Dynamic risk spillovers between gold, oil prices and conventional, sustainability and Islamic equity aggregates and sectors with portfolio implications

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A B S T R A C T
This paper investigates the time-varying equicorrelations and risk spillovers between crude oil, gold and the Dow Jones conventional, sustainability and Islamic stock index aggregates and 10 associated disaggregated Islamic sector stock indexes (basic materials, consumer services, consumer goods, energy, financials, health care, technology, industrials, telecommunications and utilities), using the multivariate DECO-FIAPARCH model and the spillover index of Diebold and Yilmaz (2012). We also conduct a risk management analysis at the sector level for commodity-Islamic stock sector index portfolios, using different risk exposure measures. For comparison purposes, we add the aggregate conventional Dow Jones global index and the Dow Jones sustainability world index. The results show evidence of time-varying risk spillovers between these markets. Moreover, there are increases in the correlations among the markets in the aftermath of the 2008–2009 GFC. Further, the oil, gold, energy, financial, technology and telecommunications sectors are net receivers of risk spillovers, while the sustainability and conventional aggregate DJIM indexes as well as the remaining Islamic stock sectors are net contributors of risk spillovers. Finally, we provide evidence that gold offers better portfolio diversification benefits and downside risk reductions than oil.

1. Introduction

The global financial system has increasingly become more complex due to ongoing structural changes including technological improvements and innovative financial products, which have affected the world’s economy and the global financial architecture. In particular, the last two decades have been an era of global financial integration connecting several asset classes together and leading to amplified correlations between them. In the eyes of asset managers and policymakers, this complex situation is a tough challenge that requires hedging through diversification and other protection measures to provide financial stability.

Consequently, the Islamic finance industry has become an alternative business model to its conventional counterparts in the world of financial intermediation and a promise for more diversification opportunities and financial stability. Over the past two decades, the Shariah-compliant industry has experienced significant growth due to growing interest from the Western world and faith-oriented investors, particularly after the 2008 financial crisis, and as a result of accumulation of oil wealth in faith-supporting countries and a strong participation from faithful investors, combined with a keen willingness of regulators to give more room for this industry. Current estimates of the size of the global Islamic finance assets under management range between USD 1.7 and 2.1 trillion in 2016 and the Islamic Finance industry is expected to grow further in the future.

The Islamic-listed stock securities, which are part of the Islamic finance industry, are a subset of the broader global Islamic securities universe that meets defined screening criteria to assess their compliance with the Shariah principles, and hence their suitability to be considered as Shariah compliant securities. Therefore, the volatility and pricing movements in global stock markets also have an effect on the Shariah-compliant securities (IFSI Stability Report, 2016). This fact leads one to search for more viable alternative asset classes to foster
the diversification sought by global investors who prefer to include Islamic securities in their investments. Commodities, gold and oil, in particular, are the very first candidates that come to mind in this process. From a traditional perspective, the commodity and equity markets (whether Shariah-compliant or not) are normally inversely related, and therefore commodities are considered to be good portfolio diversifiers (Kang, 2012). For example, gold has traditionally been used as a hedge against inflation and crises. As the US dollar weakens and inflation creeps up, investors would prefer to invest in gold in order to take advantage of potentially higher inflation (Baur and McDermott, 2010). Similarly, in times of substantial price decreases in the stock market, not only gold but also oil may tend to increase in price (Dorsman et al., 2012). If gold is to reduce the risk of Islamic equity portfolios, the literature has not paid much attention to combinations that include gold, oil and Islamic equity indexes.

Examples of those studies that have paid some attention to this asset mixture include Abdullah et al. (2016), Mensi et al. (2015a, 2015b), and Nagayev et al. (2016). However, the problem with these examples is that the first two studies focus on a very limited set of countries (namely Singapore, Malaysia, Philippines and Saudi Arabia), while the latter two consider only a global Islamic equity market index. This shows that a much deeper research is required to analyze the nexus between the most popular commodities, gold and oil, and Islamic equity markets at the aggregate and sector levels. In addition, the obvious missing point is that when we consider Islamic equities at the aggregate level, we miss the opportunity of diversification at the sectoral level. To the best of our knowledge, this study is one of the first that analyzes the interactions between vital commodities (gold and oil) and the Islamic equities at the sectoral level, employs downside risk reduction measures and investigate portfolio diversification benefits. We also consider the aggregate conventional Dow Jones global index (W1DOW) and Dow Jones sustainability world index (W1SGI) for comparison purposes.2 It is clear that such an analysis would be invaluable in risk management and portfolio construction. Therefore, in this study, we focus on the relationship between gold and oil, and both the Dow Jones aggregate conventional, sustainability, Islamic equity indexes as well as the 10 dis-aggregate Islamic equity sectors at a global scale. This comprehensive analysis should make this study the first in the literature in this regard.

In particular, using daily data covering almost 20 years, we first implement the multivariate dynamic equicorrelation-fractionally integrated asymmetric power autoregressive conditional heteroskedasticity (DECO-FIAPARCH) model to measure dynamic correlations among conventional stock index, sustainability stock index, the aggregate Islamic stock market, their 10 Islamic sectors and the two commodity markets (oil and gold). Then, we apply the generalized spillover index of Diebold and Yilmaz (2012, 2014, 2016) to examine the directional spillovers and net spillovers across the commodities and the Islamic sector indices. Further, we use the approach of Kroner and Ng (1998) and variance-minimizing hedging strategies to find the time-varying optimal portfolio weights, using the commodities and the Islamic sectoral indexes together to investigate the usefulness of the gold and oil markets for risk management in the Islamic sectoral stock markets. Finally, we estimate the corresponding Value-at-Risk (VaR), Semivariance (SV) and the Regret (Re) measures to help guide portfolio managers planning to use Islamic equities in designing their strategies.

Our contributions to the literature are three-fold. First, as indicated above, this is the first study that investigates the diversification benefits and the interactions between commodities such as gold and oil, and the Islamic equities at the sectoral level in a global environment. In fact, the aggregate DJIM is sector oriented as the Shariah-compliant firms are heavily concentrated in some sectors like basic materials, technology and industrials. These dissimilarities motivate us to address these interactions and diversification with Islamic indexes. Second, the study covers almost 20 years of daily data which includes crucial events such as the 2001 dotcom bubble, the 2008 global financial crisis (GFC) and the 2012 European sovereign debt crisis (ESDC). Such events allow us to examine the dynamics of equicorrelations, volatility spillovers, optimal portfolio structures and hedging strategies during crisis periods. Third, we use the state of the art methodologies such as the DECO-FIAPARCH, the generalized spillover index of Diebold and the Yilmaz (DY) (2012), optimal portfolio weighting by Kroner and Ng (1998) in our analysis. Further, the findings are strengthened by various risk effectiveness measures.

Our results show a time-varying equicorrelations for the commodity and Islamic stock markets. Furthermore, the spillover index analysis reveals that gold has a lower impact on the Islamic stock markets than the crude oil market, and the latter is a greater receiver of shocks than gold. The results indicate that oil and gold are net receivers of volatility, while surprisingly the aggregate Islamic stock (DJIM) index is a net contributor to volatility spillovers. Furthermore, the recent GFC and the ESDC intensify the total volatility spillovers across the considered markets. Among the 10 Islamic sectors, the consumer goods and the industrials are the highest net volatility contributors, while the finance, technology and telecommunication sectors are the lowest contributors of volatility spillovers, and in fact they are net receivers with the finance sector being the most vulnerable. Further, the risk spillovers between the Islamic stock sectoral markets are globally weak. We find that the optimally weighted portfolio offers both the best risk reductions and the largest downside risk reduction for all oil-Islamic stock sector pairs, the gold–DJIM, gold-Islamic consumer services, the gold-Islamic consumer goods, the gold-Islamic health care, and the gold-Islamic industrials. For the rest of the gold-Islamic sector stock pairs, the hedged portfolio provides the best risk reductions. Finally, gold offers better diversification benefits, risk reductions and the largest downside risk reductions than oil.

The remainder of this study is organized as follows. Section 2 presents the literature review. Section 3 discusses the methodology. Section 4 describes the data and conducts some preliminary analysis. Section 5 reports and discusses the empirical results. Section 6 provides concluding remarks.

2 Literature review

The early empirical literature has focused on the relative performance of the Islamic finance industry in comparison to its conventional counterparts (e.g., Hayat and Kraussl, 2011; Milly and Sultan, 2012; Beck et al., 2013; Jawadi et al., 2014; Al-Khazali et al., 2014). However, with the occurrence of the recent global financial crisis and the following eurozone debt crisis, researchers and policy makers redirected their attention to the potential risk management applications of Islamic financial assets. The major part of those recent studies focuses on analyzing spillovers between Islamic and conventional assets, and shows how to use those assets in portfolio constructions. The earlier studies in the literature consider combining conventional equities with their Islamic counterparts. For example, in a theoretical framework, Umar (2017) considers two types of stock investors: faith-based and conventional-based. The faith-based investors invest in Shariah compliant equities only and exclude conventional equities from the asset menu. On the other hand, the conventional investors’ asset

1 However, with the easy access of commodities through financialization in the recent years, commodity prices are not only determined by their primary supply and demand anymore but also by this process. Therefore, the traditional interpretations of the relation between equities and commodities have been questioned lately (Silvermoen and Thorp, 2012).

2 The Dow Jones Sustainability Indices are a family of best-in-class benchmarks for investors who have recognized that sustainable business practices are critical to generating long-term shareholder values and who wish to reflect their sustainability convictions in their investment portfolios. The family was launched in 1999 as the first global sustainability benchmark and tracks the stock performance of the world’s leading companies in terms of economic, environmental and social criteria. For further information the reader can refer to the following link http://webcache.googleusercontent.com/search?q=cache:http://www.sustainability-indices.com/index-family-overview/djsi-family-overview/
Fig. 1. Time variation of all sample returns. Note: The shaded areas highlight regimes of excess volatility according to the two regime Markov-switching dynamic regression (MS-DR). For further details on the MS-DR model, see Hamilton (1988) and Hamilton and Susmel (1994). The MS-DR method is conducted by Ox metrics.
Both results are indirectly supported by Yilmaz et al. (2015) and Sensoy (2016). Indeed, among the whole literature, the studies that take into account the interactions of such sector indexes can be counted on the fingers of one hand. For example, Balcilar et al. (2015) assess the risk exposures of major Islamic sector indexes with respect to shocks in global conventional markets but without including refuge assets and find positive risk exposures of Islamic equity sectors with respect to developed market shocks. Those authors find that both the in- and out-of-sample results suggest that portfolios supplemented with positions in the Islamic equity sectors yield much improved risk-adjusted returns, thereby implying significant international diversification benefits. In particular, the Financials, Healthcare, Telecommunication and Utilities sectors are found to have greater significance in global diversification strategies due to their higher weights allocated in the optimal portfolios. A recent study by Mensi et al. (2016) takes a different perspective of Islamic sector investing from the one undertaken by Balcilar et al. (2015). Accordingly, Mensi et al. (2016) analyze the dynamic spillovers across 10 Dow Jones Islamic and conventional sector index pairs. Using four different MGARCH-DCC models, they find evidence of the claim that the conditional correlations for all the sector pairs (except those of the Telecommunication and Utilities sectors) increase after the onset of the global financial crisis, suggesting non-subsidizing risks, contagion effects and gradual greater financial linkages. Accordingly, the Islamic sectors’ risk exposure can be effectively hedged over time in diversified portfolios containing conventional sector stocks. However, to the best of our knowledge, there is no study that analyzes the interaction between commodities such as gold and oil, and the Islamic equities at the sectoral level as explained in the introduction section. The extensive literature reviewed above suggests that such an analysis would be invaluable in risk management, in particular for portfolio construction.

### 3. Empirical method

This section discusses the empirical methods used in this study. First, we present a multivariate DECO-FIAPARCH model, which measures the dynamic conditional correlations between the markets under consideration as explained earlier. Second, we present the spillover index of Diebold and Yilmaz (2012), which identifies the dynamics of directional volatility spillovers across the commodity and stock markets under consideration.

### Table 1

Descriptive statistics of gold, WTI oil, Dow Jones sustainability world index, conventional Dow Jones global index, DJM index and the Islamic sector stock index returns.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Max.</th>
<th>Min.</th>
<th>Std. dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>JB</th>
<th>Q(30)</th>
<th>Q(300)</th>
<th>ADF</th>
<th>KPSS</th>
<th>ARCH-LM(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GOLD</td>
<td>0.0345</td>
<td>8.8303</td>
<td>-9.8105</td>
<td>1.1784</td>
<td>-0.143</td>
<td>9.045</td>
<td>6206</td>
<td>517.6**</td>
<td>713.8**</td>
<td>-63.62**</td>
<td>-63.62**</td>
<td>0.1589</td>
</tr>
<tr>
<td>WTI</td>
<td>0.0327</td>
<td>16.407</td>
<td>16.544</td>
<td>2.3971</td>
<td>-0.255</td>
<td>7.344</td>
<td>3342</td>
<td>56.09**</td>
<td>3289</td>
<td>-66.02**</td>
<td>-66.08**</td>
<td>0.2827</td>
</tr>
<tr>
<td>W1DOW</td>
<td>0.0153</td>
<td>11.470</td>
<td>7.6568</td>
<td>0.1536</td>
<td>-0.280</td>
<td>15.448</td>
<td>15.17**</td>
<td>100.7**</td>
<td>7744**</td>
<td>-56.26**</td>
<td>-55.96**</td>
<td>0.0763</td>
</tr>
<tr>
<td>W1SGI</td>
<td>0.0085</td>
<td>12.221</td>
<td>7.7746</td>
<td>1.1699</td>
<td>-0.072</td>
<td>11.50</td>
<td>12.26**</td>
<td>119.9**</td>
<td>5880**</td>
<td>-57.99**</td>
<td>-57.74**</td>
<td>0.0669</td>
</tr>
<tr>
<td>D1JM</td>
<td>0.0169</td>
<td>10.984</td>
<td>8.1854</td>
<td>1.0993</td>
<td>-0.283</td>
<td>10.67</td>
<td>10.04**</td>
<td>47.83**</td>
<td>6345**</td>
<td>-41.91**</td>
<td>-70.21**</td>
<td>0.0900</td>
</tr>
<tr>
<td>DJBS</td>
<td>0.0224</td>
<td>12.652</td>
<td>12.551</td>
<td>1.4318</td>
<td>-0.546</td>
<td>12.62</td>
<td>15.88**</td>
<td>264.7**</td>
<td>8711**</td>
<td>-41.02**</td>
<td>-64.62**</td>
<td>0.0831</td>
</tr>
<tr>
<td>DJJCY</td>
<td>0.0174</td>
<td>8.6724</td>
<td>8.2846</td>
<td>1.1479</td>
<td>-0.167</td>
<td>7.677</td>
<td>3725**</td>
<td>200.5**</td>
<td>2950**</td>
<td>-43.57**</td>
<td>-73.36**</td>
<td>0.1106</td>
</tr>
<tr>
<td>DJJCYC</td>
<td>0.0201</td>
<td>7.8587</td>
<td>6.1352</td>
<td>0.8502</td>
<td>-0.325</td>
<td>10.96</td>
<td>10.81**</td>
<td>352.5**</td>
<td>4610**</td>
<td>-43.89**</td>
<td>-71.57**</td>
<td>0.1242</td>
</tr>
<tr>
<td>DJJNE</td>
<td>0.0191</td>
<td>16.879</td>
<td>13.905</td>
<td>1.5287</td>
<td>-0.456</td>
<td>14.08</td>
<td>48.11**</td>
<td>122.6**</td>
<td>7227**</td>
<td>-42.93**</td>
<td>-73.14**</td>
<td>0.0814</td>
</tr>
<tr>
<td>DJJFIN</td>
<td>0.0111</td>
<td>17.277</td>
<td>16.581</td>
<td>1.5741</td>
<td>-0.023</td>
<td>20.18</td>
<td>50.02**</td>
<td>199.0**</td>
<td>6533**</td>
<td>-43.86**</td>
<td>-181.4**</td>
<td>0.0450</td>
</tr>
<tr>
<td>DJJICR</td>
<td>0.0219</td>
<td>10.747</td>
<td>6.1933</td>
<td>0.9841</td>
<td>-0.112</td>
<td>10.35</td>
<td>91.78**</td>
<td>139.6**</td>
<td>3010**</td>
<td>-44.12**</td>
<td>-69.80**</td>
<td>0.2114</td>
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<tr>
<td>DJJIDU</td>
<td>0.0215</td>
<td>10.231</td>
<td>8.3919</td>
<td>1.1872</td>
<td>-0.332</td>
<td>9.251</td>
<td>6695**</td>
<td>192.9**</td>
<td>6136**</td>
<td>-60.46**</td>
<td>-66.94**</td>
<td>0.0876</td>
</tr>
<tr>
<td>DJJITC</td>
<td>0.0125</td>
<td>11.719</td>
<td>8.2984</td>
<td>1.6886</td>
<td>0.120</td>
<td>7.424</td>
<td>3533**</td>
<td>443.8**</td>
<td>43.19**</td>
<td>-73.84**</td>
<td>0.1316</td>
<td></td>
</tr>
<tr>
<td>DJJIJ</td>
<td>0.0069</td>
<td>12.426</td>
<td>8.0750</td>
<td>1.1992</td>
<td>0.088</td>
<td>9.457</td>
<td>7069**</td>
<td>106.1**</td>
<td>3949**</td>
<td>-43.59**</td>
<td>-70.37**</td>
<td>0.0826</td>
</tr>
<tr>
<td>DJJIIT</td>
<td>0.0024</td>
<td>16.509</td>
<td>9.3299</td>
<td>1.1455</td>
<td>0.097</td>
<td>24.30</td>
<td>76.93**</td>
<td>166.1**</td>
<td>4559**</td>
<td>-44.29**</td>
<td>-71.35**</td>
<td>0.1227</td>
</tr>
</tbody>
</table>

Notes: J-B denotes the empirical statistics of the Jarque-Bera test for normality, the Ljung-Box Q(30) and Q(300) tests for no autocorrelation of the residuals and the square residuals, respectively. ADF, PP and KPSS are the empirical statistics of the Augmented Dickey and Fuller (1979), and the Phillips and Perron (1988) unit root tests and the Kwiatkowski et al. (1992) stationarity test, respectively. The ARCH-LM(10) test of Engle (1982) checks the presence of ARCH effects. The asterisk ** denotes the rejection of the null hypothesis of normality, no autocorrelation, unit root, stationarity, and conditional homoscedasticity at the 1% significance level.

1 Alternatively, some studies suggest that combining the conventional U.S. markets with emerging Islamic equity markets leads to improved portfolio performance (see Majdoub and Mansour, 2014; Saiti et al., 2014).

2 Both results are indirectly supported by Yilmaz et al. (2015) and Sensoy (2016).
3.1. The DECO-FIAPARCH model

Engle (2002) develops the dynamic conditional correlation (DCC)-GARCH model, which offers flexibility to simultaneously model the multivariate conditional volatility of stock returns and their time-varying correlations. Despite its flexibility, the DCC estimation involves computing the correlation of too many pairs sampled $n(n-1)/2$ times, which produces results that are difficult to interpret (Aboura and Chevallier, 2014). To overcome this limitation, Engle and Kelly (2012) propose to use the DECO-GARCH model, which can eliminate the computational and presentational difficulties of high-dimensional systems (Pan et al., 2016). The DECO model is a special version of the DCC model in which the correlations across all pairs of assets are equal but the common equicorrelation is time-varying. Another advantage of equicorrelation is that it provides superior forecasting ability during the crisis periods across the various portfolios (Clements et al., 2014).

The AR(1) model in which the dynamics of current stock returns are explained by their lagged returns is defined as follows:

$$t_i = \mu + \xi t_{i-1} + \epsilon_i, \ t \in T \text{ with } \epsilon_i = z_i \sqrt{h_i}$$

(1)

where $|\mu| \in [0,\infty], |\xi| < 1$ and the innovations $\{z_i\}$ follow the Student’s t-distribution ($z_i \sim \text{ST}(0,1,\nu)$). The Student’s t-distribution is estimated as the density ($q_{1/2}$) of the Student’s t-distribution ($\nu$) which represents the number of degrees of freedom ($q_{1/2}$) and measures the degree of leptokurtosis displayed by the density (Fiorentini et al., 2003). The conditional variance $h_i$ is positive with probability one and is a measurable function of the variance-covariance matrix $z_{i-1}$.

The FIAPARCH $(p,d,q)$ model of Tse (1998) is formally expressed as follows:

$$h_i^{1/2} = \omega [1 - \beta (L)^{-1}]^{-1} \left[1 - [1 - \beta (L)^{-1}]^{-1} \Phi (L) (1 - L)^d \right] (\epsilon_i - \lambda \epsilon_i)^{\delta},$$

(2)

where $\omega, \beta, \delta, d$ and $\Phi$ are the parameters to be estimated. The parameter $d$ where $0 \leq d \leq 1$ measures the long-memory in the conditional volatility, $L$ denotes the lag operator, $\delta$ is the power term of returns for the predictable structure in the volatility persistence, and $\lambda > 0$ represents the asymmetry parameter indicating that negative shocks give rise to higher volatility than positive shocks of equal size.

We follow Engle (2002) to obtain the dynamic conditional correlations. We assume that $E_t[\epsilon_i] = 0$ and, $E_t[\epsilon_i \epsilon_i'] = H_0$, where $E_t[\cdot]$ is the conditional expectation on using the information set available at time $t$. The conditional variance-covariance matrix, $H_0$, can be written as:

$$H_0 = D_t R_t D_t$$

(3)

where $D_t = \text{diag}(h_{11}^{1/2}, \ldots, h_{NN}^{1/2})$ is the $N \times N$ diagonal matrix of conditional standard deviations of the residuals, which are obtained from taking the square root of the conditional variance modelled by an univariate AR(1)-FIAPARCH(1,1,1) model. Moreover, $R_t$ is a matrix of time-varying conditional correlations, which is given by:

$$R_t = \{Q_t^{1/2}, Q_t^{-1/2}\},$$

(4)

$$Q_t = \text{diag}(Q_{ii}) = (1 - a - b)S + a u_{t-1} u_{t-1}' + b Q_{t-1},$$

(5)

where $u_t = [u_{t1}, \ldots, u_{tn}]'$ is the standardized residuals (i.e. $u_{ti} = \epsilon_i / h_{ii}$), $S = [s_{ij}] = E[u_t u_t']$ is the $N \times N$ unconditional covariance matrix of $u_t$, and $a$ and $b$ are non-negative scalars satisfying $a + b < 1$. The resulting model is called the DCC model.

In this context, Aielli (2013) proves that the estimation of the covariance matrix $Q_t$ in this way is inconsistent because $E[R_t] \neq E[Q_t]$, and suggests the following consistent model ($cDCC$ model) for the correlation-driving process:

$$Q_t = (1 - a - b) S + a \left( Q_{t-1}^{1/2} u_{t-1} u_{t-1}' Q_{t-1}^{1/2} \right) + b Q_{t-1},$$

(6)

where $S$ is the unconditional covariance matrix of $Q_t^{1/2} u_t$.

Engle and Kelly (2012) suggest that we model $\rho_t$ by using the $cDCC$ process to obtain conditional correlation matrix $Q_t$ and then taking the mean of its off-diagonal elements. This approach, which reduces estimation time, is called the dynamic equicorrelation (DECO) model.

The scalar equicorrelation is defined as:

$$\rho_t^{\text{DECO}} = \frac{1}{n(n-1)} \left( \sum_{i=1}^{n} q_{ii} - \sum_{i=1}^{n} q_{ij} - \sum_{j=1}^{n} q_{ij} \right),$$

(8)

where $q_{ij} = \rho_t^{\text{DECO}} + a^{\text{DECO}} (u_{i,t-1} u_{j,t-1} - \rho_t^{\text{DECO}}) + b^{\text{DECO}} (q_{ij,t-1} - \rho_t^{\text{DECO}})$, which is the $(i,j)$th element of the matrix $Q_t$ from the $cDCC$ model. We then use this scalar equicorrelation to estimate the conditional correlation matrix:

$$R_t = \{\rho_t h_n + \rho_t h_n\},$$

(9)

where $h_n$ is the $n \times n$ matrix of ones and $I_n$ is the $n$-dimensional identity matrix.
Table 3: Estimation of the multivariate AR(1)-FIAPARCH(1,d,1)-DECO model.

<table>
<thead>
<tr>
<th>Gold</th>
<th>WTI</th>
<th>W1DOW</th>
<th>W1SGI</th>
<th>DJIM</th>
<th>DJBSC</th>
<th>DJICY</th>
<th>DJINCY</th>
<th>DJIENE</th>
<th>DJIIN</th>
<th>DJIENE</th>
<th>DJIFIN</th>
<th>DJIHCR</th>
<th>DJIINDU</th>
<th>DJITEC</th>
<th>DJITLS</th>
<th>DJIUTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const. (μ)</td>
<td>0.0346***</td>
<td>0.0328***</td>
<td>0.0051</td>
<td>-0.0007</td>
<td>0.0066</td>
<td>0.0219</td>
<td>0.0137</td>
<td>0.0138</td>
<td>0.0307</td>
<td>0.0264</td>
<td>0.0114</td>
<td>0.0161</td>
<td>0.0200</td>
<td>0.0146</td>
<td>0.0310**</td>
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<td>(0.1235)</td>
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</table>

Panel B: estimates of the DECO model

| COBJ | 0.6368*** |
| (0.0972) |
| 0.0382*** |
| (0.0070) |
| 0.9006*** |
| (0.0077) |
| 7.6079** |
| (0.2171) |

Notes: Q(30) and Q2(30) are the Ljung-Box test statistic applied to the standard residuals and the squared standardized residuals, respectively. The p-values are in brackets while the standard error values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.
Note that the estimation of the DECO model is carried out using a two-step maximum likelihood of the probability density function of a multivariate Student’s t-distribution expressed as:

\[ I(\theta) = \log \left( \frac{\Gamma\left(\frac{v+2}{2}\right)}{\sqrt{c(\nu)}} \right) \left[ \left( \frac{\nu\pi}{2} \right)^{\frac{1}{2}} \left( 1 + \left( \frac{\nu}{2} \right) \right)^{-\frac{1}{2}} \right] \times (v+2) \log \left[ 1 + \left( \frac{\nu}{2} \right)^{-1} \right] \left( \frac{v+2}{2} \right) \],

where \( I(\cdot) \) is the Gamma function, \( \nu \) is the degree of freedom for the Student’s t-distribution, \( H_t \) is a conditional variance-covariance matrix, \( \theta \) is a parameter vector with all of the coefficients of the DECO-FIAPARCH model.

3.2. Spillover index framework

We apply the generalized VAR methodology, variance decomposition, and the generalized spillover index of Diebold and Yilmaz (2012) to examine the directional spillovers and net spillovers across the two commodity futures prices (Gold and WTI) and Islamic sector indices. Following Diebold and Yilmaz (2012), we assume a covariance stationary \( n \)-variable VAR\( (p) \):

\[ y_t = \sum_{t=1}^{p} \Phi_i y_{t-i} + \epsilon_t, \]

where \( y_t \) is the \( n \times 1 \) vector of endogenous variables, \( \Phi_i \) are \( n \times n \) autoregressive coefficient matrices, and \( \epsilon_t \) is a vector of error terms that are assumed to be serially uncorrelated. If the VAR system above is a covariance stationary, then a moving average representation is written as \( y_t = \sum_{j=0}^{p} \Phi_j \epsilon_t \), where the \( n \times n \) coefficient matrix \( \Phi_j \) obeys a recursion of the form \( \Phi_j = \Phi_1 A_{j-1} = \Phi_2 A_{j-2} + \ldots + \Phi_p A_{j-p} \) with \( A_0 \) being the \( n \times n \) identity matrix and \( A_0 = 0 \) for \( j < 0 \). The total, directional, and net spillovers are generated by generalized forecast-error variance decompositions of the moving average representation of the VAR model. The framework of generalized variance decompositions eliminates any dependence of the results on the ordering of the variables.

Koop et al. (1996) and Pesaran and Shin (1998) propose the following \( H \)-step-ahead generalized forecast-error variance decomposition:

\[ \theta_{ij} (H) = \frac{\sum_{h=0}^{H} \left( e_{t-h}^{\prime} A^\prime_h \Sigma e_t \right)}{\sum_{h=0}^{H} \left( e_{t-h}^{\prime} A^\prime_h \Sigma e_t \right)} \]

where \( \Sigma \) is the variance matrix of the vector of errors \( e \), and \( \sigma_{ij} \) is the standard deviation of the error term of the \( j^{\text{th}} \) equation. Finally, \( e_{t-h}^{\prime} \) is a selection vector with a value of one for the \( i^{\text{th}} \) element, and zero otherwise. The spillover index yields a \( n \times n \) matrix \( \theta (H) = [\theta_{ij} (H)] \), where each entry gives the contribution of variable \( j \) to the forecast error variance of variable \( i \). Own-variable and cross-variable contributions are contained in the main diagonal and the off-diagonal elements of \( \theta (H) \) matrix, respectively.

Because the own- and cross-variable variance contribution shares do not sum to one under the generalized decomposition (i.e., \( \sum_{j=1}^{n} \theta_{ij} (H) \neq 1 \)), each entry of the variance decomposition matrix is normalized by its row sum as follows:

\[ \hat{\theta}_{ij} (H) = \frac{\theta_{ij} (H)}{\sum_{j=1}^{n} \theta_{ij} (H)} \]

where \( \sum_{j=1}^{n} \hat{\theta}_{ij} (H) = 1 \) and \( \sum_{i=1}^{n} \hat{\theta}_{ij} (H) = n \) by construction. This allows us to define a total spillover index as:

\[ TS (H) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \hat{\theta}_{ij} (H)}{\sum_{i=1}^{n} \theta_{ij} (H)} \times 100 = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \hat{\theta}_{ij} (H)}{\sum_{i=1}^{n} \theta_{ij} (H)} \times 100 \]

This index measures the average contribution of spillovers from shocks in all (other) markets to the total forecast error variance. Additionally, this index is flexible and enables the identification of the directional spillovers among all markets. Specifically, the directional spillovers received by market \( i \) from all other markets \( j \) are defined as:

\[ DS_{i \rightarrow j} (H) = \frac{\sum_{j=1}^{n} \sum_{i=1}^{n} \hat{\theta}_{ij} (H)}{\sum_{i=1}^{n} \theta_{ij} (H)} \times 100 = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \hat{\theta}_{ij} (H)}{\sum_{i=1}^{n} \theta_{ij} (H)} \times 100 \]

Similarly, the directional spillovers transmitted by market \( i \) to all other markets \( j \) are defined as:

\[ DS_{i \leftarrow j} (H) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \hat{\theta}_{ij} (H)}{\sum_{i=1}^{n} \theta_{ij} (H)} \times 100 = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \hat{\theta}_{ij} (H)}{\sum_{i=1}^{n} \theta_{ij} (H)} \times 100 \]

The set of directional spillovers provides a decomposition of total spillovers into those coming from (or to) a particular market. For instance, in the present application this means that this spillover matrix \( \theta (H) \) consists of the main diagonal elements reflecting...
own-market spillovers, and the off-diagonal elements reflecting cross-market spillovers.

Finally, subtracting Eq. (16) from Eq. (15), we compute the net volatility spillovers from each market to all other markets as:

\[
NS_i(H) = DS_{i\rightarrow j}(H) - DS_{i\leftarrow j}(H)
\]  

The net spillovers demonstrate whether a market is a receiver or transmitter of spillovers in net terms. It is also our interest to examine the net pairwise spillovers (NPS) as following:

\[
NPS_{ij}(H) = \left[ \frac{\hat{\theta}_{ij}(H)}{\sum_{j=k,i}^{p} \theta_{jk}(H)} - \frac{\hat{\theta}_{ij}(H)}{\sum_{j=k,i}^{p} \theta_{jk}(H)} \right] \times 100
\]  

The net pairwise spillover between markets \(i\) and \(j\) is simply the difference between the gross shocks transmitted from market \(i\) to market \(j\) and those transmitted from \(j\) to \(i\).

Fig. 3. Dynamic equicorrelation for stock indices and commodity futures; (a) within stocks; (b) gold-stocks; (c) WTI-stocks.
Table 4
Total volatility spillovers.

<table>
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<tr>
<th>To (i)</th>
<th>GOLD</th>
<th>WTI</th>
<th>WIDOW</th>
<th>W1SGI</th>
<th>DJIM</th>
<th>DJIBSC</th>
<th>DJJCYC</th>
<th>DJINCY</th>
<th>From (j)</th>
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Notes: The underlying variance decomposition is based on a daily VAR of order 4 (as determined by the Schwarz information criterion), identified using a generalized VAR spillover framework by Diebold and Yilmaz (2012). The (i,j)th element of the table shows the estimated contribution to the variance of the 10-day-ahead forecast error of i coming from innovations to variable j. The diagonal elements (i=j) are the own variance shares estimates, which show the fraction of the forecast error variance of market i that is due to its own shocks. The last column “From others” shows the spillover effects directed by a particular market to all other markets, while the row “To others” shows the spillover effect directed by a particular market to all other markets. The lower right corner “Total” indicates the level of total spillovers.

4. Data and preliminary analysis

4.1. Data

We use daily closing spot price data for gold, WTI crude oil and the aggregate and disagggregate Dow Jones Islamic sectoral indexes. The futures crude oil benchmark, the reference crude for the United States, is traded on NYMEX. Concerning the Islamic equities, they include the Dow Jones Islamic Market (DJIM) Index and the associated ten disaggregate sectors including Basic Materials, the Consumer Services, the Consumer Goods, the Energy, the Financials, the Health Care, the Industrials Index, the Technology, the Telecommunications, the Utilities. For comparison purposes, we consider the Dow Jones global index (W1DOW) and Dow Jones Islamic market (DJIM) Index and the aggregate Dow Jones Islamic Market (DJIM) Index and the associated ten disaggregate sectors including Basic Materials, the Consumer Services, the Consumer Goods, the Energy, the Financials, the Health Care, the Industrials Index, the Technology, the Telecommunications, the Utilities.

5 Table A1 in the Appendix summarizes the notations of these Islamic sectoral indexes, and the DJ aggregate conventional and sustainability indexes.

As an illustration, Fig. 1 shows the dynamics of return series under consideration during the sample period. We see that the commodity and stock returns are especially volatile after the mid-2008. The volatility clustering of oil market is more pronounced than gold market.

4.2. Preliminary analysis

We calculate the continuously compounded daily returns by taking the difference in the logarithms of two consecutive prices. Table 1 presents the descriptive statistics of the daily commodity, conventional Dow Jones global, Dow Jones sustainability equity index and Dow Jones Islamic (aggregate and sectors) stock return series. As shown in this table, the average daily returns are positive for all return series. Additionally, gold reveals the highest average returns, while the utilities present the lowest average returns. The unconditional volatility as measured by the standard deviation ranges is the highest for oil, followed by the technology index and the financial index. The gold price, the health care index and the consumer goods index are the least volatile among all indices. Note that the Dow Jones sustainability equity index is more volatile than both the conventional and Islamic (aggregate) equity indexes. The skewness coefficients are negative for the majority of the return series with the exception of the telecommunications, technology and utilities index return. The kurtosis coefficients are above three for all the return series which is the value for the Gaussian distributions. These findings show that the probability distributions of all return series are skewed and leptokurtic, thus rejects the normal distribution which is also confirmed by the Jarque-Bera statistic (JB). Further, we apply the conventional augmented Dickey and Fuller (1979) and the Phillips and Perron (1988) unit root statistics, and the stationarity property under the null using the Kwiatkowski et al. (1992) test. The results indicate that all return series are stationary.

Further, we examine the existence of the ARCH effects, which shows that all return series exhibit the ARCH behavior, underscoring that some stylized facts such as fat-tails, clustering volatility and persistence characterize the commodity and Islamic stock sector returns. Table 2 presents the results of the unconditional correlation levels between the conventional Dow Jones stock index, Dow Jones sustainability stock index, aggregate Islamic stock index, Islamic stock sectoral indexes, oil and gold market returns. The results show that the correlations between gold and Islamic stock sector index returns are close to zero or negative. In contrast, the correlations between oil and the Islamic index returns are...
positive and weak for all pairs. Similar results are found for correlations of the conventional stock index and the Dow Jones sustainability stock index with commodity markets as these correlations are positive and weak. More precisely, for the gold market, the highest correlation is with the energy sector, followed by the basic materials, while the lowest correlation is for the technology-gold pair followed by the consumer services-gold pair. Looking at the WTI crude, this market presents the highest (lowest) correlation with energy and basic materials (financial and consumer services) sectors. These results may be explained by the differences in the market concentration of some sectors. In fact, the basic materials sector is characterized by high market concentration. More interestingly, the Islamic stock sectoral indices are less correlated with gold than oil, implying the presence of more portfolio diversification benefits using the yellow metal than the black gold.

Finally, the long memory test results reveal the presence of long memory behavior for all squared return series (as a proxy variable of volatility), which clearly supports our decision to use the fractionally integrated APARCH-based approach to examine the issue of time-varying correlations among the markets under consideration. The results are available upon request.

5. Empirical results and policy implications

5.1. Marginal model results

To select the best marginal model, we examine different GARCH models (standard GARCH, FIGARCH, FIEGARCH and FIEGARCH) by considering different combinations of the parameters $p$, $q$, $r$ and $m$ for values ranging from zero to a maximum lag of 2. Table 3 presents the estimated results of the marginal model. The estimates of the univariate FIAPARCH model (Panel A) show that the one-lagged returns of the mean equation...
are positive and statistically significant at the 1% level for all stock returns (but not for gold and oil), indicating that the historical returns are instantaneously and rapidly embodied in the current returns for these stock markets. Moreover, the fractionally integrated coefficient \((d)\) is significant for all the markets considered, revealing a high level of persistence. Among the commodity markets, the highest \((d)\) parameter is bestowed on the WTI crude oil. Concerning the Islamic stock sectoral market indexes, the lowest long memory parameter is for the industrial sector, while the financial sector is the highest persistent sector. These results reflect the relative dissimilarity of weights between the sectors in the aggregate DJIM index.

Looking at the aggregate level, the conventional Dow Jones stock index is less persistent than both the Dow Jones sustainability and DJIM indexes. Moreover, the degree of freedom \((df)\) of the Student t-distributions are significant at the 1% level, suggesting that the tails of the error terms are heavier than those of the normal distribution. This result thus indicates that using the Student t-distribution to deal with these properties is appropriate.

Panel B of Table 3 presents the estimates of the DECO process. The \(a_{DECO}\) and \(b_{DECO}\) coefficients are positive and significant at the 1% level. This finding emphasizes the importance of shocks between the commodity and the Islamic stock sectoral markets. Furthermore, the \(b_{DECO}\) parameter is significant and very close to one, revealing a higher persistence of volatility across the considered markets. It is worth noting that the significance of the parameters \(a_{DECO}\) and \(b_{DECO}\) indicates the appropriateness of the DECO-FIAPARCH model in modeling the time-varying equicorrelations between the considered markets. Moreover, the sums of \(a_{DECO}\) and \(b_{DECO}\) coefficients are <1, indicating that the estimated DECO parameters lie within the range of typical estimates from the GARCH model. However, the dynamic equicorrelation is statistically significant at the 1% level. It is positive and less than one, suggesting the presence of diversification benefits. Investors can thus have the opportunity to allocate their portfolio in distinctive sectors.

The diagnostic tests summarized in Panel C show no evidence of misspecification in our marginal model. In fact, the Ljung-Box test statistics for the standardized residuals and the squared standardized residuals do not reject the null hypothesis of no serial correlation for most cases.

Fig. 6 displays the net pair-wise directional spillovers between gold, DJIM and both conventional, sustainability and the ten Islamic sectors—network diagram. The figure shows the net pair-wise directional spillovers between gold and both the aggregate and disaggregate Islamic stock markets. The size of a node shows the magnitude of a net transmission/reception TO/FROM gold. The colors of the nodes indicate the magnitude of net transmitters (red (strong), orange (medium), light blue (weak) and green (very weak)). The edge size underscores the magnitude of the pair-wise spillovers. The edge arrow indicates pairwise directional connectedness.

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between the considered markets, confirming the recoupling hypothesis. This significant increase in the cross-market correlations after a shock hits indicates a pure contagion or herding and may reflect a shift in investors’ appetite for or aversion to risk. It is worth noting that this is a minor crisis comparing to the 1997–1998 Asian crisis and the 2007–2008 GFC episodes. More interestingly, we show that the correlations are positive along the sample period and reflect phases of decreases and increases. This means that changes in the volatility transmission imply changes in diversification opportunities. In fact, contagion decreases the role of oil and gold as potential vehicles for diversification benefits. Looking at the sample after 2012, we view a decrease in the correlations for all cases, which is an indication of the presence of diversification benefits. The dynamic equicorrelation varies approximately between 0.2 and 0.7 but with elevated levels during the 2008–2009 GFC and the 2010–2012 ESDC, supporting the contagion effects.6

Fig. 3 plots the time-varying equicorrelation for the stock indices, the oil-stock and the gold-stock blocks. Similarly to Fig. 2, we observe a variation in the correlations. Also, the trajectories of all blocks are similar but with differences in magnitude. Graphically, we see that the correlations between gold and stock are lower than those of only stock or oil-stock. To sum up, investors investing in Islamic stock companies may see more benefits in diversifying and investing in the gold and oil markets. The presence of positive and increasing correlations underscores an increasing integration between commodity and Islamic stock markets during the last years.

5.2. Total volatility spillover index and rolling-sample spillover analysis

Table 4 summarizes the estimates of the total volatility spillover matrix. The $(i,j)$th entry in each panel is the estimated contribution to the forecast-error variance of variable $i$ coming from innovations of market $j$. The row sums excluding the main diagonal elements (termed ‘From others’) and the column sums (termed ‘To others’) report the total spillovers to (received by) and from (transmitted by) each volatility.

The total volatility spillovers reach 79.79%. Looking at the directional spillovers transmitted ‘To others’, gold has a much lower impact on the Islamic stock markets than the crude oil market does. In fact, gold contributes only 0.58% to the forecast-error variance of the DJIM index, 1.03% to the forecast-error variance of oil and 7.94% to those of the associated Islamic sectors, 0.72% to the conventional DJ global index, 0.65% to the DJ sustainability index, while oil contributes 1.67% to that of the DJIM index, 15.24% to those of the ten sectors and the remaining to both conventional and sustainability Dow Jones index.

Islamic stock indexes also contribute to the forecasting error variance of the gold metal and oil markets. In fact, the DJIM index contributes 128% to the remaining markets (oil, gold, conventional index, sustainability index and the ten sector indexes). This index also contributes 2.78% to the forecasting-error variance of gold and 4.24% to that of oil. Oil and gold respectively contribute 0.167% and 0.58% to the forecasting variance of the DJIM index. This result indicates that gold provides greater diversification benefits than oil market. On the other hand, oil acts as a price discovery tool for the DJIM index. Conventional DJ global index and sustainability index contributes significantly to the aggregate and disaggregate Islamic indexes.

Among the Islamic sectors, the consumer goods and the industrials are the highest net volatility contributors, while the finance, the technology and the telecommunication are the lowest contributors to

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6 Forbes and Rigobon (2002) define the contagion as a significant increase in cross-market linkages after a shock to one country (or a group of countries). Thus, contagion does not occur if two markets show a high degree of comovement during both stability and crisis periods. The interdependence is used instead if strong linkages between the two economies exist in all states of the world. Ahmad et al. (2013) define the contagion as significant increases in cross market correlations during the turmoil period, while any continued increase in cross market correlation at high levels is referred to as interdependence.
Fig. 8. Net volatility spillover index. Notes: The notations are defined in the appendix.
Fig. 8 (continued).
volatility spillovers. Further, the risk spillovers between the Islamic stock sectoral markets are globally weak. Taking for example the industrial sector, the risk spillover coefficient varies between 6.4% for the telecommunications sector and 10.28% for the technology sector. For the financial sectors, these sectors receive similar risk spillovers from the industrials. Looking at the telecommunications sector, one can see that this sector has similar spillovers to the rest of the financial sectors, with the exception of technology. The interpretations of the remaining sectors are similar.

Fig. 4 plots the risk spillover network diagram and shows that conventional stock index, sustainability stock index, DJIM and the cyclical basic materials and industrials sectors are among the largest net receivers of shocks from the rest of the markets. Figs. 5 and 6 display respectively the net pairwise directional spillovers between the oil- stock and the gold- stock pairs. These figures synthetically display the main results for our dynamic analysis of the net pairwise directional connectedness. They provide a visualization of the complex network of innovation among 15 markets. In fact, they synthetically illustrate the main results of our analysis of the net directional connectedness using the DY’s (2014) graphical methodology. We show that gold imports volatility from financial sectors, while oil imports volatility from the aggregate DJIM index and the cyclical basic materials and industrials sectors (see Figs. 5 & 6).

Table 6

Optimal portfolio weights and hedge ratios for the commodity futures and stock indices.

<table>
<thead>
<tr>
<th>Pairs</th>
<th>Optimal portfolio weights</th>
<th>Hedge ratios</th>
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<tr>
<td></td>
<td>Mean</td>
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<tr>
<td>W1DOW/Gold</td>
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<td>DJITL/G Gold</td>
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<td>DJIBSC/WTI</td>
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<td>0.1243</td>
</tr>
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</table>

Note: This table reports the optimal weight of a commodity (ωi) at time t in a commodity-Islamic sector (or conventional or sustainability) stock portfolio, while the corresponding remaining portions are for equities. It also summarizes the hedge ratio consisting of a long position of one USD in the (Islamic, conventional or sustainability) sectoral stock market hedged by a short position of β USD in the commodity market.
Fig. 10. Time-varying hedge ratios between the GOLD and stock markets.
More precisely, the volatility spillovers attain their maximum level during the turbulent years 2008–2009 and 2010–2012, which correspond to the GFC and ESDC periods. In addition, we can conclude that the time-varying volatility spillovers can be affected by other major economic events like the high oil price instability in summer 2008 and January 2014, the 2003 gulf war and the 2007–2008 commodity crisis. These major events increase the spillovers between these markets, and thereby decrease the investment diversification opportunities.

5.3. Net volatility spillover and robustness tests

We deepen our study by determining the directional volatility spillovers among the conventional, sustainability, Islamic sector and commodity markets. In fact, we determine the net receivers and net contributors to volatility spillovers. Specifically, we decompose the total volatility spillover index into two directional spillovers as illustrated in Table 5: (i) the receiver of volatility spillovers, termed directionally as ‘from’, and (ii) the transmitter of volatility spillovers, termed directionally as ‘to’. The dynamic net volatility spillover index is then quantified by subtracting directional ‘to’ spillovers from directional ‘from’ spillovers. Then positive (negative) values indicate a source (recipient) of return and volatility to (from) others. The results (shown in Table 5) indicate that oil and gold are net receivers of volatility, while the conventional index, the sustainability index and the DJIM index are net contributors to volatility spillovers. Regarding the Islamic sectors, five out of the ten sectors are net contributors to volatility. These sectors are the consumer services, consumer goods, health care, industrials and utilities sectors. The remaining sectors are net receivers of volatility. Among the ten sectors, the highly cyclical industrial sector is the most contributor of risk to the other markets, while the financial
sector is the most receiver of risk from the other markets. Financial sectors are marked by their volatility. For the two commodities, oil is a more receiver of shocks than gold is, which is significantly used in central banks' international reserves and is a store of value. Oil is a cyclical commodity, while gold is a safe haven.

The graphical evidence shown in Fig. 8 confirms the results of Tables 4–5. The figure plots the time-variations of the net volatility spillover index for each Islamic stock sector, the conventional index, the sustainability index, gold and oil, and highlights that the magnitude of volatility spillovers has often changed during the GFC.

To do the robustness analysis, we have conducted two tests to check the sensitivity of the spillover results. First, we check the choice of the order of the VAR. For this purpose, we compute the spillover index for orders 2 to 6 and plot the minimum, maximum, and the median values in Fig. 9(a). Second, we plot the index for the forecast horizons varying from 5 to 10 days in Fig. 9(b). These figures show that the spillover indexes appear to follow similar patterns whatever the choice of the order of the VAR or the choice of the forecast horizon, suggesting that the total spillover plot is not sensitive to the choice of the order of the VAR or the choice of the forecast horizon. Similar alternative values as robustness tests are also adopted by previous studies in the literature (Diebold and Yilmaz, 2009, 2012, 2014; Chau and Deesomsak, 2014; Antonakakis and Kizys, 2015 among others).
5.4. Portfolio risk implications

The empirical evidence reported above has important implications in terms of asset allocations and portfolio risk management. To help individual and institutional investors make more informed decisions, we thus analyze the usefulness of the oil and gold commodity markets in constructing better portfolios. Specifically, we follow Mensi et al. (2015a) to investigate the usefulness of these commodity markets in having better portfolio risk management of the conventional index, the sustainability index and the Islamic stock sectoral markets. We compare the risks for three different portfolios with that of a benchmark portfolio (Portfolio I) composed exclusively of the stock indexes in this case. We could thus assess the potential reduction in the portfolio risk generated by the inclusion of commodities in a more diversified portfolio.

First, we consider the risk-minimizing commodity-stock (sector) portfolio (Portfolio II) without reducing the expected return. According to Kroner and Ng (1998), at time $t$ the optimal weight of a commodity in this portfolio ($w^C_t$) is given by:

$$ w^C_t = -\frac{h^C_t - h^{CS}_t}{h^C_t - 2h^{CS}_t + h^S_t}, $$

where $(h^C_t), (h^{CS}_t)$ and $(h^{CS}_t)$ are the conditional volatility of a commodity market, the conditional volatility of the stock market and the conditional covariance between the commodity and the stock markets at time $t$, respectively. From the budget constraint, the optimal weight of the (conventional or sustainability or Islamic) sector market is equal to $(1 - w^C_t)$. For each commodity-(conventional, sustainability or Islamic) stock pair, all information needed to compute $w^C_t$ is obtained from the bivariate DECO-FIAPARCH model with Student-$t$ distributions.

Second, we consider another portfolio where the weights are exogenously determined (Portfolio III), i.e., an equally weighted portfolio, which usually has a good out-of-sample performance (DeMiguel et al., 2009). Finally, we consider a fourth portfolio where the weights are determined according to a variance minimization-hedging strategy (Portfolio IV), consisting of a long position of one USD in the (conventional, sustainability or Islamic) aggregate or sectoral stock market hedged by a short position of $\beta$ USD in the commodity market, where $\beta$ at time $t$ is given by:

$$ \beta_t = \frac{h^{CS}_t}{h^C_t}. $$

The risk-reduction effectiveness of each portfolio is evaluated by comparing the percentage reduction in the variance of any portfolio with respect to that of Portfolio I, expressed as:

$$ RE_{Var} = 1 - \frac{\text{Var}(P_i)}{\text{Var}(P_I)}, $$

where $\text{Var}(P_j)$ and $\text{Var}(P_I)$ are the variances of Portfolio $j$ and Portfolio I, respectively, and $j = II, III, IV$ for the portfolios. $RE_{Var}$ takes values in $[0,1]$, where a higher value indicates a greater variance reduction.

Further, we assess the attractiveness of the commodity markets (oil and gold) in providing downside risk protection, using three different downside risk measures. For each portfolio, we estimate the Value-at-Risk (VaR), the Semivariance (SV) and the Regret (Re). The VaR provides the maximum loss in a portfolio value for a given time period and a given confidence level.\footnote{The reader can refer to Mensi et al. (2015a) for further information on the specification of these risk measures.}

The downside risk gains are evaluated by considering the downside risk reductions for Portfolios II, III and IV with respect to Portfolio I, using the risk-reduction ratio in Eq. (21) for each downside risk measure.

Table 6 shows the optimal portfolio weights and the hedge ratios for the conventional index, the sustainability index, Islamic sector indices and the commodity futures (oil and gold). Let us take the gold asset first. We find that investors should hold 32.72% of this yellow metal and 67.28% of the budget in the DJIM index. For the gold-Islamic sector pairs, the optimal weight for gold varies between 2.86% for the consumer goods sector and 60.86% for the energy sector. This result means that for the consumer goods sector the optimal weight of the gold holding in a one-dollar gold stock portfolio should be 2.86%, while the remaining 97.14% should be invested in the consumer goods. Similar interpretations hold for the other sectors and both conventional and sustainability indices. On the whole, we conclude that investors should hold more stocks than gold in their portfolios in order to minimize the risk while keeping the expected return unchanged. More interestingly, the net receiver sectors (energy, finance, telecommunication and technology) require more commodity assets than the net contributor sectors.

As for the WTI crude oil, we find that investors should also hold more (Islamic, conventional and sustainability) stocks than oil in their portfolios. By comparing the oil and gold markets, an investor should hold a greater proportion of her wealth in a gold- stock pair than in an oil-stock pair in order to minimize risk. This result is explained by the better diversification benefits bestowed by gold on portfolios, compared to the high instability of the oil market. The value of the hedge ratio is higher when the investor uses gold than oil to do hedging. Taking for example the gold-DJIM pair, a hedge ratio of 0.3986 implies that one USD long in gold should be shorted by about 39.86% of the DJIM index. Similar interpretations are valid for the other cases.

Fig. 10 displays the dynamic hedge ratios across the gold and stock markets. The paths suggest a variability is in order for the estimated hedge ratio. In fact, we observe significant time-varying hedge ratios over the sample data, suggesting a dissimilarity between the Islamic sectors, conventional and sustainability indexes and also a switching behavior of investors toward risk. Therefore, investors adjust their portfolio structure and hedging positions frequently according to the (Islamic, conventional and sustainability) stock and commodity market conditions (bear, normal and bull markets).

To deepen our analysis, we assess the risk and downside risk-reductions of the different pairs. The risk evaluation results for the oil-stock and the oil-stock pairs at the 99% confidence level are presented in Tables 7–8. Viewing Table 7, the optimally weighted Portfolio II offers the best risk reduction and the largest downside risk reduction for the conventional index, the sustainability index, the DJIM index, and the consumer services, consumer goods, health care and industrials sectors. For the remaining sectors, Portfolio IV provides the best performance in terms of risk reduction, VaR reduction, semivariance and regret reduction. It is worth noting that among the ten Islamic sectors, the best risk reductions are detected for the technology sector, followed by the energy and industrials sectors. The highest risk reduction is for the basic material-gold pairs followed by the energy-gold and the consumer services-gold pairs. These results indicate that including gold in the Islamic stock portfolios helps investors to manage effectively their portfolios.

For the oil market (see Table 8), we find that for all cases the optimally weighted Portfolio II offers the best risk reduction and the largest downside risk reduction than the other competing portfolios (i.e., Portfolio II and Portfolio III). Among the Islamic stock sectors, we show that the basic materials, energy and technology sectors present higher risk reductions and VaR reductions than the remaining sectors. This result shows that investors attain the highest risk reductions by including oil in the stock portfolio.
6. Conclusion

International stock markets and major commodities (particularly gold and oil) have recently become more integrated due to the financialization of commodity markets and the globalization of financial markets. These developments in the world’s asset markets have made hedging more difficult, and thereby reducing the benefits from diversification. On the other hand, understanding the risk spillovers between the major commodities (oil and gold) and the behaviors of new business models such as the Islamic stock markets (particularly at the sectoral level) is of great importance for the purpose of asset allocation and portfolio risk management.

The aim of this paper is to examine the risk spillovers between the two major commodity markets, crude oil and gold, and the aggregate Dow Jones Islamic index and its associated ten stock sectors, using the dynamic equicorrelation models and the Diebold and Yilmaz (2012) index. For comparison purposes, we consider the aggregate conventional and sustainability indexes. The current study is conducted on daily data over the period November 9, 1998 through March 5, 2015, which includes several major financial crises that are accused of increasing correlations and causing portfolio re-balances. It also evaluates four portfolios in terms of risk reduction and downside risk reduction, using the risk measures VaR, semivariance and regret tools.

Our results find a dynamic equicorrelation between all the commodity and Islamic markets under consideration, as explained earlier. Moreover, the equicorrelation increases during the 2008–2009 global financial crisis period. Using the DY index, we show time-varying risk spillovers between oil, gold and the aggregate and the associated ten Islamic sectoral stock indexes. More interestingly, the results reveal that both the oil and gold markets and the Islamic energy, financial, technology and telecommunications sectors are net receivers of risk spillovers, while the DJJM index, consumer goods, services, health care, industrials, utilities sectors are net contributors to risk spillovers. The basic materials sector is found to be risk spillover-neutral.

Using the downside risk reduction measures the VaR, semivariance and regret measures, we find that the optimally weighted portfolio offers the best risk reduction and the largest downside risk reduction for all the oil-Islamic sector pairs, the gold-DJJM, the gold-Islamic consumer services, the gold-Islamic consumer goods, the gold-Islamic health care and the gold-Islamic industrials sector. For the rest of the gold-Islamic sector pairs, the hedged portfolio provides the best risk reduction. Additionally, gold offers better diversification benefits, risk reductions and downside risk reductions than oil. Based on this result, we can recommend gold as a better diversifier and risk reducer than oil. This finding may fit well with many of the wealthy faithful individual and institutional investors who reside in major oil-producing countries whose economies and stock markets are propelled by oil revenues. Further, the Islamic equity sectors show an increasing financial integration with the commodity markets. But these sectors do not respond in similar ways to the commodity price shocks. The basic materials, energy, financial, telecommunications and technology sectors are net risk receivers of spillovers, while the rest of sectors are net risk contributors.

Investors can consider commodity prices to predict the sector equity prices. More interestingly, investors have the opportunity to allocate their portfolio in distinctive sectors. Finally, gold is helpful for investors dealing with the technology sector, while those investing in the basic materials sector can include oil in their portfolios for risk-reduction purposes. Finally, the Sharia-compliance rules are not restrictive enough to make the Islamic stock equity market very different from the conventional indexes and immune against commodity price shocks.

The results have important implications for investors and portfolio managers. Investing in gold as a complement to Islamic sector investments offers a better way for the investor to diversify their portfolio when their expectations are heterogeneous in terms of risk tolerance and time preference. It will be intriguing in the future to extend this work by considering the impact of oil and gold on Islamic sector stock market liquidity in the short, medium and long runs.

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Appendix A. Supplementary data

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