ONLINE Appendix

This online appendix provides the technical discussions that are not included in the text due to space limitation. Please refer to the paper for the Tables and Figures referenced in this appendix.


A1. Regime properties

Panel C in Table 2 presents several statistics describing the properties of the three market regimes identified by formal tests explained earlier. We observe that the first regime is the most persistent regime with an average duration of 7.36 weeks. The smoothed probability estimates presented in Figure 1 indicate that the first regime largely corresponds to periods of lowest historical volatility (2006–2008, mid 2010–mid 2011, 2012– mid 2013, and the post-2013 period). The second regime is the least persistent regime with an average duration of 2.80 weeks and the smoothed probability estimates in Figure 1 suggest that this regime mainly corresponds to high volatility periods surrounding large market downturns or crashes in global markets. On the other hand, the third regime, which is more persistent than the high volatility regime, corresponds to the period from mid-2008 to the end of 2009, exactly matching the largest crash in the Islamic bond market following the credit crunch of 2007/2008 and the global recession.¹ We find that the average duration for the crash regime is 3.15 weeks while the smoothed probability estimates for this regime equal 1 due to the prolonged crash period. Further examining the regime statistics in Panel C of Table 2, we observe long-run probabilities of 60%, 31%, and 9% for the low, high, and extreme (or crash) volatility regimes, respectively. Overall, the analysis of regime properties provides further support for the three-regime specification and suggests that the third regime is not a statistical artifact, but in fact, proxies a structural break in return dynamics.

¹ Regime switching parameters of the MS-DCC-GARCH model relate to correlations. It is rather difficult to specify the regimes based on correlations since correlations are dynamic and do not follow a systematic pattern across the regimes. As a matter of practical convenience, we specify the regimes based on the periods that the maximum of the smoothed probability estimates correspond to. These periods differ markedly in terms of their volatility levels.
Panel B presents the estimates for parameters $\alpha(s_t)$ and $\beta(s_t)$, $s_t \in \{1, 2, 3\}$, that generate regime-specific conditional correlations in the MS-DCC-GARCH model. We observe that $\alpha(s_t)$ and $\beta(s_t)$ estimates are highly significant at 1% level for all three regimes, indicating significant time-varying or regime-dependent dynamic correlations among the series in all regimes. However, observing different estimates for $\alpha(s_t) + \beta(s_t)$ across the different regimes, i.e. 0.97, 0.90, and 0.78 for the low, high, and extreme volatility regimes respectively, suggests that these regimes are characterized by very different dynamic correlation structures. Since these parameters control correlation persistence implied by the model, we conclude that the correlations are more persistent in the low volatility regime than in the high and extreme volatility regimes. Moreover, higher values of $\alpha(s_t) + \beta(s_t)$ for the low and high volatility regimes imply that the correlation persistence is more pronounced in these regimes.

A2. Volatility spillover analysis

The generalized multivariate specification in Equations (1) and (2) allows eight possible volatility transmission channels to Islamic bonds, i.e. from conventional and Islamic stock markets (developed, emerging, and Islamic), from conventional bond markets (developed and emerging), as well as from proxies of global risk sentiment and liquidity represented by the U.S. and emerging market volatility indexes (VIX) and U.S. Treasuries, respectively.² It must be noted, however, that the spillover parameters estimated by the multivariate model measure the partial effects as the model considers all interactions among the return series. It is therefore possible to obtain different results in a bivariate framework. However, the bivariate specification would fail to consider interactions among these markets in a broad context. Thus, the multivariate specification allows us to discover a more accurate picture of the volatility interactions which would not be possible to explore in a bivariate framework.

Panel A in Table 2 reports the parameter estimates of the MS-DCC-GARCH model for Islamic bond returns. The volatility spillover parameters \((a_{i,j}, b_{i,j})\) relating to Equation (2) are generally found to be highly significant, implying significant risk transmission from conventional stock and bond markets to Islamic bonds. We observe a highly significant and negative spillover effect from developed bonds whereas a positive spillover effect is observed from emerging market bonds. This suggests that positive fundamentals in bond markets from advanced nations would decrease conditional volatility in the market for Islamic bonds. On the other hand, uncertainty surrounding emerging bond market returns spills over to the market for Islamic bonds, implying an association of risk across emerging conventional and Islamic bond markets. Similarly, our findings do not yield any risk transmission from Islamic bonds to developed bonds whereas a positive spillover effect is observed from Islamic bonds to emerging market bonds. The bi-directional risk transmission between Islamic and emerging market bonds suggests the presence of common fundamentals affecting emerging and Sharia-compliant bond markets.

In the case of volatility spillovers from stock markets to Islamic bonds, we find a significant positive spillover effect from developed stock markets to Islamic bonds whereas negative volatility spillovers are observed from emerging market stocks as well as Islamic stocks to the market for Islamic bonds. It is possible that good news in emerging equity markets (including Islamic equities) diverts global capital to these equity market segments, crowding out funds in the market for Islamic bonds, thus leading to a negative spillover effect. As will be discussed in the next section, the regime-switching dynamic correlations also support the negative association between Islamic bonds and Islamic and emerging market stocks.

Table A1 in this appendix presents the results of volatility spillover tests. We report three formal tests in this table. The first is a multivariate Wald (MV-Wald) test involving two zero restrictions on the relevant elements of matrices \(A\) and \(B\). For example, the null hypothesis of no volatility spillover from the emerging market bonds to Islamic bonds is tested by imposing the
restriction $a_{13} = b_{13} = 0$. The second is the bivariate causality in variance test (HH) of Hafner and Herwartz (2006). This test is an LM test and avoids estimation of a possibly complicated model under the alternative. The third volatility spillover test is the bivariate robust LM causality in variance test (NT) of Nakatani and Teräsvirta (2010) which is also an LM test based on a univariate GARCH model that is robust to mis-specified zero conditional correlations. In the last row of Table A1, we also present a joint volatility spillover test from all other variables to Islamic bonds.

The direct test of volatility spillover based on the MV-Wald test does not reject volatility spillover form any of the markets examined to Islamic bonds at 1% significance level. This suggests that the MV-WALD test indicates significant volatility spillovers from conventional bond and stock markets as well as from proxies of global risk and liquidity conditions. Not surprisingly, the MV-WALD test also suggests significant risk transmission from Islamic stocks to the market for Islamic bonds. The joint volatility test further supports the individual tests, suggesting volatility spillovers to Islamic bonds.

Examining the findings for the causality in variance tests, we observe that the HH test rejects the no causality in variance hypothesis for any of the variables examined at 1% level, further supporting the findings from the MV-Wald tests. On the other hand, we observe that the robust NT test does not reject the null of no causality in variance hypothesis for emerging market related variables, i.e. bonds, stocks, and the volatility index, whereas the test results for all other markets are consistent with the first two formal spillover tests. Overall, our analysis yields significant evidence of volatility spillovers from conventional developed markets to the market for Islamic bonds. Spillover tests for emerging markets provide mixed evidence, however, with the NT causality in variance test suggesting no significant spillover effect from emerging markets while the MV-Wald and HH tests indicate otherwise.

\textit{A3. Dynamic conditional correlations}
The specification in Equations (1) through (3) allows for regime-specific conditional correlations where regime-switching is governed by a discrete Markov process. A battery of tests discussed in Section 4.2 clearly point to a three-regime model in which three distinct market regimes are identified in terms of the level of return volatility. As shown in Panel (c) in Figure 1, the extreme (crash) volatility regime, accounts largely for the global financial crisis period with the maximum regime probability observed for this regime during the second half of 2008 and late 2009. This suggests that the third regime is not simply a statistical artifact, but proxies a true market regime observed during the crisis period. Similarly, high volatility regime is observed during late 2007 and early 2008 while episodes of high volatility regime are also observed during the first and second Greek bailout periods in mid-2010 as well as during late 2011.

Figure 2 presents the plots for the dynamic correlations between Islamic bond returns and the other variables included in the analysis. Since the correlations are estimated as regime-specific correlations, we compute the regime independent correlation between markets $i$ and $j$ for period $t$ as

$$\rho_{ij,t} = p_{1,t} \rho_{ij,1,t} + p_{2,t} \rho_{ij,2,t} + p_{3,t} \rho_{ij,3,t}$$

where $p_{k,t} = P(s_t = k \mid \psi_{t-1})$ and $k=1,2,3$, is the predictive probability of being in regime $k$ at time $t$. We observe that the dynamic correlation estimates presented in Figure 2 are highly time-varying, providing support for the DCC specification against a constant correlation specification. Examining the correlations between Islamic bonds and conventional counterparts, we observe a significant structural break in late 2008 with the correlations displaying a positive trend after this period. On the other hand, examining the correlations between Islamic bonds and stock markets, we observe fairly low correlation values not exceeding 20% in most cases. This implies the presence of diversification potential of these bonds for conventional as well as Islamic stock portfolios. Interestingly, we observe negative correlations between Islamic bonds and conventional stock markets more significantly during the 2008 global crisis period, suggesting that Islamic bonds could have served as a safe haven for stock market investors during that period. The finding of negative dynamic correlations between Islamic stock
and bond markets is consistent with Aloui et al. (2015) who point to the “flight to quality” phenomenon that drives comovement dynamics across stock and bond markets. Overall, our analysis of dynamic conditional correlations clearly suggest a low degree of association between Islamic bonds and stock market returns with episodes of negative correlations observed, particularly during market crisis periods.

References

Eichengreen, B., Mody, A., 1998. Interest rate in the north and capital flows to the south: is there a missing link? International Finance 1, 35-57.


### Table A1: Volatility Spillover Tests

<table>
<thead>
<tr>
<th>Cause Variable</th>
<th>MV-Wald</th>
<th>HH</th>
<th>NT-NR</th>
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<tr>
<td>DEVBOND</td>
<td>996.089***</td>
<td>14.397***</td>
<td>16.380***</td>
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<tr>
<td>EMRBOND</td>
<td>1537.635***</td>
<td>15.734***</td>
<td>2.542</td>
</tr>
<tr>
<td>DEVSTOCK</td>
<td>1070.775***</td>
<td>121.275***</td>
<td>12.302**</td>
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<tr>
<td>EMRSTOCK</td>
<td>147.987***</td>
<td>128.358***</td>
<td>4.587</td>
</tr>
<tr>
<td>ISLSTOCK</td>
<td>3784.835***</td>
<td>94.638***</td>
<td>11.375**</td>
</tr>
<tr>
<td>USVIX</td>
<td>1921.626***</td>
<td>32.025***</td>
<td>7.833*</td>
</tr>
<tr>
<td>EMRVIX</td>
<td>1205.291***</td>
<td>23.226***</td>
<td>0.827</td>
</tr>
<tr>
<td>USTB10</td>
<td>1196.118***</td>
<td>16.203***</td>
<td>13.992***</td>
</tr>
<tr>
<td>Joint</td>
<td>24878.878***</td>
<td>264.221***</td>
<td>229.016***</td>
</tr>
</tbody>
</table>

**Note:** The table reports the test results for the null hypothesis of no volatility spillover from the variables in the first column to Islamic bonds as well as a joint volatility spillover test from all other variables to Islamic bonds. The multivariate Wald (MV-Wald) tests are reported for the no volatility spillover restrictions imposed on Equation (1). The MV-Wald test is distributed as Chi-square with 2 degrees of freedom. HH test is the Hafner and Herwartz (2006) LM test of causality on conditional variance. NT is the Nakatani and Teräsvirta (2010) robust test of the causality in conditional variance. HH and NT tests are LM tests and GARCH(1,1) is used for univariate specification of conditional variances. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.