products and services. These would include alcohol, pornography, gambling, pork-related products, tobacco, conventional financial institutions, etc. (BinMahfouz and Ahmed 2014, Derigs and Marzban 2008, Rizaldy and Ahmed 2019). The companies that pass the qualitative screening go through the second quantitative screening that involves passing certain financial benchmarks related to acceptable levels of conventional debt, liquidity, impure income and/or interest-based investments of the company (Derigs and Marzban 2008, Rizaldy and Ahmed 2019). Firms that pass both qualitative and quantitative screenings are considered Shariah-compliant stocks.

S*ukuk* is defined as a certificate representing the "shares and rights in tangible assets, usufructs and services, or equity of a given project or equity of a special investment activity" (AAOIFI 2015). AAOIFI identifies different types of *sukuk* that can be classified broadly as assets, debt, equity and investment-agency based (AAOIFI 2015, Safari et. al. 2014). *Sukuk* are securities representing ownership in equity, real assets, usufruct, debt or any combination thereof. *Sukuk* can have fixed or variable returns and may be tradable depending on its underlying contractual basis. While sukuk representing equity, real assets and usufruct can be traded at negotiable prices, those representing debt cannot be sold at a discount (Abdel-Khaleq and Richardson 2007).

Islamic money market instruments can also be structured as equity, asset and be debt-based. While equity and asset-based sukuk can be used as money market instruments, some specific money market instruments also exist. These instruments include equity-based certificates (such as *mudarabah* and *musharakah* certificates) and debt-based instruments such as *murabahah* and *salam*-based certificates (Hakim 2007). A key difference between equity-based and debt-based certificates is that while the former are tradeable at negotiable prices, the latter being debt cannot be traded.

Given the information spillover and liquidity-based theoretical perspectives, the extent of transmissions to and from Islamic assets would depend on their underlying contractual structures (Ahmed and Elsayed 2019, Maghyereh and Awartani 2016). Furthermore, the impact of information spillovers on the co-movement of asset prices and volatility linkages will depend on institutional constraints, transactions costs, and other considerations that limit cross-market hedging (Ahmed and Elsayed 2019). Specifically, Islamic contracts that underlie the capital and money market instruments are linked to real transactions which change the nature of risk-return features of financial products and affect the degree to which the prices of assets can change in response to shocks.

Since the screening of Islamic stocks excludes firms with high leverage and are a subset to conventional stocks, the volatility of the former is expected to be relatively lower than the latter. For sukuk and money market instruments, the transmission of volatility would depend on a number of key features. First, the extent to which the prices of Islamic assets can adjust would depend on whether the instruments are equity/asset based or debt based. While the prices of equity/asset based products can adjust to shocks due to monetary shocks and information spillovers, debt-based instruments cannot adjust since their prices are fixed at the commencement of the contract. Second, since debt instruments cannot be sold at a discount, their market liquidity is low which can exacerbate the transmission of liquidity shocks.

The contractual features also have implications on the transmission of shocks among Islamic and conventional assets in terms of the sources of shocks. While in conventional markets the changes in the equity markets can be considered as a proxy for the real economy, volatility in money markets reflect short-term financial market conditions (Chudik and Fratzscher 2011). In Islamic financial markets, the impact of shocks arising from both the real economy and money markets will depend on the underlying contracts used. Specifically, the disturbances arising from the real economy would affect stocks and also equity and asset-based sukuk and money market products but have little to no impact on debt-based products. Similarly, negative shocks arising from changes in interest rates will also affect the equity/asset based sukuk and money market instruments, but not debt-based securities. This is because the former can adjust their prices when the benchmark interest rates change while in the latter prices are fixed. Thus, in both sukuk and Islamic money markets, a larger share of equity and asset-based securities would make them more responsive to shocks than those that are debt based.

2.3. Islamic and conventional financial assets: Empirical literature

The empirical research on the relationship between Islamic and conventional assets can be broadly classified as those examining stock market funds and indices, bond market indices, and others that include both stocks and bonds. Several studies which examine the relationship between Islamic and conventional stock markets find a close affinity with no significant difference between them (Abderrezak, 2008, Ajmi et al. 2014, Dewandaru et al. (2014), Haddad et al. (2009), Hoepner et. al (2011), Hassan and Girard (2010), Mannoudeh et. al (2014), Rizvi et al. (2015), Shahzad et al. (2017) and Yilmaz et al. 2015). However, other studies such as Majdoub

[1] Detailed expositions of the different principles of Islamic financing are found in Ahmed (2011), Ayub (2007), and Usmani (1999).

and Mansur (2014) and Rizvi and Arshad (2014) confirm a weak correlation between Islamic and conventional indices supporting the decoupling hypothesis.

A second group of studies analyse the relationship between the bonds and sukuk markets where results appear to support differences. For example, Cakir and Raei (2007) find a weak correlation in the returns on sukuk and Eurobonds. Although El Mosaid and Boutti (2014) show a positive correlation between the returns on sukuk and bond indices, there is a significant difference in their average returns. Similarly, Hassan et al. (2019) finds that while sukuk, EU and US bonds are cointegrated, the former has less volatility compared to the latter.

Finally, a few studies examine the interactions between Islamic/conventional equity markets and bonds/sukuk markets. Maghyereh and Awartani (2016) examine the transmissions between equity indices and sukuk/bond indices and find that sukuk are more exposed to net-transmissions from both equities and bonds. They also find that during the crisis period there is a significant unidirectional volatility spillover from the sukuk market to the stock market. Using the daily return data for 19 Islamic and non-Islamic countries over the period 2002–2014, Akhtar et al. (2017) analyse the impact of the global financial crisis on Islamic/conventional stock and bond markets. Their findings show that while Islamic financial markets are not protected against recessions and business cycles, they are in general more stable compared to their conventional counterparts, especially during periods of turbulences.

Against this backdrop of the literature, it is clear that existing empirical studies examining the spillovers and transmission mechanisms between Islamic and convention asset classes do not include money markets. To this end, this paper tends to fill this gap in the literature by investigating the role that Islamic and conventional money markets play in the transmission of shocks along with the stocks and sukuk/bonds markets in an economy with dual financial sectors. In addition, we investigate the determinants of the shock contagion in both the short run and long run by examining the impact of macroeconomic and global risk factors on volatility transmissions.

3. Econometric methodology

Firstly, we scrutinised the time-varying equicorrelations among Islamic and conventional financial markets based on the DECO-GJR-GARCH model developed by Engle and Kelly (2012). Further, patterns of volatility spillovers and risk transmission across stock, bonds/sukuk and money markets are examined using the spillover approach of Diebold and Yilmaz (2012, 2014). Finally, short run and long run determinants of correlation and contagion between Islamic and conventional financial markets are investigated using the error correction form of Autoregressive Distributed Lag model (ARDL).

3.1. Deco-Gjr-Garch

To examine the dynamic equicorrelations between Islamic financial markets and their conventional counterparts, the DECO-GJR-GARCH (1,1) model is developed following Engle and Kelly (2012). The estimation of the DECO model requires two stages. First, we estimate the univariate conditional volatility followed by the estimation of equicorrelations among our variables as a second stage of the estimation process.

Now, the return on stocks i at time t is assumed to follow the ARMA(1,1) model in the form of:

$$r_{i,t} = \mu_{i,} + \varphi r_{i,t-1} + \delta_i \varepsilon_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is stock return of Asset i, $\mu_{i,}$ is a constant vector, and $\varepsilon_{i,t}$ is the vector of residuals. Next, we used the GJR-GARCH model introduced by Glosten et al. (1993) to estimate the conditional variance $\left(h^2_{i,t}\right)$ and to capture the asymmetric effects of volatility:

$$h^2_{i,t} = \omega_i + \alpha\varepsilon^2_{i,t-1} + \beta h_{i,t-1} + \gamma I_{t-1}\varepsilon^2_{i,t-1} \tag{2}$$

where ω_i is a constant. α represents the ARCH effect whereas β shows the impact of past volatility on the current one (GARCH parameter). γ measures the asymmetric volatility due to positive and negative shocks where I_{t-1} takes a value of one, if $\varepsilon_{t-1} < 0$ and a value of zero otherwise. If γ is positive and statistically significant, negative shocks have a higher effect on conditional volatility than positive ones.

In the second step, the DECO-GARCH model estimates the time-varying correlations using the GJR-GARCH model residuals of each market based on which the covariance matrix is calculated. In particular, the conditional correlation matrix, H_t can be modelled as follows:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{4}$$

where $D_t = diag\left[h_{1,t} \cdots\cdots h_{n,t}\right]$ represents the diagonal matrix of conditional variances while the $R_t isn \times n$ matrix represents the conditional correlation matrix. Following Engle (2002), the correlation matrix,R_t, is obtained as follows:

$$R_t = \left\{Q_t^*\right\}^{-1/2} Q_t \left\{Q_t^*\right\}^{-1/2} \tag{5}$$

where $Q_t^* = diag\left(q_{ij,t}\right)$, is the square root of the diagonal elements in the covariance matrix Q_t which is derived as follows:

$$Q_t = (1-\psi-\xi)K + \psi n_{t-1}n_{t-1}^{'} + \xi Q_{t-1} \tag{5}$$

n_t represents the standardised residuals (i.e., $n_{i,t} = \varepsilon_{i,t}/h_{i,t}$) where K is the $(n \times n)$ unconditional covariance matrix of n_t. $\xi and \psi$ are positive parameters satisfying the condition $\psi + \xi < 1$. Consequently, for each elements of the correlation matrix, R_t is estimated using the following form:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{6}$$

Finally, the equicorrelations conditional correlation matrix ($\left(R_t^{DECO}\right)$ is defined following Engle and Kelly (2012) as follows:

$$R_t^{DECO} = (1-\rho_t)I_n + \rho_t J_n \tag{7}$$

Where I_n is the n-dimensional identity matrix and J_n is an $(n \times n)$ unit matrix. The modified dynamic conditional correlation (ρ_t) is now the conditional equicorrelation which is calculated as the average of the DCC correlations:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(\hat{J}_n R_t^{DCC} J_n - n\right) = \frac{2}{n(n-1)}\sum_{i \neq j}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{8}$$

Where:

$$q_{ij,t} = \rho_t^{DECO} + \alpha_{DECO}\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \rho_t^{DECO}\right) + \beta_{DECO}\left(q_{ij,t} - \rho_t^{DECO}\right)qij \tag{9}$$

3.2. Volatility spillover approach

Following Diebold and Yilmaz (2012, 2014), we consider a K-variable VAR model of p-th order given by:

$$y_t = \sum_{i=1}^{p}\Phi_i y_{t-i} + \varepsilon_t, with \varepsilon_t \; i.i.d(0,\Sigma) \tag{10}$$

Here $y_t = (y_{1t}, y_{2t}, \cdots, y_{Kt})$ represents a vector of K conditional volatilities of both Islamic and conventional financial markets[2], Φ_i are $K \times K$ parameter matrices where $i = 1, 2, \cdots p$ and ε_t is a vector of identically and independently distributed errors with zero mean and Σ variance–covariance matrix. Assuming covariance stationarity, the moving average representation of the VAR(p) model can be written as follows:

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{11}$$

where the coefficient matrices A_i are of dimension $K \times K$ and recursively defined by $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$ where A_0 is the $K \times K$ identify matrix and $A_i = 0$ for all $i < 0$.

Using the variance decomposition function, the forecast error variances of each variable can be divided into two parts: own-variance shares and cross-variance shares (hereafter spillovers). Own-variance shares represent the proportion of the h-step-ahead error variance in forecasting y_i due to its own shocks whereas cross-variance shares show the fraction of h-step-ahead error variance in forecasting y_i that is attributable to shocks in other variables, where $j \neq i$.

Diebold and Yilmaz (2009) suggest decomposing the forecast error variances based on the Cholesky decomposition approach which is commonly used to identify VAR model shocks. However, the resulting variance decomposition is sensitive to the ordering of the variables in the VAR model. To address this issue, Diebold and Yilmaz (2012, 2014) utilize the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) that provide variance decompositions that are invariant to the VAR ordering. The main advantage of this VAR specification is that it allows the data to declare the direction and strength of spillover effects. Based on this framework, the h-step-ahead forecast error variance can be written as follows:

$$\phi_{ij}(h) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i^{'} A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i^{'} A_h \sum A_h^{'} e_i\right)} \tag{12}$$

Here, σ_{jj} denotes the standard deviation of the error term for the *j-th* equation, $\sum$ is the variance matrix for the error vector ε, and e_i represents the selection vector with one for *i-th* elements and zero otherwise. The resultant matrix ϕ_{ij} represents the contribution of variable j to the h-step-ahead error variance in forecasting variable i. Hence, the main diagonal elements of this matrix show the own-variance shares while the off-diagonal elements indicate cross-variance shares (spillovers). Unlike the Cholesky variance decomposition, the generalized variance decomposition matrix does not orthogonalize the shocks to each variable, and, as a result, the sum of each row does not add to unity $\left(\sum_{j=1}^{K}\phi_{ij}(h) \neq 1\right)$. Therefore, each entry of the generalized variance decomposition matrix is normalized

[2] Unit root results of conditional volatilities are reported in table A.1 in Appendix A. Test statistics indicate that all series of conditional volatilities are stationary at levels which motivates the use of the VAR model.

by the row sum as follows:

$$\widetilde{\phi}_{ij}(h) = \frac{\phi_{ij}(h)}{\sum_{j=1}^{K}\phi_{ij}(h)} \tag{13}$$

where $\sum_{i=1}^{K}\widetilde{\phi}_{ij}(h) = 1$ and $\sum_{j=1}^{K}\widetilde{\phi}_{ij}(h) = K$. Consequently, the Total Spillover Index (TSI) is defined as follows:

$$TSI(h) = \frac{\sum_{i,j=1,i\neq j}^{K}\widetilde{\phi}_{ij}(h)}{\sum_{i,j=1}^{K}\widetilde{\phi}_{ij}(h)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{K}\widetilde{\phi}_{ij}(h)}{K} \times 100 \tag{14}$$

The index captures the average contribution of spillovers due to shocks to the total forecast-error variance across all markets. This representation is convenient because the normalized elements of the generalized variance decomposition matrix allow us to calculate directional spillover indices across markets. More specifically, the directional spillovers received by market *i from* all other markets *j* are defined as:

$$DS_{i\leftarrow j}(h) = \frac{\sum_{j=1,j\neq i}^{K}\widetilde{\phi}_{ij}(h)}{\sum_{i,j=1}^{K}\widetilde{\phi}_{ij}(h)} \times 100 \tag{15}$$

Likewise, the spillover effects transmitted by market *i to* all other markets *j* are calculated as:

$$DS_{i\rightarrow j}(h) = \frac{\sum_{j=1,j\neq i}^{K}\widetilde{\phi}_{ji}(h)}{\sum_{i,j=1}^{K}\widetilde{\phi}_{ji}(h)} \times 100 \tag{16}$$

Given these directional spillover indices, net spillovers from market *i* to all other markets *j* can be obtained by subtracting total volatility shocks transmitted by market *i* and those received from all other markets *j* as follows:

$$NS_i(h) = DS_{i\rightarrow j}(h) - DS_{i\leftarrow j}(h) \tag{17}$$

The so defined net directional spillover indices provide information on whether each market is a net transmitter or a receiver of shocks. In other words, for positive values of the NS_i the index indicates that the market *i* is a net transmitter, i.e. the spillovers that market *i* transmits exceed those received from all other markets. Conversely, negative values suggest that market *i* is a net receiver of spillovers.

Finally, the net pairwise spillovers between each pair of markets (*i* and *j*) are estimated by the difference between total volatility spillover transmitted from market *i* to market *j* and those transmitted from *j* to *i*:

$$NPS_{i\rightarrow j}(h) = \left(\frac{\widetilde{\phi}_{ji}(h)}{\sum_{i,n=1}^{K}\widetilde{\phi}_{in}(h)} - \frac{\widetilde{\phi}_{ij}(h)}{\sum_{j,n=1}^{K}\widetilde{\phi}_{jn}(h)}\right) \times 100 \tag{18}$$

Recently, financial markets have become increasingly interconnected due to increasing globalization, financial innovations, and technological advances. Information can easily and very quickly be transmitted from one market to another in a short amount of time. Although this phenomenon has created opportunities for improving efficiency and diversification, it has also increased volatility spillover and contagion across financial markets. In the next section, we present and discuss the results from the dynamic equi-correlations as well as the volatility spillovers and risk transmissions among both Islamic and conventional financial markets in Malaysia.

3.3. Autoregressive Distributed Lag model (ARDL)

We have applied the Error Correction Form of the Autoregressive Distributed Lag model to examine the short and long run determinants of co-movements and contagion between Islamic and conventional financial markets. This model corrects the bias resulting from the omitted lagged variable and provides an unbiased estimate for the coefficients of explanatory variables (Inder, 1993). In addition, the ARDL model is very effective and reliable in small and finite sample sizes (Samargandi et al., 2014). Following the literature, the long-run relationship among the variables of interest can be formulated based on $ARDL(p,q)$ of Pesaran et al. (2001) as follows:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_0 x_t + \theta_1 x_{t-1} + \cdots + \theta_q x_{t-q} + u_t \tag{19}$$

Where *c* is the intercept, y_t is the dependent variable, x_t is the explanatory variable and u_t is the error term which is independent and identically distributed with zero mean and variance $\sigma^2, u_t\ iid(0,\sigma^2)$.

the above ARDL model equation can be transformed into an unrestricted error correction model of the form:

$$\Delta y_t = c + \alpha y_{t-1} + \theta x_{t-1} + \sum_{j=1}^{p-1}\gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1}\psi_j \Delta x_{t-j} + v_t \tag{20}$$

Table 1
Descriptive Statistics and Correlation Matrix.

	CS	IS	CB	IB	CM	IM
Mean	0.0001	0.0002	0.0002	0.0002	−0.0005	−0.0004
Std. Dev.	0.0078	0.0086	0.0012	0.0010	0.0421	0.0263
Max.	0.0679	0.0565	0.0112	0.0081	0.4500	0.3500
Min.	−0.1022	−0.0996	−0.0156	−0.0306	−0.7500	−0.7100
Skewness	−0.7919	−0.5754	−0.8465	−7.8096	−1.9522	−7.7292
Kurtosis	16.495	13.469	21.891	198.923	48.391	241.912
JB	29074***	17473***	56656***	6083748***	326907***	9027863***
ADF	−56.45***	−57.36***	−35.53***	−23.42***	−44.77***	−64.32***
PP	−56.49***	−57.34***	−49.38***	−49.47***	−96.03***	−64.81***
Q(10)	31.44***	19.72***	275.67***	447.39***	388.71***	16.61***
$Q^2(10)$	426.19***	400.34***	754.55***	25.47***	7.26	1.18
Correlation Matrix						
CS	1					
IS	0.873	1				
CB	0.125	0.095	1			
IB	0.124	0.112	0.645	1		
CM	0.009	0.004	−0.075	−0.056	1	
IM	−0.016	−0.011	−0.122	−0.097	0.414	1

Notes: This table reports descriptive statistics for Islamic financial markets and their conventional counterparts (e.g., conventional stocks (CS), Islamic stocks (IS), conventional bond (CB), Islamic bond or sukuk (IB), conventional money market (CM), and Islamic money market (IM). J-B is the Jarque–Bera test for Normality. ADF and PP denote the empirical statistics of the Augmented Dickey-Fuller and Phillips-Perron unit root tests. Q(10) and $Q^2(10)$ are the Ljung–Box statistics for serial correlation in raw series and squared residuals. Finally, ***, ** indicate significance at 1, and 5% levels.

Where c is the intercept, α is the error correction term which is negative and should satisfy the stability condition ($-1 < \alpha < 0$). The long-run parameter (β) can be easily estimated as $\left(\beta = \frac{\theta}{-\alpha}\right)$ whereas γ_j and ψ_j are the short-run dynamic adjustment parameters for the dependent and independent variables respectively. Finally, v_t is the error term with zero mean and variance σ^2.

4. Data sources and empirical results

The paper explores the transmission of shocks among the Islamic and conventional stock, sukuk/bond and money markets for Malaysia, a country with developed capital and money markets. In December 2021, the total market capitalization of stocks listed in the Malaysian exchange market was RM1,789.20 billion of which RM1,204.28 billion were Shariah-compliant, with the latter constituting 67.3 percent of the former (Securities Commission Malaysia, 2022). The total bonds and sukuk outstanding over the same period was RM2,845.09 billion of which RM1,740.83 billion were bonds and RM1,104.26 comprised of sukuk (Securities Commission Malaysia, 2022). The overall Islamic capital markets (stocks and sukuk) is significant in the country, constituting RM2,308.53 billion which is 65.4 percent of the overall capital market valued at RM3,530.02 billion. Malaysia introduced the Islamic Inter Bank Money Market (IIMM) in 1994 and has several Islamic money market instruments that include the Mudarabah Interbank Investment (MII), Wadia Acceptance, Government Investment Issue (GII), Bank Negara Monetary Notes (BNMN-i), Sell and Buy Agreement (SBBA), Islamic Acceptance Bills (IAB), Islamic Negotiable Instruments (INI), Islamic Private Debt Securities and Sukuk Bank Negara Malaysia Ijarah (SBNMI).[3] The total Islamic interbank transactions were RM5,969.52 billion in 2020.[4]

4.1. Data sources and preliminary analysis

The daily prices of the two Islamic and two conventional indices are obtained from DataStream, these are: MSCI Malaysia Islamic Stock Market Index (IS), MSCI Malaysia Stock Market Index (CS), Thomson Reuters Sukuk Index (IB) and Thomson Reuters Conventional Bond Index (CB) whereas Islamic and Conventional Interbank Rates are collected from Bank Negara Malaysia. [5]The sample period spans January 3, 2007 to June 30, 2021. The sample period has been determined by the availability of data. To render the series stationary, we take the log-difference of stock and bond indices to calculate log-returns. As for the case of the interest rate, we take the first differences to ensure stationarity.

Table 1 displays the descriptive statistics and correlation matrices for the stock returns, bond, and money market for both Islamic

[3] https://iimm.bnm.gov.my/index.php?ch=4&pg=4&ac=22.

[4] https://iimm.bnm.gov.my/index.php?ch=15&pg=86.

[5] The MSCI Malaysia Islamic Stock Market Index measures the performance of the large and mid-cap companies in the Malaysian market that are Sharia-compliant. The index includes 14 constituents and applies stringent screens process based on two categories: permissible business activities and financial ratios derived from total assets. On the other hand, the MSCI Malaysia Stock Market Index is designed to measure the performance of the large and mid-cap segments of the Malaysian market. It includes 34 constituents and covers about 85% of the Malaysian stock market. For further information, please follow the links below:https://www.msci.com/documents/10199/ea8e4fdc-f184-49ba-9080-731cd4510310https://www.msci.com/documents/10199/32b9330d-5d08-4b85-9e51-4f63e42fe4cf.

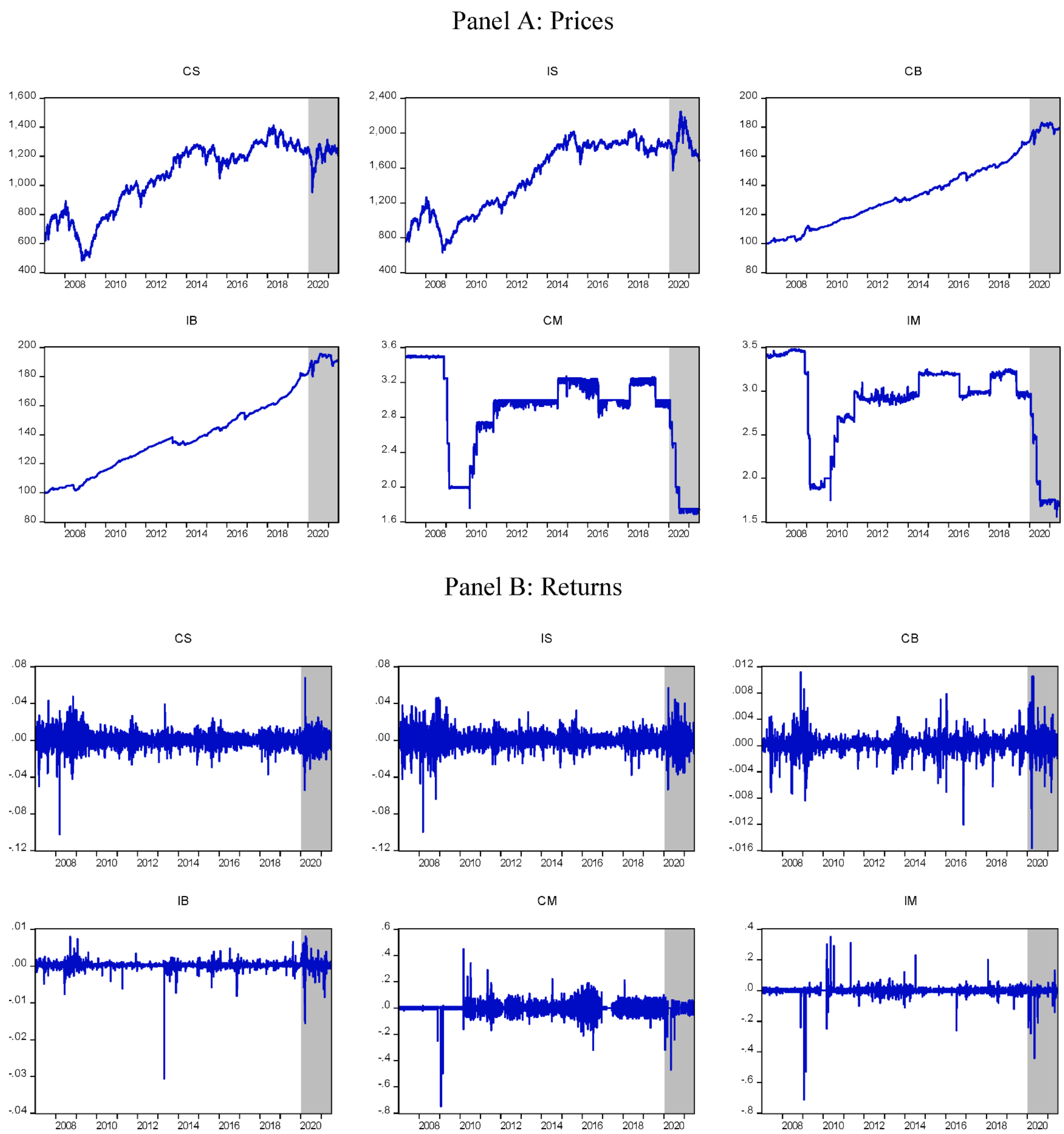

Fig. 1. Prices and returns over time.

financial markets and their conventional counterparts. The means of stock returns and bonds for both Islamic and conventional are all positive while this average is negative for conventional and Islamic money markets (see the upper panel of Table 1). Both conventional and Islamic money market (CM and IM) have a higher volatility compared to bond and stock markets, evident by the highest standard deviation values whereas the bonds and sukuk markets are the lowest. All variables exhibit negative skewness and excess kurtosis. These results are in line with the results of the JB normality test which confirms that all variables are not normally distributed.

We further examine whether our variables are appropriate to model volatility by testing the existence of autocorrelation in returns and squared returns. The Ljung–Box statistics reject the null hypothesis of no serial correlation up to lag 10 in both the main series and squared residuals ($Q^2(10)$) which imply nonlinear dependence and hence the appropriateness of the ARCH model to capture the volatility clustering in the data. This is also confirmed by Fig. 1. In order to examine the time series properties of the variables under consideration, both Augmented Dickey-Fuller (Dickey & Fuller, 1981) and Phillips and Perron (1988) tests confirm that all variables under consideration are levels stationary. The correlation matrix (reported in the lower panel of Table 1) indicates a high correlation between Islamic and conventional stocks (0.87), and between Islamic bonds and conventional bonds (0.65), while weak correlations were confirmed with other variables. On the other hand, all variables are independent from both conventional and Islamic money market as the correlation coefficients are almost zero (except for conventional banks). However, there is a weak (but positive) correlation between Islamic and conventional money markets.

Table 2
Estimation of the DECO-GJR-GARCH model.

	IS	CS	IB	CB	CM	IM
Panel A: Estimates of the univariate GJR-GARCH model						
Const.(μ_i)	0.0002**	0.0001	0.0002***	0.0002***	−0.0001	−0.0002
AR (ψ_i)	0.2574*	0.2657*	0.5460***	0.4095***	0.1272**	0.7420***
MA (δ_i)	−0.1972	−0.1774	−0.3046*	−0.2144**	−0.7945***	−0.8174***
Const.(ω_i)	0.5026**	0.7162***	0.3980	0.0183*	0.0610	0.0861**
ARCH (α_i)	0.0464***	0.0546***	0.2029	0.1070***	0.0198***	−0.0017
GARCH (β_i)	0.9171***	0.8942***	0.3777	0.8599***	0.9388***	0.9668***
GJR (γ_i)	0.0652***	0.0846***	0.1892	0.0777*	0.0985***	0.0562**
Panel B: Estimates of the DECO model						
ρ_{DECO}	0.1235***					
λ	0.0822*					
π	0.6849***					
Panel C: Diagnostic tests						
$Q(20)$	13.698 [0.845]	15.237 [0.762]	27.753 [0.115]	19.370 [0.497]	57.075 [0.000]	10.407 [0.960]
$Q^2(20)$	30.024 [0.069]	13.742 [0.843]	0.021 [0.999]	17.858 [0.596]	2.401 [0.999]	1.758 [0.999]

Notes: $Q(20)$ and $Q^2(20)$ are the Ljung-Box test statistics applied to the standardized residuals and the squared standardized residuals with 20 lags, respectively. The p-values are in brackets. ***, **, and * denote statistical significance at 1%, 5%, and 10 % levels, respectively.

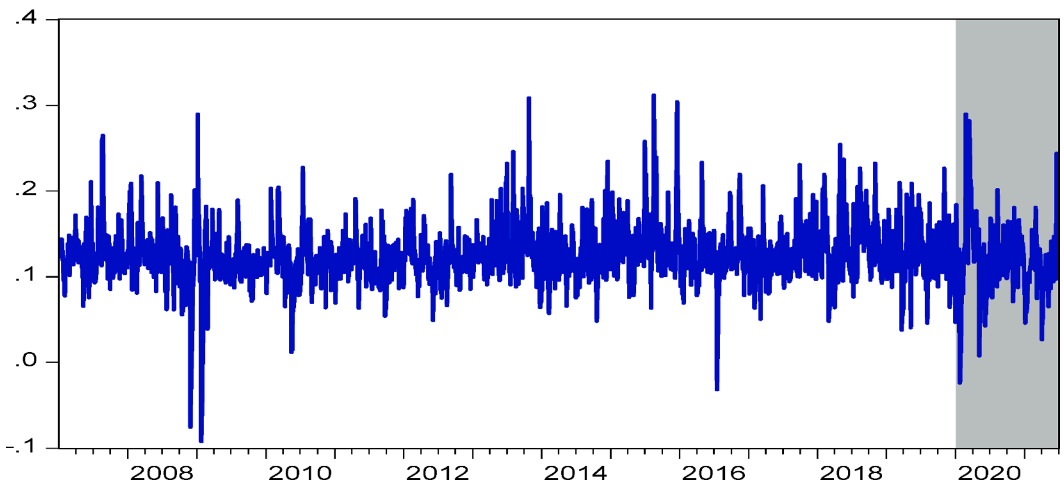

Fig. 2. Dynamic equicorrelation among Conventional and Islamic markets.

Fig. 1 portrays plots of the prices (panel A) and return data (panel B). Panel A displays that the prices almost follow the same pattern in each market. All markets experience a significant price drop during the Global Financial Crisis period (2007/2008) and the COVID-19 pandemic, though its magnitude varies across markets. For instance, these are noticeable in both conventional and Islamic money markets. Other markets (stocks and bonds) behave in a similar manner, which might be interpreted as a sign of connectedness among these markets. Panel B (returns) confirms some stylized facts of financial data such as volatility clustering, namely high (low) changes appear to be followed by high (low) fluctuations of either sign. For example, a high volatility is witnessed in all return series during GFC as well as in March 2020.

4.2. Empirical results

4.2.1. Estimation of the DECO-GJR-GARCH model

The findings of the DECO-GJR-GARCH (1,1) model between Islamic financial markets and their conventional counterparts are reported in Table 2. It is evident that both ARCH $(\alpha_i)$and GARCH(β_i) are significant for all markets (except for IB). This implies that past shocks and conditional volatility have a noticeable impact on the current volatility (McIver and Kang, 2020, and Demiralay and Golitsis, 2021). The coefficient (ψ_i) is significant for all markets, confirming that the price of stocks, bonds and money markets in both Islamic and conventional markets is instantaneously updated in response to any new relevant market information. This can be explained by Efficient Market Hypothesis (EMH), in which case asset prices fully reflect all relevant information.

The term (γ_i), representing the asymmetric effect confirms that conditional volatility is more responsive to negative shocks than positive ones (McIver and Kang, 2020). This coefficient is significant and positive for both Islamic and conventional markets (except for

Table 3
Volatility connectedness between Conventional and Islamic financial markets (Full sample).

	CS	IS	CB	IB	CM	IM	FROM others
CS	51.24	35.09	4.57	2.99	3.97	2.16	48.76
IS	36.26	51.78	3.37	2.3	3.97	2.31	48.22
CB	7.81	5.05	60.42	19.88	4.22	2.61	39.58
IB	5.76	4.05	18.53	64.99	3.91	2.75	35.01
CM	2.12	1.96	3.78	3.17	74.03	14.95	25.97
IM	2.61	2.66	2.76	2.84	18.14	70.99	29.01
TO others	54.57	48.8	33.01	31.18	34.21	24.78	226.56
Inc. own	105.81	100.58	93.43	96.17	108.24	95.77	TSI = 37.76%
NET	5.81	0.58	−6.57	−3.83	8.24	−4.23	

Notes: This Table summarizes the empirical results of the total, directional and pairwise spillovers from the DY static analysis over the full ample period (January 3, 2007 to June 30, 2021). All the results are based on the generalized variance decompositions from a VAR model of order 4 with 10-day ahead forecast errors. 'TO others' directional spillovers correspond to the off-diagonal column sums and represent spillovers from market i to all markets j. 'FROM others' directional spillovers denote the off-diagonal row sums and show spillovers from all markets j to market i. Net spillovers are simply the "To others" minus "FROM others" differences. Finally, the Total Connectedness Index, which appears in the lower right corner of the Table, captures on average how much of the shocks spill over across all markets, expressed as a percentage.

Table 4
Volatility connectedness between Conventional and Islamic financial markets (COVID-19 pandemic).

	CS	IS	CB	IB	CM	IM	FROM others
CS	63.47	22.45	4.82	6.5	1.57	1.2	36.53
IS	25.61	64.56	3.78	2.59	1.96	1.49	35.44
CB	11.35	5.97	61.18	19.32	1.17	1.01	38.82
IB	9.85	4.94	28.75	54.42	0.95	1.09	45.58
CM	0.92	2.47	4.15	0.49	56	35.97	44
IM	1.05	2.19	0.9	0.13	34.01	61.73	38.27
TO others	48.77	38.02	42.4	29.02	39.66	40.76	238.64
Inc. own	112.25	102.58	103.58	83.45	95.66	102.49	TSI = 39.77%
NET	12.25	2.58	3.58	−16.55	−4.34	2.49	

Notes: This Table summarizes the empirical results of the total, directional and pairwise spillovers from the DY static analysis during the COVID-19 pandemic (December 31, 2019 to June 30, 2021).[71] All the results are based on the generalized variance decompositions from a VAR model of order 2 with 10-day ahead forecast errors. 'TO others' directional spillovers correspond to the off-diagonal column sums and represent spillovers from market i to all markets j. 'FROM others' directional spillovers denote the off-diagonal row sums and show spillovers from all markets j to market i. Net spillovers are simply the "To others" minus "FROM others" differences. Finally, the Total Connectedness Index, which appears in the lower right corner of the Table, captures on average how much of the shocks spill over across all markets, expressed as a percentage.

IB). Our interesting findings with regard to IBs can be explained in terms of their business model and the principles of Islamic finance, which limit their exposure to high risk activities compared to their conventional counterparts. For instance, Islamic banks are not supposed to be involved in speculative activities. Therefore, this makes them less responsive to financial shocks and more resilient to volatility (Baldwin et al., 2019; Caporale et al., 2020).

Next, the results of the DECO model are displayed in panel B of Table 2. All coefficients of the DECO model are significant, confirming a time-varying co-movement across all markets (conventional and Islamic). One interesting result is that the coefficient on standardised residual (λ) is significant and positive, implying the important role of shocks on equicorrelations.

We also find significant evidence of co-movement among those markets as the coefficient on ρ_{DECO} is statistically significant and positive. The estimate of (π) is significant and positive (0.6849) implying a high level of persistence and slow mean-reversion in the time-varying equicorrelations. In order to examine the properties of the DECO-GJR-GARCH model, a battery of diagnostic tests was carried out and reported in "Panel C" based on the Ljung-Box test. These tests fail to reject the null hypothesis of no serial correlation, which confirms that the standardized residuals and the squared standardized residuals do not exhibit any serial correlation. This result supports the statistical appropriateness of our model in all markets.

Fig. 2 shows the average correlation among markets and confirms a positive correlation among all markets under consideration. However, there are noticeable spikes during turbulent crisis periods such as the 2008/2009 Global Financial Crisis (GFC), the 2010–2012 European Debt Crisis (EDC), the 2014–2016 oil price collapse, China's stock market crisis in 2015, and the ongoing COVID-19 pandemic. During these turmoil crisis time, the real economy across the whole world faced significant reduction and massive selloffs in the stock markets.

4.2.2. Volatility spillover analysis

Table 3 displays the empirical results of the static volatility spillover over the full ample period based on the generalized variance decompositions from a VAR model of order four and with a 10-day ahead Forecast Error Variance Decomposition (FEVD). [6]The Total Spillover Index (TSI) is 37.76%, which captures on average how much of the shocks spillover across all conventional and Islamic financial markets. Diebolda and Yilmaz (2012) argued that the increased level of spillover across asset classes might be an important aspect of the 2007/08 financial crisis. It is evident that the main contributor to the forecast FEVD is the conventional stock (54.57%), while this market receives 48.76% from other market. The net contribution is calculated as the difference between contribution to others and contribution from others. Therefore, this makes conventional stock a net contributor to other markets by 5.81% compared to what it receives. Our findings are in line with those of Ahmed and Elsayed (2019) who find that conventional financial markets are net transmitters to other markets. Islamic stock seems to be the second largest contributor to other markets with a rate of 48.8%. However, its net contribution is less than 1% as it receives 48.22% from the other markets. A high interlink and connectedness aomong Islamic and conventional stock markets are confirmed. It is evident that 35.09% of the forecast FEVD for CS comes from IS and a 36.26% of the forecast FEVD for IS is from CS. This could be explained by the charactiristics of Islamic stock, which includes sector specific and financing screenings on all stocks (Ahmed and Elsayed 2019). On contrary, the results reveal that both bonds (conventional and Islamic) are net recipients with −6.57 and −3.83 respectively. Further, the Islamic money market is a net recipient (-4.23) while the conventional money market is the main net transmitter of shocks to other market (8.24%). IM, on the other hand, is the lowest contributor to the shocks to other markets. This means that the IM is less vulnerable to shocks than other markets in Malaysia, making it a good choice for diversification amid market stress.

Table 4 displays the volatility spillover analysis during the COVID-19 pandemic period based on a VAR model of order two and with 10-day ahead forecast errors variance. Substantial differences in terms of the sign and magnitude of the Islamic–conventional market relationships can be observed during the full sample in comparison to the COVID-19 pandemic subsample. For instance, the average of the shock spillover across all markets is 2% higher during the COVID-19 period, which is represented by a total spillover index of 39.77%. The increase of spillover across all markets is attributed to unstable market conditions during COVID-19 pandemic confirming the contagion theory.

More specifically, Sukuk (IB) is the highest net receiver of shocks from other markets accounting for 45.58% followed by CM (44%), while CS is the highest net transmitter of shocks to other markets accounting for 48.77% followed by CB (42.4%). Our findings are similar to those reported by Yarovaya et al. (2021) who examine the effect of COVID-19 on volatility spillovers across conventional and Islamic stock/bond markets. Their findings confirm that the spillovers between both markets (conventional and Islamic stock) become stronger during the COVID-19 epidemic. These findings contrast with those of Hkiri et al. (2017) and Owusu Junior (2022), who found that Islamic indices are less affected and disconnected from their conventional counterparties during market turbulences. The magnitude of the net contributions of both CS and IS are increased by 6.44% and 2% respectively compared to the full sample. Further, both CB and IM became a net contributor of shocks to other markets (3.58 and 2.49 respectively), while CM became a net recipient of shocks (-4.34%).

Fig. 3 displays the dynamic spillover analysis, revealing that the time-varying total volatility spillover index shows a large variation over the sample period. More specifically, a high degree of volatility spillovers can be observed during political and economic turbulence, including the 2008/2009 Global Financial Crisis (GFC), China's 2015 stock market crisis, and the political instability in November 2016, as well as the ongoing COVID-19 pandemic (see Ahmed and Elsayed, 2019).

Finally, Fig. 4 reports the net-pairwise directional connectedness among each of two markets. It confirms the previous results and discussion from Tables 3 and 4 that the magnitude and strength of the average spillover between CS and IS has remained unchanged during the COVID-19 pandemic compared to the full sample. However, CB became a net transmitter of volatility to other markets during the COVID19 period compared to the full sample period, while IB remains a net receiver in both period (but higher magnitude during COVID19 period). IM and CM swapped their positions during the COVID-19 crisis where IM turned out to be a net transmitter, while CM became a net receiver during the COVID19 period compared to the full sample period. To sum up, it is obvious that the CS, IS, CB and IM are transmitters of volatility shocks to other market, while IB and CM are recipients of volatility with CS being the main transmitter and IB being the main receiver of shocks during the pandemic period. Fleming, Kirby, and Ostdiek (1998) argued that the price co-movement across financial markets could be described by information spillovers and cross hedging. However, the underlying contractual structures of conventional and Islamic asssets may have an impact on the inter-linkages among these markets. For instance, Islamic finance uses profit and loss sharing, and restricts excessive uncertainty, and, as such, these factors may change the direction of infomation spillovers across Islmaic and conventional markets.

4.2.3. Determinants of dynamic co-movement and volatility spillovers across markets

We further analyse the determinants of the dynamic equicorrelation and volatility connectedness across conventional and Islamic markets. First, we transfer the total spillover index[8] and the dynamic equicorrelation estimates extracted from the daily DECO-GJR-GARCH and the spillover models into monthly data to be consistent with the frequency of the macroeconomic variables that are only available at monthly observations. Furthermore, the Fisher transformation of correlation is applied to the DECO estimates to ensure

[6] We estimated the DY Spillover analysis based on the logarithmic transformation of the conditional volatilities. Our results remain statistically and qualitatively unchanged indicating that our findings are robust against the logarithmic transformation of the conditional volatilities. These results are not reported to save space, however, they are available upon request.

[8] The index captures the average contribution of spillovers due to shocks to the total forecast-error variance across all markets.

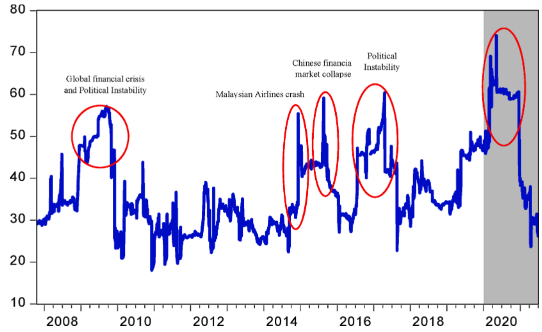

Fig. 3. Dynamic total volatility **spillover** index.

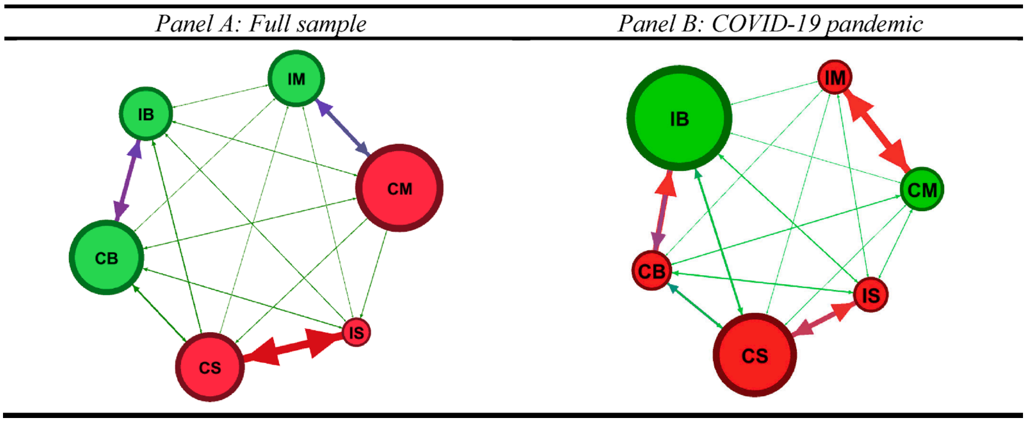

Fig. 4. Directional pairwise connectedness network.

that it is not confined to the interval [1-, +1]. Accordingly, the adjusted DECO correlation is calculated as follows:

$$AdjustedDECO_t = log(1 + \rho_{DECO})/(1 - \rho_{DECO})) \tag{21}$$

Where ρ_{DECO} is the estimated dynamic equicorrelation coefficients.

Following on from this, we perform several regression analyses to investigate the determinants of the dynamic co-movement and risk transmission across Islamic and conventional markets under consideration. To this end, data for the key macroeconomic variables and global risk factors have been collected from DataStream. The main determinants included in the analysis are the Malaysian industrial production index, inflation rate, exchange rate, Malaysian crude palm oil, Malaysian Geopolitical Risk index, CBOE volatility index, WTI crude oil price, S&P Gold index, Global Geopolitical Risk index, and Global Economic Policy Uncertainty. These factors are included based on theoretical foundations and are widely used in the previous literature (see among others Dyhrberg, 2016; Ji et al., 2019; Demiralay and Golitsis, 2021; Yarovaya et al., 2021, among others).

We start the analysis by examining the stationarity prosperities of all variables under consideration using the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1981) and Phillips-Perron (PP) (Phillips & Perron, 1988) tests. Results from the unit root tests confirm that all variables are either level stationary [I(0)] or stationary at first difference [I(1)] which motivates the use of the Autoregressive Distributed Lag (ARDL) model.[9]

Table 5 presents the results of the Bounds cointegration tests. The F-statistic for the dynamic equicorrelation model (11.906) is higher than the upper bound critical value at all levels of significance given by Pesaran et al. (2001). These findings confirm strong and significant long-run relationships between estimates of dynamic equicorrelation and macroeconomic and global factors under consideration. This suggests a strong explanatory power of the determinants in explaining the dynamic equicorrelation among our variables. On the other hand, the F-statistic for the second model (2.869) falls between the lower and upper bounds. Therefore, it suggests an inclusive cointegration relationship between volatility connectedness and all explanatory variables. The alternative efficient way of establishing cointegration is testing the significance of the error-correction term (Bahmani-Oskooee, 2001, Iwata et al., 2012, Kremers et al., 1992, Kyophilavong et al., 2013, Shahbaz et al., 2012). As can be seen, the lagged error-correction term is negative and significant which confirms the existence of the cointegration relationship between volatility connectedness and all

[9] For the sake of brevity, we do not include the descriptive statistics and stationarity tests of the explanatory variables. However, these results are available upon request form the authors.

Table 5
Bounds cointegration tests for ARDL models.

Model	F Statistics	K
(1) Dynamic equicorrelation	11.906	10
(2) Volatility connectedness	2.869	10
Critical Bound Values		
Significance Levels	I (0) Bound	I (I) Bound
10%	1.83	2.94
5%	2.06	3.24
2.5%	2.28	3.5
1%	2.54	3.86

Note: This table presents the results of the Bounds cointegration tests. For the ARDL models, the dependent variables are the dynamic equicorrelation estimates extracted from the daily DECO model and the total volatility index respectively. The null hypothesis to be tested is the absence of cointegration.

explanatory variables (see Table 6, Panel C). Therefore, we use the ARDL model to examine both the short-run and long-run relationships.

The empirical findings of both short and long-run relationships are reported in Table 6. Results of model 1 assert that macroeconomic and global factors affect co-movements among variables in both the short and long run. However, it only affects volatility transmission in the short run according to model 2. This might be due to the fact that risk and volatility transmission is mainly happening in the short run rather than the long run horizon due to the nature of the financial markets. Further, our findings reveal different magnitudes in term of significance, sign and size of the determinants across the two models. Our results are similier with those of He et al. (2020) who investigate the dynamic frequency between stock prices in the US and the crude oil prices. Their findings confirm that both volatility and return spillovers are much higher over the short-term than in the long run period. The higher volatility transmission in the short run could be related to investor sentiments, speculation and overreaction of investors to financial news (Mensi et al., 2021). On the one hand, inflation has a positive and significant effect on dynamic co-movements among financial markets in the long run while exchange rate, Malaysian geopolitical risk, VIX, and oil have negative and significant impacts (see Table 6, Panel B). On the other hand, the findings suggest that only industrial production has significant and negative impact on volatility connectedness.

More specifically, our findings show that global uncertainties (CBOE volatility index and Global Economic Policy Uncertainty) have a significant and negative impact on the dynamic co-movements, but they are not significant in the case of volatility connectedness. These findings are in line with Yarovaya et al. (2021) who finds that VIX and EPU are strong predictors of the correlation between the conventional and Islamic markets. This implies that the attitude of investors towards global risk and economic uncertainty drive conventional and Islamic market equicorrelation.

Finally, a number of diagnostic tests to the ARDL model were applied to confirm the robustness of our empirical results. Firstly, findings show a negative and a statistically significant Error Correction Term (ECM) in both models, suggesting evidence of short-run adjustment (see Panel C of Table 6). It confirms the long-run cointegration relationships among the dynamic equicorrelation and the determinants from one hand (model 1) and volatility spillover and the determinants on the other hand (model 2). Furthermore, there is no evidence of serial correlation in both models. Finally, to examine the stability of our equations, we run both CUSUM and the CUSUMSQ with recursive residuals following Pesaran and Pesaran (1997). The CUSUM and the CUSUMSQ stability test is reported in Table 6, Panel C. Both parameter stability tests of ARDL models stay within the critical boundaries for the 5% significance level except for the CUSUMSQ test for model 1 (see Fig. A in Appendix B). Our findings confirm that both short-run and long-run coefficients in the error correction models are stable and affect dynamic equicorrelation and volatility connectedness (see Samargandi et al., 2014; Caporale and Helmi, 2018).

5. Conclusion

A large body of literature examines financial contagion and the transmission of shocks between Islamic assets/markets and their conventional counterparts. However, an important segment of the financial system is missing in previous studies, namely that of money markets. Money markets constitute an important component of the financial sector and can provide useful insights on originating and transmitting shocks across different assets and/or sectors. To this end, this paper intends to fill this gap in the literature by examining the dynamic co-movements and risk transmission across Islamic and conventional stock, bonds/sukuk indices and money market rates in a dual financial system over the period from January 3, 2007 to June 30, 2021. This not only allowed us to study interconnectedness and volatility spillovers between the financial sectors under extreme market conditions but also enables us to highlight the key role played by the money markets.

Empirical results from the DECO-GJR-GARCH model provide strong evidence that all markets are highly interconnected and have significantly responded to any new relevant market information. Furthermore, results confirm a time-varying co-movement among conventional and Islamic financial markets with a high level of persistence and slow mean-reversion. On the other hand, evidence from the spillover approach proposed by Diebold and Yilmaz (2012, 2014) show that conventional stock and conventional money markets are the main transmitters of shocks to other markets while the Islamic money market and bond markets are net recipients over the full

Table 6
Estimates of ARDL models and diagnostic tests.

	(1) Dynamic Equicorrelation			(2) Volatility Connectedness		
	Coefficient	Std. Error	T- Statistic	Coefficient	Std. Error	T- Statistic
Panel A: Short-run estimates						
c	1.519***	0.437	3.471	122.338***	39.516	3.095
y_{t-1}	−0.903***	0.090	−9.962	−0.228***	0.045	−4.952
ip_{t-1}	0.006	0.113	0.059	−26.24**	11.19	−2.345
inf_{t-1}	0.035***	0.010	3.407	0.049	0.577	0.084
ex_{t-1}	−0.210***	0.078	−2.667	5.022	7.317	0.686
$palm_{t-1}$	−0.016	0.012	−1.321	0.417	1.078	0.386
gpr_m_{t-1}	−0.065***	0.017	−3.760	−1.805	1.344	−1.342
vix_{t-1}	−0.036***	0.013	−2.647	−0.619	1.205	−0.514
oil_{t-1}	−0.096***	0.025	−3.773	−0.916	2.352	−0.389
$gold_{t-1}$	−0.005	0.033	−0.138	1.649	2.949	0.559
gpr_g_{t-1}	0.023**	0.011	1.934	−0.595	0.835	−0.712
epu_g_{t-1}	−0.043*	0.025	−1.723	0.891	1.571	0.567
Δinf	0.009	0.006	1.311	–	–	–
Δinf_{t-1}	−0.017**	0.006	−2.555	–	–	–
Δex	0.045	0.141	0.319	–	–	–
Δex_{t-1}	0.334**	0.149	2.235	–	–	–
Δex_{t-2}	0.381**	0.147	2.587	–	–	–
$\Delta palm$	–	–	–	−5.938***	2.245	−2.644
Δgpr_m	−0.006	0.009	−0.615	−0.957	0.807	−1.186
Δgpr_m_{t-1}	0.047***	0.015	3.119	1.493	1.253	1.191
Δgpr_m_{t-2}	0.033**	0.012	2.589	2.211**	1.082	2.043
Δgpr_m_{t-3}	0.016*	0.009	1.663	2.150**	0.838	2.564
Δvix	−0.012	0.014	−0.875	−1.049	1.208	−0.868
Δvix_{t-1}	–	–	–	−3.754***	1.189	−3.157
Δoil	–	–	–	−9.055***	2.902	−3.119
$\Delta gold$	–	–	–	6.327	6.482	0.976
$\Delta gold_{t-1}$	–	–	–	−16.79***	6.288	−2.671
Δgpr_g	−0.021**	0.011	−1.903	–	–	–
Δepu_g	−0.013	0.020	−0.635	–	–	–
Δepu_g_{t-1}	−0.014	0.021	−0.641	–	–	–
Δepu_g_{t-2}	0.015	0.019	0.770	–	–	–
Δepu_g_{t-3}	0.036**	0.018	1.983	–	–	–
Panel B: Long-run estimates						
ip	0.007	0.125	0.059	−115.228**	45.885	−2.511
inf	0.040***	0.012	3.170	0.214	2.530	0.084
ex	−0.233**	0.091	−2.548	22.049	30.586	0.720
$palm$	−0.019	0.014	−1.322	1.830	4.778	0.383
gpr_m	−0.073***	0.019	−3.738	−7.926	6.121	−1.294
vix	−0.040***	0.015	−2.686	−2.722	5.422	−0.501
oil	−0.107***	0.029	−3.665	−4.022	10.461	−0.384
$gold$	−0.005	0.036	−0.138	7.241	12.521	0.578
gpr_g	0.025*	0.013	1.856	−2.615	3.693	−0.708
epu_g	−0.048*	0.027	−1.730	3.914	7.032	0.556
Panel C: Diagnostic test						
$\overline{R}^2$	0.496			$\overline{R}^2$	0.345	
ECT_{t-1}	−0.903***			ECT_{t-1}	−0.228***	
LM test	2.631			LM test	0.627	
CUSUM	Stable			CUSUM	Stable	
CUSUMQ	Unstable			CUSUMQ	Stable	

Note: $y, ip, inf, ex, palm, gpr_m, vix, oil, gold, gpr_g$, and$epu_g$ represent the dependent variable (estimates of the dynamic equicorrelation and the volatility connectedness), industrial production index, inflation, exchange rate, Malaysian crude palm oil, Malaysian Geopolitical Risk index, CBOE volatility index, WTI crude oil price, S&P Gold index, global Geopolitical Risk index, Global Economic Policy Uncertainty, respectively. $\overline{R}^2$ indicates the adjusted R-Squared value whereas ECT is the error correction term; LM test refers to the Lagrange multiplier test for serial correlation; CUSUM and CUSUMQ give the stability of short-run and long-run coefficients. Finally, the Optimal ARDL lag is determined based on Akaike Information Criterion (AIC). ***, **, and * indicate significance at the 1%, 5%, and 10% significant level respectively.

sample period. In addition, our findings indicate that the spillovers between both conventional and Islamic financial markets become stronger during the COVID-19 epidemic. One interesting finding is that the global uncertainties have significant and negative impacts on the dynamic co-movements, but not on volatility connectedness.

Overall, our findings have important implications for portfolio managers, investors, and policymakers, to learn more about the dynamic co-movements and risk spillovers between the money market and other asset classes in a dual financial system. To mitigate the effect of spillover among different types of asset classes and markets, investors should diversify their investment using a portfolio including assets from both money and capital markets. Further, investors should learn the sensitivity of their portfolio to the spillovers, and hence, should factor in volatility trading strategies. Policymakers should also enhance financial stability in a dual financial system during times of negative shocks such as during the COVID-19 pandemic. Despite providing valuable insights and evidence on volatility transmission across Islamic and conventional financial markets, it would be remiss if we did not indicate the limitation of this study due to the fact that some of the Malaysian companies could be listed under the stock market index as well as the Islamic stock index.

Further research could include the global risk factors within the spillover model to explore financial connectedness among these factors and both Islamic and conventional financial markets. Another interesting avenue for future research would be to explore the risk transmission and volatility spillovers between Islamic and conventional financial markets under different time horizons and different market conditions using the frequency connectedness approach developed by Barunik and Krehlik (2018) and the quantile connectedness measure proposed by Ando et al. (2022).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Table A1.

Table A1
Unit root tests of conditional volatilities.

	CS	IS	CB	IB	CM	IM
ADF	−9.071***	−8.199***	−10.712***	−38.508***	−6.953***	−5.878***
PP	−9.622***	−7.709***	−9.945***	−38.606***	−7.777***	−6.281***

Notes: This table reports results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. ***, **, * indicate significance at 1, 5, and 10% levels.

Appendix B

See Fig. B1.

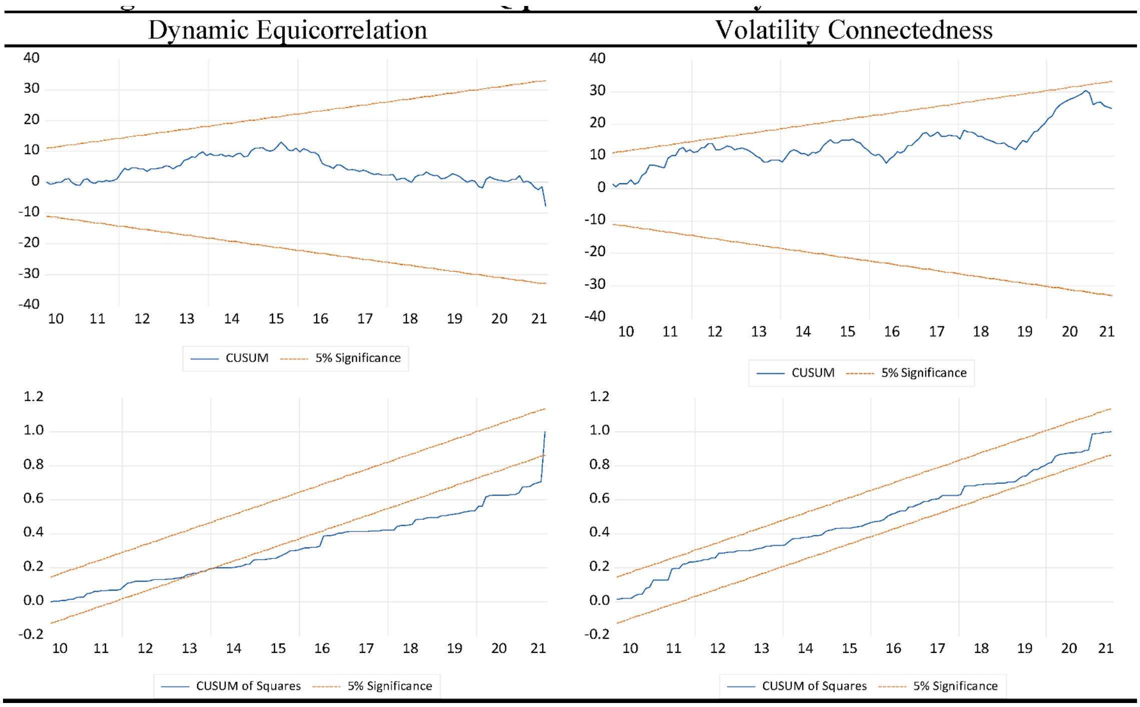

Fig. B1. CUSUM and CUSUMSQ parameter stability test of ARDL Models.

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