From dotcom to Covid-19: A convergence analysis of Islamic investments

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Abstract

This paper goes beyond the extant comparisons of Islamic and conventional investments by econometrically assessing their convergence dynamics, in a dataset spanning over 1996-2020, covering ten business sectors and five episodes of crisis. We use a dynamic multivariate framework to estimate time-varying correlations, which we submit to beta and sigma-convergence analysis. Subsequently we examine how convergence dynamics affect portfolio risk management and crisis propagation. Our results show strong convergence of Islamic and conventional investments. During crises conventional convergence rates double, but Islamic ones are less affected. Sectoral diversification works best for conventional investments; Islamic ones behave as a single entity. On average we document a 7% risk diversification benefit from Islamic investments, at a 64 basis points cost. Yet, at the epicentre of the Covid-19 financial crisis this rises to 466 basis points and highlights the resilience of these investments in an exogenous event. Islamic investments reduce volatility spillovers in the financial system, but they are progressively less insulated across time. Our findings withstand a battery of robustness checks and are primarily useful to policy makers and investors.

Keywords: Convergence; Contagion; Crisis; Difference-in-difference; Dynamic correlation; Economy sectors; Islamic finance; Portfolio

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1. Introduction

In modern finance the unrestricted portfolio of investments is considered the best option for an investor wishing to allocate funds. This view may be contrasted with the appeal of ethical, environmental, sustainable, faith-based as well as social and responsible investments over the past couple of decades (EUROSIF, 2014); a trend partially aided by financial crises (e.g., dotcom technology bubble, Global Financial Crisis) and financial scandals (e.g., Enron). A commonality of these investments is the selection procedure entailed, which allows non-financial attributes to influence investments (Riedl & Smeets, 2017). From an investor perspective the gain from such investments may be superior return, lower risk during crisis, reputation management or a kind of "emotional dividend" (Bollen, 2007; Riedl & Smeets, 2017). Investments classified as Islamic or Shariah-compliant may be viewed as religious-based ethical investments.[2] They feature multiple business type (e.g., alcohol, tobacco) and financial screening criteria (e.g., leverage), which are transparent and standardised across providers of such investments.[3]

Islamic finance is establishing itself on the global financial system with total assets under management more than two trillion US dollars, with a high annual growth rate and investment returns (IFSB, 2019). These growth characteristics have spurred interest from practitioners and academics alike, with a range of studies focusing on the comparative performance across a wide array of assets, financial institutions, metrics and market conditions. Islamic stock returns are explained by standard financial and macroeconomic characteristics; thus showing resemblance to the conventional stock universe (Narayan et al., 2016). Similarly to conventional markets, Islamic markets react to news (Almansour & Ongena, 2018; El Ouadghiri & Peillex, 2018; Narayan & Bannigidadmath, 2017). It is often argued that trading strategies involving Islamic stocks have superior returns (Alaoui et al., 2015; Narayan & Phan, 2017), but this is often counterweighted by the risk these stocks typically exhibit (Narayan et al., 2017; Narayan & Phan, 2017) or is method and/or sample-dependent. No "Islamic factor" has been verified for stock returns. In terms of risk, Islamic stocks have been found to be less affected by crises (Erragragui et al., 2018; Kenourgios et al., 2016; Rizvi et al., 2015; Sensoy, 2016) owing to their leverage restrictions (Durand et al., 2013).[4] Empirical evidence suggests that Islamic markets are aligned to their conventional counterparts (Ajmi et al., 2014; Alaoui et al., 2015; Alexakis et al., 2017; Hammoudeh et al., 2014; Hkiri et al., 2017; Mazouz et al., 2016; Paltrinieri et al., 2019), and these co-movements have increased the formers' vulnerability to crises (Alaoui et al., 2015; Yarovaya et al., 2021). Overall, the inclusion of Islamic investments in a portfolio reduces risk particularly during financial crises (Balcilar et al., 2015; Mensi et al., 2017), although performance-wise significant gains are not warranted (Ashraf, 2016; Nainggolan et al., 2016). For more comprehensive reviews we direct you to Delle Foglie and Panetta (2020) and Narayan and Phan (2019).

However, studies related to stock markets are typically *point-in-time* investigations that compare and contrast the "performance" of Islamic and conventional investments; thus, supporting or refuting the

[2] Islamic finance is considered a form of ethical finance and a topic of great ambiguity (Jawadi et al., 2018b). Proponents argue that unique features, such as the shunning of interest, debt instruments and complex derivatives as well as the use of risk-sharing and equity participation to mobilise investments, create a new financial paradigm and enhance ethical investing. Critics argue that the differences between the theoretically envisaged Islamic financial model and what is observed in reality are substantial (F. Khan, 2010). For a quick introduction to Islamic finance products and cross-country differences, we direct you to M. M. Khan and Bhatti (2008).

[3] By contrast, the screening procedure of environmental, ethical and socially responsible investments (e.g., S&P Environmental & Socially Responsible Index, MSCI ESG Indices) shows high heterogeneity as the taxonomies of such investments are not clearly defined with attempts to rectify this led by the EU Commission's action plan (EU, 2019b, 2019a).

[4] A similar conclusion is reached for Islamic equity funds (Erragragui et al. 2018, Nainggolan et al. 2016).

claim that Islamic investments are different.[5] Our approach is different, insofar as it is *dynamic* in design. First, we investigate the convergence between Islamic and conventional investments across a long period of time. Second, we conduct a series of analyses spanning from the dotcom to the Covid-19 exogenous shock whereby each compares the performance of Islamic and conventional investments. Hence our approach not only examines the *difference* between Islamic and conventional investments, but also how this has *changed* (i.e., converged) across time. Despite the plethora of comparative studies in this field, we are only aware of two convergence studies, which deal with performance and efficiency of Islamic and conventional banks (Johnes et al., 2021; Olson & Zoubi, 2017); no study has yet investigated convergence between Islamic and conventional investments.

Theoretically a convergence may be expected for several reasons.[6] First, due to worldwide financial integration, common regulatory frameworks, trade and monetary unions, global banking presence and cross-country investment holdings. Second, in most countries Islamic financial institutions operate alongside conventional ones, competing for a similar pool of customers.[7] Competitive forces may induce a mimicking behaviour of Islamic financial institutions; thus transforming conventional products covering particular needs into Shariah-compliant ones. For example, credit cards would not have been permissible in the theoretical paradigm of Islamic finance (Usmani, 2002), but in order to satisfy customer needs, such instruments have been made available through Shariah-compliant financial engineering (Çokgezen & Kuran, 2015). Likewise, Islamic preferred shares have been introduced as conventional preferred shares are prohibited due to the contractual payment offered to the holder, which is similar to interest rate (Al-Suhaibani & Naifar, 2014). Fintech entrepreneurs are working on a Shariah-compliant cryptocurrency in order to make this type of investment available to users of Islamic finance, while digital Islamic banks are also being introduced (FT, 2019; IslamicMarkets, 2020).[8] Involvement of large Western banks in Islamic finance through dedicated subsidiaries (e.g., Islamic windows) and increasing competition between Islamic and conventional banks, see Azmat et al. (2020), may be expected to aggravate this trend. Third, several conditions, both of a financial and a business nature, need to be verified for an investment to be classified as Islamic, and such rules and thresholds are subject to revision. For example, the Malaysian Securities Exchange Commission (SEC) has long been regarded as quite "liberal" by allowing higher percentages of non-permissible income, in an attempt to boost the investible universe of Shariah-compliant stocks, contrarily to the practices of the Middle-East countries.[9] Post-2013, the SEC has aligned itself with the thresholds employed by DJ/MSCI in an attempt to increase worldwide standardisation. Fourth, unethical firm behaviour that is uncovered and made public has a negative impact on the value of the stock (Rao & Hamilton, 1996). Unethical behaviour (or rumours of) being uncovered and made public is arguably amplified by the increasing use of the internet and the social

[5] A similar argument is applicable for Islamic banks, which have been shown to be more profitable (Hasan & Dridi, 2011), feature superior asset quality and capitalisation (Beck et al., 2013); have superior risk profile (Abedifar et al., 2013; Baele et al., 2014; Čihák & Hesse, 2010; Misman & Bhatti, 2020; Pappas et al., 2017), exhibit higher technical efficiency (Johnes et al., 2014), and exert a certain customer loyalty (Beck et al., 2019) relative to conventional banks. We direct you to Hassan and Aliyu (2018) for a comprehensive review on Islamic banking.

[6] The convergence process relates to certain observable characteristics, making no direct connection to the largely unobserved practices within Islamic financial product structuring.

[7] Islamic financial institutions may have a theoretical advantage in attracting religious customers. However, in practice, whether the religiosity of the customer would depend on factors like the remuneration differential between Islamic and conventional financial institutions, the disposable income, or country characteristics, among others, has not been explored. Nevertheless, even in countries that are Muslim dominated, the percentage of Islamic banking assets does not exceed 50%, suggesting that both banking systems compete for their customers.

[8] For a comprehensive review on Fintech and banking, we direct you to Thakor (2020).

[9] Malaysia is the first country to introduce an Islamic equity index, see Naughton and Naughton (2000) for a discussion on the issues identified with the Shariah-conformity of stock trading.

media in particular.[10] Hence, it may be anticipated that in fear of high reputational risk more firms may behave in an ethical way.

Motivated by the theoretical arguments for convergence between Islamic and conventional investments, this paper addresses four questions. First, using novel techniques in this context we examine the convergence between these two types across time. Second, we examine if convergence dynamics differ across business sectors and several endogenous and exogenous episodes of crises. Third, we investigate the extent to which the possible convergence dynamics diminish the appeal of Islamic investments in portfolio risk management. Fourth, we assess whether the convergence dynamics suggest that Islamic investments' reactions to crises are progressively aligned to conventional investments, and how different is the impact of an exogenous shock like the Covid-19.

We address the above questions using various approaches and techniques. First, a multivariate framework is used to provide time-dependent estimates of correlation between the two types of investments. Conditional beta and sigma-convergence models are used within a difference-in-difference (DiD) framework, which allows us to compare and contrast convergence rates across investment types, business sectors and episodes of crises.

Second, we underscore the practical relevance of convergence using a mean-variance portfolio allocation. The use of a mean-variance framework to evaluate investment performance has been widely employed (Christoffersen et al., 2014; Nolte & Xu, 2015). Furthermore, we disentangle the risk diversification benefit offered by Islamic investments into two parts; one related to their relative risk differential, another to the correlation to conventional investments.

Third, we explore whether Islamic investments behave as a transmitting channel of shocks using the financial contagion framework. Performing a series of financial contagion analyses across episodes of crisis allows us to identify the extent that Islamic investments overall and/or at specific sectors can act as a protective cushion.

Our main findings are as follows. We document strong convergence of Islamic and conventional investments across time. During crisis, the convergence rate approximately doubles in magnitude; a reflection of financial markets becoming highly aligned. However, Islamic investments distinctiveness is pronounced as they show significantly decreased convergence rates compared to the conventional ones. Sectoral divergence is evidenced in conventional investments, suggesting that investors can identify those sectors hit the hardest and take appropriate action. By contrast, the sectoral convergence in Islamic investments hints that these are rather viewed as a single entity. Sectoral diversification in Islamic investments should be least effective during crises. On average Islamic investments offer around 7% risk reduction in a well-diversified portfolio. This markedly increases during all but the 2014-15 oil crisis, possibly reflecting the "Achilleas heal" of these investments. We show that overtime the relative diversification benefit is decreasingly affected by the relative risk differential, and increasingly affected by the rising correlation between the two investments. This pronounced role of correlation is reflected on the performance fee, with a risk-averse investor willing to pay 466 (64) basis points monthly during the Covid-19 crisis (overall) for the risk diversification benefits of Islamic investments. A series of financial contagion investigations across the five crises shows that Islamic investments are progressively less insulated from financial crises. Still, even though financial contagion is verified for the exogenous shock of Covid-19; Islamic

[10] The increased availability of the internet and social media have fostered a market for firm reputation, which has been under the microscope of firms (Rathore et al., 2017). In particular, the increased availability of information in such markets has been shown to reduce informational asymmetries and moral hazard between entrepreneurs and venture capitalists (Smith, 1998).

investments are significantly less affected. A battery of robustness checks confirms our results. Specifically, convergence is robust to endogeneity and verified through alternative gamma-convergence and volatility spillover approaches. Additionally, endogenous breakpoint detection confirms the appropriateness of the crisis periods for both investment types.

Our paper offers four main contributions. This is the first study to assess the convergence between Islamic and conventional investments. We go beyond the simple point-in-time analyses between Islamic and conventional investments by focusing on their convergence dynamics over a sample spanning more than two and a half decades, covering ten business sectors and five episodes of crisis. This is important as convergence rebuttal across would give *prima facie* evidence that the two investments have retained their distinct dynamics. On the other hand, convergence evidence would imply that they have become closely aligned overtime. Second, we decompose portfolio risk diversification benefits offered by Islamic investments into two components: relative risk, and correlation to conventional investments. This is important as we associate a rising cost of Islamic diversification benefits to their convergence dynamics. Third, we deploy a series of financial contagion analyses that document Islamic investments progressively act as a transmitting channel of global shocks. Fourth, we evaluate the impact of five episodes of crises, spanning the dotcom technology bubble, the 2007 Global financial crisis (GFC), the European Sovereign Debt Crisis (ESDC) recession, the 2014-15 period of historically low oil price, and the unprecedented exogenous pandemic shock (Covid-19) upon convergence dynamics, portfolio diversification benefits and financial contagion.

The remainder of the paper is organised as follows: Section 2 presents the data, while section 3 presents the econometric methodology. Section 4 presents and discusses the results. Section 5 provides robustness tests. A final section concludes.

2. Data

2.1 Descriptive statistics

The data comprises daily prices of the Dow Jones world aggregate and sector equity indices for conventional and Shariah-compliant firms. We use equity indices for several reasons. Most importantly, the relatively long history of Islamic equity indices allows us to use a large data window for a valid statistical analysis. Equity indices are, perhaps, the first financial instrument that enabled Shariah-compliant investments on a large scale. Dow Jones launched a family of Islamic equity indices in the mid-1990s, which was intended to cater for those investors that were either concerned about the ethical implications of their investments or wanted to explore the gains offered to their portfolios by these (then) new financial products.[11] The Dow Jones Islamic Market feature broad-market and thematic indices that have passed rules-based screening for Shariah compliance via an independent and diverse Shariah Supervisory Board, with the screening mechanism adhering to the Auditing and Accounting Organization of Islamic Financial Institutions (AAOIFI) (Hammoudeh et al., 2014). The first step is a business sector screening based on Shariah Law acceptable products and business activities. According to this type of screening, business income from the following sources cannot exceed 5% of business revenue: alcohol, tobacco, pork-related products, conventional financial services, casinos/gambling, pornography. After removing companies with unacceptable primary business activities, a financial screening takes place to ensure acceptable levels of leverage and tangibility. Accordingly the following financial ratios must be less than 33%: total debt divided by 24 months trailing average market capitalization; total cash and interest-bearing securities divided by 24

[11] Other index providers offered their variants of Islamic indices; for example the MSCI World Islamic Index was launched in 2007. Islamic bond (sukuk) indices have also been made available more recently; for example, the S&P MENA Sukuk Index was launched in 2013.

months trailing average market capitalization; accounts receivables divided by 24 months trailing average market capitalization (S&P, 2021). All indices are value-weighted and exclude dividends. The sectors are the following: Consumer Goods, Consumer Services, Financials, Healthcare, Industrials, Materials, Oil & Gas, Technology, Telecommunications and Utilities. The analysis spans the period from 1/1/1996 to 12/10/2020, thus giving us 6,466 observations for each index. For every index, we compute the continuously compounded percentage return as $r_t = \log(p_t/p_{t-1}) \times 100$, where p_t is the closing price at day t. Figure 1 plots a representative selection of conventional (Panel A) and Islamic (Panel B) sectoral equity indices. An initial observation of the graphs shows largely similar patterns across the full sample period, with the notable spikes of the Technology sector around the dotcom technology bubble and the dip around the global financial crisis. The upward trend of the Islamic Utilities sector in the years leading to the global financial crisis is a notable difference compared to the conventional equivalent.

[Figure 1 around here]

Table 1 presents key descriptive statistics of the equity indices under investigation. All returns exhibit the stylised facts of skewness and excess kurtosis. In particular, the conventional Oil & Gas sector shows particularly negative skewness and high kurtosis values. It is of importance to note that we observed the highest values of kurtosis for the Oil & Gas, Financials and Utilities sectors for both the Islamic and conventional indices. The risk/return profile of the two types of indices does not always appear aligned, as suggested by the ranking information. For example, Technology exhibits the highest mean return and volatility, a commonality between the two indices. However, the lowest returns for conventional and Islamic indices are found in Financials and Oil & Gas respectively.

[Table 1 around here]

2.2 Crisis identification

Identification of turmoil periods can follow an economic and/or a statistical approach. The economic approach uses major economic and financial events (Forbes & Rigobon, 2002), while the statistical approach relies on endogenously identified breakpoints and regime shifts (Boyer et al., 2006). No definite winner exists. In the economic approach it may be restrictive to assume that one event is equally applicable to all examined countries or sectors. Likewise, an abundance of statistical methods exist to identify regimes in financial times series, such as smooth transition autoregressive models (SETAR) (Teräsvirta, 1994), Markov-Switching models and structural break-point tests (Bai & Perron, 2003). To hit a fine balance, some researchers opt for a combination of an economic and a statistical approach (Kenourgios & Dimitriou, 2015). In this study we rely on an economic identification of crisis events as follows.[12]

The dotcom crisis is assumed to range from March 11, 2000 to October 9, 2002, which corresponds to the peak and trough of the NASDAQ index. The official timelines separate the GFC into four phases (BIS, 2009; Federal Reserve Board of St. Louis, 2009). Phase 1 spans from 1st August 2007 until 15th September 2008 and is defined as "initial financial turmoil". Phase 2 is described as "sharp financial market deterioration" and covers the period from 16th September 2008 until 31st December 2008. Phase 3 is defined as "macroeconomic deterioration" (1st January 2009 - 31st March 2009), while Phase 4 is a phase of "stabilization and tentative signs of recovery" (1st April - 1st November 2009). Therefore, the core of the crisis can be defined from 16th September 2008 until 31st March 2009,

[12] We eschew a statistical approach with endogenous breakpoint identification due to the size (cross-sectionally and time-wise) of the data set. We run a robustness test with an endogenous breakpoint selection methodology, and present it in section 5.2

covering the second and third phases. The identification of the ESDC is based on information sourced by the European Central Bank (ECB) and Reuters. We construct a timeline of the crisis by merging the events and dates from the two sources as follows. The ESDC begins shortly before the Greek bailout in May 2010 (23rd April 2010), when the Greek Prime Minister announced that the austerity packages were not enough and requested a bailout plan from the Eurozone and the IMF. The poor performance of the European banking system and the spread of the crisis to other European economies led to fears of a potential "Grexit" and a breakdown of the Eurozone. Thus, the ESDC extends from April 2010 until the exit of Cyprus from the economic adjustment program in the March 2016. The oil-price crash extends from July 2014 to December 2015, where the average oil price dropped from \$103 to around \$31.[13] During the Covid-19 exogenous shock the Dow Jones and the SP500 plunged 35% withing 6 weeks. On the 9th of March 2020 stock markets plunged with a magnitude comparable in scale to what was observed after the Lehman Brothers' collapse in 2008, while trading was halted in NYSE. We assume that the Covid-19 financial crisis between February 2020 and July 2020.

3 Methodology

3.1 Estimation of conditional correlation

Several techniques may be used to infer a time-variant measure of interrelationship across markets, such as asymmetric dynamic conditional correlation (ADCC)-GARCH models (Gjika and Horváth, 2013), wavelet techniques (Aloui et al., 2015; Bodart & Candelon, 2009), BEKK models (Koedijk et al., 2002), and dynamic copulae (Bhatti & Nguyen, 2012; Jayech, 2016; Nguyen & Bhatti, 2012; Okimoto, 2008; Ye et al., 2012).[14] The asymmetric dynamic conditional correlation (ADCC)-GARCH model (Cappiello et al., 2006) provides a robust analysis of time-varying linkages by allowing conditional asymmetries in both volatilities and correlations, and investigates the second-order moment dynamics of financial time-series, while overcoming the heteroscedasticity concern of Forbes and Rigobon (2002). Recent empirical studies show that the ADCC approach compares rather well to other techniques available in the literature and provides similar results (Dimitriou et al., 2020; Kenourgios et al., 2011, 2019). Wavelet techniques allow for more complexity in the dynamics, but at the expense of interpretability. We adopt an asymmetric dynamic conditional correlation (ADCC)-GARCH model, which accounts for the time varying nature and asymmetry of the conditional volatilities and correlations. First introduced by Engle (2002), Dynamic Conditional Correlation (DCC)-GARCH, was followed by two kinds of extensions. The first takes place in the volatility modelling phase where models that account for asymmetries (EGARCH, GJR-GARCH), long-memory (FIGARCH) and regime changes (MS-GARCH) have been introduced. The second is related to the DCC estimator *per se*, of which the asymmetric DCC (ADCC) model allows for asymmetric effects in the conditional correlations (Cappiello et al., 2006). The estimation of an ADCC-GARCH type of model comes in three phases (Engle, 2002). First, univariate GARCH models are fitted to the asset returns. Second, the unconditional correlation and covariance matrices of positive and negative standardised returns are estimated. Third, a quasi-maximum likelihood estimation procedure for the conditional correlation dynamics occurs.

[13] Oil price data obtained from FRED, available here: https://fred.stlouisfed.org

[14] Extreme value theory (EVT) may also be applicable in assessing financial contagion since it helps modeling upper- and lower-tail dependence. Recent empirical evidence suggests that EVT combined with dynamic mixture copulas can be superior to alternative copula models. However, this is achieved at the expense of severe computational limitations and large data requirements, which preclude its use in multiple-asset/country financial contagion applications (Rocco, 2014).

To illustrate the mechanics, consider a $T \times 1$ vector of asset returns in which, r_t is normally distributed with mean zero and variance h_t

$$r_t | \mathcal{F}_{t-1} \sim N(0, h_t) \tag{1}$$

$$h_t^2 = \omega + \sum_{i=1}^{p} \boldsymbol{A}_i \, u_{t-i}^2 + \sum_{j=1}^{q} \boldsymbol{B}_j \, r_{t-j}^2 + \sum_{k=1}^{r} \boldsymbol{\Gamma}_k \, u_{t-k}^2 I_{t-k} \tag{2}$$

where $\boldsymbol{\mathcal{F}}_{t-1}$ is the information set at time $t-1$, $I_t = 1$ if $u_t < 0$ and zero otherwise, and the variance process is modelled by a threshold GARCH process. We opt for the GJR-GARCH(1,1,1) specification that allows for asymmetric effects in the volatility process, given by:

$$r_t = \theta_0 + \varphi_1 r_{t-1} + u_t, u_t \sim iid(0, h_t) \tag{3}$$

$$h_t^2 = \omega_0 + a_1 u_{t-1}^2 + \beta_1 h_{t-1}^2 + \gamma_1 u_{t-1}^2 I_{t-1} \tag{4}$$

The time-varying covariance matrix $\boldsymbol{H}_t$ is defined as a product of time-varying standard deviations and time-varying correlations for the $N \times T$ matrix of asset returns as:

$$\boldsymbol{H}_t = \boldsymbol{D'}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{5}$$

where

$$\boldsymbol{D}_t = diag\{h_{1t}^{1/2}, \dots, h_{Nt}^{1/2}\} \tag{6}$$

Asymmetries are incorporated in the correlation dynamics where Cappiello et al. (2006) modify the conditional correlation equation to:

$$\boldsymbol{Q}_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\overline{\boldsymbol{R}} - \sum_{k=1}^{K} g_k \overline{\boldsymbol{N}} + \sum_{m=1}^{M} a_m (\varepsilon_{t-m}\varepsilon'_{t-m}) + \sum_{k=1}^{K} g_k (n_{t-k} n'_{t-k}) + \sum_{n=1}^{N} b_n \boldsymbol{Q}_{t-n} \tag{7}$$

where n_t takes the value 1 when $\varepsilon_t < 0$, zero otherwise, representing therefore bad news. For the matrix $\boldsymbol{Q}_t$ to be positive definite, a set of restrictions is imposed. These restrictions require that: i) $a_m > 0$; ii) $b_n > 0$; iii) $\tau_k > 0$; iv) $\sum_{m=1}^{M} \alpha_m + \sum_{n=1}^{N} b_n + \eta \sum_{k=1}^{K} \tau_k < 1$ and $\eta =$ maximum eigenvalue $[\overline{\boldsymbol{R}}^{-1/2} \overline{\boldsymbol{N}} \overline{\boldsymbol{R}}^{-1/2}]$ is estimated from the data. A rescaling of $\mathbf{Q}_t$ ensures that the correlation matrix is well-defined with unitary values along the main diagonal and with each off-diagonal element ranging in absolute value between zero and one. Specifically:

$$\boldsymbol{R}_t = (\boldsymbol{I} \circ \boldsymbol{Q}_t)^{-1/2} \boldsymbol{Q}_t (\boldsymbol{I} \circ \boldsymbol{Q}_t)^{-1/2} \tag{8}$$

where $\boldsymbol{I}$ is the identity matrix and $\circ$ denotes the Hadamard product.

For the multivariate part of our setting, we adopt an ADCC (1, 1, 1), which is given by:

$$\boldsymbol{Q}_t = (1 - a - b)\overline{\boldsymbol{R}} - g\overline{\boldsymbol{N}} + a(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}) + g(\boldsymbol{n}_{t-1}\boldsymbol{n}'_{t-1}) + b\boldsymbol{Q}_{t-1} \tag{9}$$

Arguably different assets may show marginal fit improvements under alternative univariate GARCH models and/or under allowance for asset-specific multivariate dynamics. However, in our set up it is important to ensure a level playing field for all assets, which would allow us to evaluate any differences in the convergence process in the follow-up regressions. Hence, we have opted for common univariate specifications and multivariate dynamics.[15]

3.2 Modelling convergence

To investigate convergence we borrow the concepts of beta-convergence and sigma-convergence from the growth literature (Inklaar & Diewert, 2016; Sala-i-Martin, 1996). The unconditional beta-convergence model captures the "catch-up effect" across correlation pairs and may be written as:

$$\Delta\rho_{ij,t} = a + \beta_0\left(ln\rho_{ij,t-1}\right) + \varepsilon_{ij,t} \tag{10}$$

where $ij = 1, \dots, N$ denoting the sector pair; $t = 1, \dots, T$ denoting the time; $\rho_{ij,t}$, $\rho_{ij,t-1}$ denote the mean conditional correlation between sectors i and j at times t and $t-1$ respectively; $\Delta\rho_{ij,t} = \ln\left(\rho_{ij,t}\right) - \ln\left(\rho_{ij,t-1}\right)$; $\varepsilon_{ij,t}$ is the error term. A negative value for the estimated β_0 parameter indicates convergence; the higher the coefficient in absolute terms the stronger the convergence.

We allow for differences between type and market conditions by augmenting the unconditional beta-convergence model using a difference-in-difference design. An Islamic dummy (ISL) takes the value 1 for Islamic indices, zero otherwise. Similarly, a Crisis dummy (CR) takes the value 1 for a period of crisis, zero otherwise. The following equation is estimated:

$$\begin{aligned}\Delta\rho_{ij,t} = a + \beta_0\left(ln\rho_{ij,t-1}\right) + \beta_1 ISL + \beta_2 ISL \times \ln\left(\rho_{ij,t-1}\right) + \gamma_1 CR + \gamma_2 CR \times \ln\left(\rho_{ij,t-1}\right) \\ + \delta_1 ISL \times CR + \delta_2 ISL \times CR \times \ln\left(\rho_{ij,t-1}\right) + \mathrm{\rho\Delta\rho_{ij,t-1}} + \varepsilon_{ij,t}\end{aligned} \tag{11}$$

In the augmented beta-convergence model (Eq.11), conventional investments have convergence rate equal to β_0, while for the Islamic investments the rate is $\beta_0 + \beta_2$. Statistical significance of the β_2 coefficient verifies a convergence rate differential between the correlations of the two investment types. Likewise, a negative γ_2 indicates higher convergence rate during episodes of crisis. Finally, coefficient δ_2 compares the convergence rate of Islamic investments in crisis.

We use sigma-convergence to assess cross-sectional dispersion in the convergence process. Cross sector heterogeneity is important for portfolio diversification. Sigma-convergence evidence suggest that sectoral diversification is of diminishing importance over time. The unconditional sigma-convergence model is given as:

$$\Delta E_{ij,t} = a + \sigma_0 E_{ij,t} + \varepsilon_{ij,t} \tag{12}$$

where $E_{ij,t} = \ln\left(\rho_{ij,t}\right) - \ln\left(\overline{\rho}_{j,t}\right)$; $\overline{\rho}_{j,t}$ and $\overline{\rho}_{j,t-1}$ are the average conditional correlation of sector j at times t and $t-1$ respectively; $\Delta E_{ij,t} = E_{ij,t} - E_{ij,t-1}$; $\varepsilon_{ij,t}$ is the error term. A negative value in the estimated σ_0 parameter indicates convergence; the higher the coefficient in absolute terms the stronger the convergence. We allow for differences between type and market conditions and augment the unconditional sigma-convergence model using a difference-in-difference design, given as:

[15] As a robustness check we have re-estimated the convergence models using conditional correlations from a symmetric DCC-GARCH specification and also allowed for asset-specific correlation dynamics (i.e., running a series of bivariate ADCC-GARCH specifications). On all occasions the convergence results remain qualitatively similar. These tabulated results are omitted for brevity but are available upon request.

$$\Delta E_{ij,t} = a + \sigma_0 E_{ij,t} + \sigma_1 ISL + \sigma_2 ISL \times E_{ij,t} + \gamma_1 CR + \gamma_2 CR \times E_{ij,t} + \delta_0 ISL \times CR + \delta_1 ISL \times CR \times E_{ij,t} + \rho \Delta \mathrm{E}_{\mathrm{ij,t-1}} + \varepsilon_{ij,t} \quad (13)$$

Growth regressions, upon which the beta and sigma convergence is based, are known to suffer from endogeneity issues (Bazzi & Clemens, 2013). To ensure that endogeneity is not affecting our key convergence results, we re-estimate the beta/sigma-convergence equation using system-GMM after including a lagged dependent variable, and conduct thorough testing.[16]

3.3 Practical applications

We examine the implications of convergence in the correlations of Islamic and conventional investments focusing on two empirical applications: portfolio analysis and financial contagion. The former evaluates the diversification benefits of Islamic investments in regard to convergence. The latter focuses on how Islamic investments have weathered major endogenous and exogenous shocks. The importance of portfolio performance and diversification during periods of market distress is particularly challenging for investors (Liu & Loewenstein, 2013).

3.3.1 Portfolio analysis

We base the analysis on the mean-variance modern portfolio theory of Markowitz (1952); however we allow for time-varying covariance structure, similar to the studies of Ackermann et al. (2017), Alexakis et al. (2017) and Eun et al. (2010). Let:

$$\mathbf{R} = \begin{pmatrix} \mathrm{r}_{1,t} \\ \vdots \\ \mathrm{r}_{N,t} \end{pmatrix} \quad (14)$$

$$\mathbf{w} = \begin{pmatrix} \mathrm{w}_{1,t} \\ \vdots \\ \mathrm{w}_{N,t} \end{pmatrix} \quad (15)$$

$$\mathbf{H} = \begin{pmatrix} h_{11,t}^2 & \cdots & h_{N1,t}^2 \\ \vdots & \ddots & \vdots \\ h_{1N,t}^2 & \cdots & h_{NN,t}^2 \end{pmatrix} \quad (16)$$

where **R** is a matrix with logarithmic daily returns; **w** is a matrix containing the time-varying weights assigned to each asset; **H** is the time-varying variance-covariance matrix, estimated from the ADCC-GARCH step in an earlier part. Optimisation of the portfolio weights would give a different return-risk composition, while the minimum variance portfolio (MVP) is the only portfolio for which no higher return may be achieved without incurring more risk.[17] The portfolio return and risk are respectively:

$$\mathbf{R}_p^* = \mathbf{w}_p'\mathbf{R} \quad \text{and} \quad \mathbf{h}_p^* = \mathbf{w}_p'\mathbf{H}\mathbf{w}_p \quad (17)$$

Therefore, the MVP may be calculated by writing a constrained minimisation problem and solving as:

[16] We implement the system-GMM via the xtabond2 command in Stata. Asymptotically one would want to use the full set of lags; however this can be problematic in finite samples; hence we limit to the first 10 lags. Besides, we collapse the instrument matrix to contain only one instrument for each lag depth. Robust, Windmeijer-adjusted standard errors are presented. For the Kleibergen and Paap (2006) LM test and Cragg and Donald (1993) / Kleibergen and Paap (2006) Wald statistics we procced as follows: we use a two-stage least squares framework for the beta-convergence equation in levels, instrumented by the same lagged differences as in the system-GMM estimation. For these tests we use the ivreg2 command in Stata, after specifying the svvar option in xtabond2.

[17] We use the portfolio optimisation routines in MATLAB.

$$\mathbf{h}_p^* = \mathbf{w}_p'\mathbf{H}\mathbf{w}_p \; s.t. \; \mathbf{w}'\mathbf{1} = \mathbf{1} \tag{18}$$

We use three investment strategies; the *Conventional* invests only in conventional equity indices, the *Islamic* only in Islamic equity indices, while the *Combined* invests in both. We acknowledge that the latter strategy may not be accepted by the most religious Muslim investors as it invests in conventional assets, but it could serve the diversification targets of a conventional investor who is not interested in the religious aspect *per se*. For each strategy we optimise the portfolio weights among the world index and all business sectors. The portfolios are rebalanced monthly, and portfolio constraints are such so that short-selling and borrowing are not allowed.[18]

3.3.2 Financial contagion

Financial contagion studies share a common framework whereby estimated conditional correlations are used as the dependent variable in a regression, with turmoil/crisis events constituting a dummy explanatory variables, see for example Baur (2012) and Kenourgios and Dimitriou (2015). Following the Forbes and Rigobon (2002) shift-contagion framework, a statistically significant increase in the conditional correlation during the financial crisis period constitutes financial contagion. However, Bekaert et al. (2014) critique that solid contagion inference may only be made after economic fundamentals have been accounted for. In our framework we account for economic conditions using a variety of controls in line with the related literature.[19]

Changing economic conditions are accounted via the use of the logarithmic change in the interest rate (yield) spread, proxied by the 10-Year US Government bond rate minus the 3-Month US Treasury bill rate. In a similar manner, we account for the change in corporate risk via the logarithmic change in the corporate bond yields spread, proxied by the AAA Corporate bond yield minus the BAA Corporate bond yield. To capture the overall stock market performance, we use the MSCI World Index. We account for the performance of commodities and real estate as these are particularly relevant in Islamic finance contracts, via the S&P GSCI Commodity Index and the DJ REIT Index respectively. The logarithm of the US TED Spread is used to account for the credit risk in the economy; the logarithm of the logarithm of the Economic Policy Uncertainty (EPU) to account for the economic uncertainty. The CBOE VIX index is a forward-looking measure of stock market volatility, derived from index options, and is included as a measure of market sentiment. The source of these data is Datastream/US Fred.[20]

Each of the crisis variables (DTCM, GFC, ESDC, OIL, COVID-19) take the value 1 during the respective crisis, zero otherwise with crisis timings outlined in an earlier section. We are mindful of the source of contagion in each case. For the dotcom (DTCM) case, the source of contagion is the Technology sector, for the GFC & ESDC the Financials, for the oil crisis (OIL) the Oil & Gas sector, for the COVID-19 the World aggregate. To cater for the change in the contagion source across the crisis we split the sample in three equal sub-periods, each characterised by the DTCM crisis (1996-2004), the GFC & ESDC crises (2005-2016), the Oil Crisis (2013-2017) and the COVID-19 (2018-2020) respectively. The following model is estimated using Newey-West standard errors in each of the sub-periods.

[18] We also construct equally-weighted portfolio of each of the three strategies. These results also confirm the benefits in risk reduction to the *Combined* strategy compared to the *Conventional*.

[19] See Appendix for a brief literature review on financial contagion.

[20] Several alternative measures have been used as robustness checks, including the interest rate spread between the 10-Year and the 3-Month German bonds, the 3-month Euribor rate, the 12-month Libor rate, the MSCI REIT Index. The qualitative nature of our results remains similar.

$$\rho_{ij,t} = \beta_0 + \beta X + kCrisis + \varepsilon_{ij,t} \quad (19)$$

where $\rho_{ij,t}$ denotes the mean conditional correlation between sectors i and j at time t (see section 3.1); X is a vector of the economic controls; $Crisis$ is each of the crisis dummy variables assigned to the specific sub-period; $\varepsilon_{i,t}$ is the error term; β_0, β, k are parameters to be estimated. We use two specifications; the first examines financial contagion *within* conventional indices only; the second financial contagion *from* conventional *to* Islamic indices, which we identify as cross-contagion. In this way we compare financial contagion marginal effects on each type of equity index and across separate crisis events.

4. Results

4.1 ADCC-GJR-GARCH results

Table 2 reports the estimated coefficients, robust standard errors, goodness-of-fit statistics for the univariate parts of the ADCC-GJR-GARCH model estimated for each sector. To accommodate the presence of skewness and kurtosis in the financial returns we have used the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992) to covariances and standard errors that are robust to conditional non-normality. Panel A reports the statistics for the conventional equity indices, while Panels B repeats for the Islamic ones. The significance and magnitude of the φ_1 coefficient suggest the presence of autocorrelation in both types of indices, although this is markedly lower in the Islamic indices. The volatility of most of the indices displays high persistence with the sum of the estimated ARCH and GARCH $(a_1 + \beta_1)$ coefficients in each case being close to unity. The leverage terms γ_1 are positive and statistically significant, suggesting that the volatility of all equity indices exhibits asymmetric responses to good and bad news. Interestingly, the Financials bears one of the highest degrees of asymmetry among conventional indices, but not in the case of the Islamic equivalent. The parameters for the ADCC model are statistically significant and non-negative, which justifies the appropriateness of the ADCC-GJR-GARCH model.

[Tables 2 and 3 around here]

The visual representation of the conditional correlation estimates for Islamic and conventional indices is interesting. Figure 2 presents these time-varying correlations for the Financial/World indices pair of conventional and Islamic indices respectively. A cursory inspection of the graph shows that for the conventional pair of indices the correlation remains at high levels (around 0.90) throughout the sample period. However, the pattern exhibited by the Islamic equivalent of these indices is dominated by an upward trend, perhaps highlighting a convergence process. In particular, pre-2000 the Financial/World conditional correlation estimates for the Islamic indices fluctuate around the 0.3 mark. By 2016, this figure would more than double and exceed 0.8. Investigation of the dynamics around the crisis periods suggests that certain drops are evidenced around periods of turmoil, namely the dotcom and GFC crises as far as conventional indices are concerned. By contrast, and for the same crises, the Islamic indices do not appear to lose their convergence momentum.

[Figure 2 around here]

A variety of sectors show similar convergence evidence between the two types of indices, as Figure 3 suggests. Time-varying correlation evidence between Financials and each other sector suggest that most of the conventional indices maintain a certain level of alignment throughout the period (e.g., Consumer Goods, Consumer Services), while others show an increase, particularly through the pre-dotcom crisis (e.g., Technology). Unique sectoral characteristics are plausibly evidenced in the volatility of the conditional correlation estimates. Interestingly, the sectoral Islamic indices show the convergence pattern that was observed in Figure 2, admittedly to varying extends. In particular, the conditional correlation of the Islamic Financial / Consumer Goods pair is around 0.3 pre-2000, while it has reached 0.75 and is virtually indistinguishable from the conventional counterpart by 2016. The following section formalises our visual findings via the use of convergence models.

[Figure 3 around here]

4.2 Convergence results

Table 4 presents the estimation results of the beta-convergence model as well as standard goodness-of-fit statistics. The negative $\hat{\beta}_0$ coefficient suggests a catch-up effect in all correlation pairs. This may be viewed as baseline evidence of integration in the financial markets across time. Islamic investments converge significantly faster – by around 61.75% – as evident by the negative β2 coefficient.[21] Episodes of financial crisis increase the convergence rate by more than two times; a reflection of financial markets becoming highly aligned. However, during financial crises Islamic investments show significantly lower convergence rate than conventional investments. This is not to say that Islamic investments are isolated during periods of crisis, rather the alignment of financial markets is significantly slower for these investments.

[Table 4 around here]

Table 5 presents the estimation results of the sigma-convergence model as well as standard goodness-of-fit statistics. The negative σ_0 coefficient suggests that cross-sectoral heterogeneity is diminishing. The effect is more pronounced within Islamic investments – by around 94.31% – as evident by the negative σ2 coefficient. Portfolio sectoral diversification benefits are diminishing faster for Islamic investments. During crisis conventional and Islamic dynamics are markedly different. For conventional investments we observe a sectoral divergence as evidenced by the positive γ2 coefficients. However, for Islamic investments sectoral convergence materialises faster as shown by the negative δ1 coefficient. It appears that sectors regain their heterogeneity during financial crisis for the conventional investments. This may be plausibly attributed to investors seeking to identify those business sectors that have been less affected. Amidst crises however, it is plausible that Islamic investments are considered as a single entity, where sectoral differences are ignored. In a related context, Hkiri et al. (2017) also find Islamic equity indices to show markedly different dynamics compared to conventional ones during turbulent periods, while using generalized VAR-based spillovers, Balli et al. (2019) document increases in volatility spillovers between these investment types.

[Table 5 around here]

A comparison across the estimation techniques presented in Tables 4 & 5, shows that key coefficients of interest retain their statistical significances and coefficient magnitudes. For example, beta-convergence speed using system-GMM is estimated at $\beta_0 = -0.0509$, while the coefficient reported in the main paper is marginally smaller at $\beta_0 = -0.0418$. The statistical significance of the triple interaction term underpinning the higher convergence rate of Islamic investments during crisis is also in line with our main findings. The lower part of the table presents a series of tests to reinforce the validity of the GMM estimation. Specifically, by GMM construction the first difference of the

[21] This is given as the logarithmic difference between the relevant estimated coefficients of Eq.11 as: $\ln\left((\hat{\beta}_0 + \hat{\beta}_2)/\hat{\beta}_0\right) = \ln(-0.0439/-0.0814)$

residuals should be autocorrelated; the second should not. The Arellano-Bond p-values confirm that only the first difference of the residuals exhibit autocorrelation at the 1% significance level. Bazzi and Clemens (2013) and Roodman (2009b; 2009a) caution against over-identification, under-identification, and the use of weak instruments. The Hansen J-statistic confirms that the null hypothesis of instrument validity is not rejected at conventional significance levels. We test for under-identification using the Kleibergen and Paap (2006) rank-based LM test. A rejection of the null hypothesis here indicates that the model is identified; the p-values in our case confirm this to be the case. However, as rejection of under-identification does not imply that the instruments are strong, we proceed to implement the Kleibergen and Paap (2006) Wald statistic, which is based on the Cragg and Donald (1993) but generalised for the cases of heteroscedasticity and/or autocorrelated errors. Both statistics are assessed against the critical values developed in Stock and Yogo (2005), for the null hypothesis that the size of the Wald test for all endogenous estimates equalling zero, is greater than 10 percent. The rejection of the null hypothesis in this case affirms that our GMM specification does not suffer from weak instrument problems. Overall, the system-GMM estimates corroborate both the beta and sigma-convergence between the Islamic and conventional investments, after accounting for endogeneity.

Table 6 presents beta and sigma-convergence models estimated for each crisis separately. Examining beta-convergence by crisis we find that the catch-up effect is consistently significant in all correlation pairs, ranging between -0.100 to -0.130 across the five crises episodes. Compared to the conventional investments, Islamic ones exhibit higher convergence rates during the dotcom, the ESDC and the Oil crisis. No difference is observed in the GFC and the Covid-19 crisis. Cross sectoral convergence is present across all crises, but with pronounced differences as the rates range from -0.0141 (Oil crisis) to -0.4334 (GFC). The high convergence rate during the GFC indicates that individual sector dynamics align fast. By contrast, the low convergence rate observed during the Oil crisis suggests that events remain isolated to specific sectors. For Islamic investments the negative $\delta 1$ coefficient suggests that cross-sectoral convergence is faster than for the conventional case during periods of crisis. As such, cross-sector differences in Islamic indices are exhausted faster compared to conventional indices. Following the Oil crisis Islamic investments have around 2.5 times higher convergence rate than conventional ones, highlighting their susceptibility to commodity crises. Overall, during the two most pronounced crises — the GFC and the Covid-19 — the convergence dynamics of conventional and Islamic indices are largely similar, perhaps limiting any benefits of Islamic investments when these would be needed the most.

[Table 6 around here]

4.3 Portfolio diversification across market conditions

The portfolio analysis results are presented in Table 7. The table reports: i) the mean percentage return and the 95% Value-at-Risk on a year-by-year basis for the three strategies; ii) the *risk diversification benefit*, defined as the logarithmic difference between the combined and the conventional strategy; iii) the *relative risk*, defined as the logarithmic difference between the Islamic and the conventional strategy; iv) the Islamic weight, which tracks the composition of Islamic investments in the combined strategy; v) the correlation, reporting the conditional correlation between the Islamic and conventional indices averaged across the business sectors. For the risk diversification benefit, positive values indicate that the addition of Islamic investments in the combined strategy lowers the total risk. Likewise, the relative risk compares the Islamic and the conventional strategy, and positive values suggest that the former is riskier.

[Table 7 and Figure 4 here]

Across the full period the risk diversification benefit is 6.92%, suggesting that incorporating Islamic investments in a well-diversified portfolio markedly lowers the risk. During episodes of crisis the risk diversification benefit increases. For example, in 2002 (dotcom) and in 2020 (Covid-19) the combined strategy records 14.14% and 30.19% lower risk than the conventional. Our findings are consistent with the hedging benefits alluded by Islamic investments, irrespective of market conditions (Rahman et al., 2021), but more so during crises (Balcilar et al., 2015; Mensi et al., 2017). Thus, ethical features can be beneficial to investment performance (Bollen, 2007; Oikonomou et al., 2018; Renneboog et al., 2008).[22]

The economic value analysis presented in Table 8 reports the performance fee (in monthly basis points) that an investor is willing to pay to switch from the conventional strategy (the benchmark in this case) to the combined and Islamic strategies respectively. The performance fee is calculated for the full sample and each of three equally-sized periods, and we consider three risk aversion levels $\gamma = 2, 6, 10$. We evaluate the statistical significance of the performance fees using the Giacomini and White (2006) test.

[Table 8 around here]

Across the full sample we find that the investor is willing to pay between 18 and 109 basis points for the combined strategy. The performance fee is positive across all risk aversion levels, and risk averse investors place a higher value on the risk diversification benefits of Islamic investments. While the performance fees for the combined strategy in the first and second periods are comparable, in the third period they reach up to 149 basis points, reflecting the much lower relative risk of Islamic investments during the Covid-19 financial crisis (see also Figure 4). However, the negative performance fee (9 to 71 basis points) of the Islamic strategy suggests that these form an inferior investment decision if compared vis-à-vis to the conventional strategy, with the exception of the second period that features the 2007 GFC.[23] Our findings here suggest that Islamic investments are primarily useful in risk diversification strategies.[24]

The *risk diversification benefit* is related to two opposing forces: *relative risk* and *correlation*. The relative risk component may be viewed as a reflection of the general economic climate, with the Islamic investments being particularly robust against endogenous financial crises and exogenous shocks. In periods when the relative risk is high, the composition of Islamic investments in the combined portfolio decreases. For example, during the 2015 Oil crisis (see figure 4) the relative risk is 75.29%, with the Islamic weight equal 8.68%; during the Covid-19 crisis the relative risk stands at -28.79%, and the Islamic weight 76.64%. However, the correlation is converging between the two types of investments as we have shown in an earlier part of this paper.

To explore further the role of these two determinants upon the risk diversification benefit, we estimate the following equation using least squares with robust standard errors.

$$RDB_t = b_0 + b_1 RR_t + b_2 \rho_{ij,t} + \varepsilon_t \tag{20}$$

[22] We are aware of studies that do not concur with the diversification benefits of Islamic investments, see for example Shahzad et al. (2017) and Ajmi et al. (2014).

[23] Our findings are comparable in magnitude to Nainggolan et al. (2016) that report Islamic equity funds to underperform their conventional peers by 40 basis points.

[24] Our motivation for the equal-sized splits is to be agnostic about the timing of calm and turmoil periods; thus giving a more accurate, average reflection of the performance fees. By contrast, the combined strategy attracts a performance fee of 466 basis points during the Covid-19 crisis, for a risk averse investor (γ=6).

where RDB denotes the risk diversification benefit, and high values indicate a large benefit; RR is the relative risk between the Islamic and the conventional strategies, and high values indicate a riskier Islamic strategy; ρ_{ij} is the conditional correlation between the Islamic and the conventional equity indices, ε_t is the stochastic error term.

Table 9 presents the estimation results for the full sample and each of three equally-sized periods. The results suggest that the risk diversification benefit of Islamic investments is inversely related to their relative risk and their correlation to conventional investments. Comparing the early to the latter parts of the sample, we find that the magnitude of the relative risk component has been reduced by around 50.19% in logarithmic terms. By contrast, that of the correlation has risen by 13.72%. Overall, the results suggest that overtime, the higher correlation between Islamic and conventional investments limits the risk diversification benefits that the former can bring in a portfolio. This is, however, offset by a "smoothing" in the relative risk differences between the two types of investments.

[Table 9 around here]

Are Islamic investments beneficial for the investor portfolio across time? The answer is yes, but it has not always been for the reasons documented in the existing literature. A large strand of the literature argues about the lower risk exposure of Islamic investments, often associated with their business model and/or screening criteria. In our analysis, the lower risk argument varies across time. This leads us to conclude that any benefit to the combined strategy investor is a blend of risk and correlation. While the risk differential of Islamic to conventional investments tends to follow a rather cyclical pattern in response to the peaks and troughs of the economy, the correlation between the two is on a strong convergence, which makes risk reduction benefits of Islamic investments costlier.

4.4 Financial contagion

Table 10 reports estimated coefficients and t-statistics for the crisis dummies in the respective period. For each crisis, the columns *Source* and *Target* show the assumed source of contagion and each of the other business sectors; hence defining the conditional correlation pair. Panel A examines the financial contagion within the conventional indices, Panel B the cross-contagion from conventional to Islamic indices. Under each panel we report the average of the estimated coefficients, while the change shows the percentage logarithmic difference (in percentage points) between the average value of Panel A to Panel B.

[Table 10 around here]

We discuss each crisis in turn. Following the dotcom, our results confirm decoupling in seven out of the ten conventional indices. Only three sectors show evidence of contagion. A similar pattern is observed in the cross-contagion case. On average the dotcom may be characterised as a decoupling event. The Islamic indices have acted as a buffer showing 35.52% lower decoupling evidence. Interestingly, there are sectors that show evidence of financial contagion within the conventional indices but decoupling when analysing cross-contagion, like the utilities. Pertaining to the GFC, we find evidence of decoupling within the conventional indices and in the case of cross-contagion, as suggested by the negative coefficients. Here Islamic investments have been more affected, showing 18.00% higher decoupling evidence. During the ESDC the evidence is in support of financial contagion across all sectors, with the case of cross-contagion showing around 52.32% stronger effect.

Financial decoupling is evidenced across the board in the case of the oil crisis, in which case the cross-contagion shows around 2.97% more pronounced effect.

The exogenous shock of Covid-19 shows significant contagion evidence for most sectors. A notable exception is the Healthcare sector being unaffected, a finding plausibly related to the Covid-19 "drug-race", also documented in Izzeldin et al. (2021). Consumer services and Consumer goods also show significant difference between the cross-contagion and the within conventional cases; thus, suggestive of a differentiated response of the two types of investments. Overall, we find that the Covid-19 exogenous shock has had around 54.86% lower contagion evidence upon Islamic indices.

It has been argued that Islamic investments due to their screening mechanisms should offer *complete* insulation from economic shocks relative to their conventional counterparts. However, empirical support has been limited owing to studies using Granger causality (Ajmi et al., 2014) and copula models (Hammoudeh et al., 2014), which have shown that Islamic investments are aligned to the conventional ones. Studies focusing instead on turbulent periods show mixed results with Hkiri et al. (2017) and Shahzad et al. (2017) confirming the decoupling of Islamic indices, while other evidence suggest contagion and/or dependence (Kenourgios et al., 2016; Rahman et al., 2021). In our analysis we have focused on the time evolution of the insulation attribute, whereby Islamic investments would show weaker contagion or stronger decoupling relative to their conventional counterparts. Our findings show that the insulation attribute has been present but limited to the dotcom crisis and the exogenous shock of Covid-19.

5. Robustness Analysis

5.1 Gamma convergence

An alternative methodological approach to the beta and sigma-convergence frameworks is the club convergence and clustering procedure recommended by Phillips and Sul (2007), also referred to as gamma-convergence. Some advantages of this methodology include the lack of specific assumptions on the stationarity of utilised variables and the reliance on nonlinear time-varying factor models, which tackle the homogeneous technological progress assumption implied by the beta and sigma-convergence frameworks. The technique has been utilised in economics (Phillips & Sul, 2009), banking (Matousek et al., 2015; Olson & Zoubi, 2017) and finance contexts (Apergis et al., 2014). We modify the framework to our needs as outlined below.

The set of observable time series with panel structure in our case is the conditional correlation estimate, denoted as $\rho_{ij,t}$ where i and j identify the correlation pairs between two indices and t is the time identifier respectively.

$$\rho_{ij,t} = \delta_{ij,t}\mu_t \tag{21}$$

where μ_t is a common path component, $\delta_{ij,t}$ is a time-varying idiosyncratic element that captures the deviation of i,j correlation pair from the common path. The relative transition parameter with respect to the panel average is defined as:

$$h_{ij,t} = \frac{\rho_{ij,t}}{N^{-1}\sum_{j=1}^{J-1}\sum_{i=1}^{N-1}\rho_{ij,t}} \tag{22}$$

The relative transition parameters to their average in any time period are given by:

$$\ln\left(\frac{H_1}{H_t}\right) = N^{-1}\sum_{j=1}^{J-1}\sum_{i=1}^{N-1}\left(h_{ij,t}-1\right)^2 \tag{23}$$

Then the gamma convergence test boils down to an ordinary least squares regression on the dispersion of the relative transition parameters, also known as log-t regression

$$\ln\left(\frac{H_1}{H_t}\right) - 2\ln[\ln(t+1)] = a + \gamma \ln(t) + e_t \tag{24}$$

where e_t is the error term.

In the presence of convergence (i.e., cross-sectional variance decreases over time), the ratio (H_1/H_t) will decrease over time. Hence for convergence a non-negative γ coefficient is required, and larger positive values indicate stronger convergence. Phillips and Sul (2007) set up the log-t test where the null hypothesis is that of convergence across time. Rejection of the null hypothesis against the one-sided alternative indicates divergence. In line with the recommendations of Phillips and Sul (2007) and similar applications (Apergis et al., 2014; Olson & Zoubi, 2017) we discard the first 20% of the observations. We use the Hodrick-Prescott filter to detrend the data, however the qualitative nature of the results is not challenged by this. Table 11 reports estimated coefficients, standard errors, and t-statistics for the log-t regression of Eq. 24. We only report the statistics for the γ coefficient as the most relevant to convergence. The full sample results suggest that the conditional correlations of Islamic indices show about three times higher convergence rate than the respective conventional ones, which is consistent with the main analysis.

[Table 11 around here]

5.2 Endogenous breakpoint detection

In the main paper we have relied on economic intuition to identify crisis events used in the financial contagion analysis. In this section we perform a robustness check to detect whether structural breaks are near the event dates that are being considered in developing the binary crisis variable. We opt for the Bai and Perron (2003) endogenous structural breakpoint test where we allow for a level shift in the underlying conditional correlation pairs.

We run the breakpoint test for the conventional and Islamic conditional correlation pairs, and for the five episodes of crisis used in section 4.4 and Table 12 presents the results. We report the percentage of conventional and Islamic conditional correlation pairs in the respective columns that exhibit a structural breakpoint during the period that corresponds to each crisis. For example, during the DTCM crisis all conditional correlation pairs exhibit a structural breakpoint. The fact that most conditional correlation pairs exhibit a breakpoint during the assigned crisis periods, and that no significant deviations exist between the two types of investments, confirm the appropriateness of the crisis dates used in the financial contagion analysis.

The Islamic Lead/Lag column measures whether Islamic conditional correlation pairs exhibited a structural break point earlier (i.e., a lead) or later (i.e., a lag) than the respective conventional ones. The Lead/Lag column is expressed in weeks and a positive (negative) number indicates a lead (lag). The findings show that during the 2008 GFC Islamic investments were affected much later than conventional ones, a result that is echoed elsewhere in the literature (Olson and Zoubi, 2017). By contrast, during the COVID-19 crisis, the two types were affected virtually at the same time.

[Table 12 around here]

5.3 Volatility spillover connectedness

In this section we complement our main correlation-based convergence results with the connectedness approach of Diebold and Yilmaz (2009; 2012; 2014) – henceforth DY. Some of the advantages of the

DY approach are: i) it distils connectedness in a system of financial assets into a compact measure, the spillover index; ii) it is asymmetric by definition; and iii) it dispenses with crisis identification.

We introduce the most relevant notation to our analysis and direct the reader to the Diebold and Yilmaz (2014) for a complete exposition. Of key interest for the construction of the connectedness measures are the forecast error variance decompositions from an N-dimensional covariance stationary VAR system, denoted as: $d_{ij}^{H} \; \forall \; i, j = 1, \ldots, N$. The inequality $i \neq j$ is used to disentangle between "own" and "cross" (or spillover) effects. The main output is the connectedness table that features the "variance decomposition matrix", denoted as $D^{H} = [d_{ij}^{H}]$, with elements $C_{i \leftarrow j}^{H} \equiv d_{ij}^{H}$ and $C_{j \leftarrow i}^{H} \equiv d_{ji}^{H}$ denoting the *directional spillovers* to asset i from asset j, and to asset j from asset i respectively. As the method is asymmetric, it boils down that $d_{ij}^{H} \neq d_{ji}^{H}$. The connectedness table also includes the off-diagonal column-sums and row-sums, defined as $C_{i \leftarrow \bullet}^{H} \equiv \sum_{j=1; j \neq i}^{N} d_{ij}^{H}$ and $C_{\bullet \leftarrow \mathrm{j}}^{H} \equiv \sum_{i=1; i \neq j}^{N} d_{ij}^{H}$, denoted as the "From" and "To" *total directional spillovers* respectively. These quantities reflect the share of the forecast error variance for each asset i *from* all other assets and for each asset j *to* all other assets, respectively. We also define the *net total directional spillovers* as $C_{i}^{H} = C_{i \leftarrow \bullet}^{H} - C_{\bullet \leftarrow \mathrm{j}}^{H}$ where positive (negative) values indicate a spillover absorber (transmitter) respectively. Finally, the *total spillover index* is defined as the sum of the off-diagonal entries of D^{H} averaged over the N-assets, namely $C^{H} = N^{-1} \sum_{i,j=1; i \neq j}^{N} d_{ij}^{H}$. Moving from a static to a dynamic analysis turns the connectedness table containing the pre-discussed metrics into a series of dynamic plots. In our setup, we implement the dynamic analysis with a 3-year rolling estimation window (w=756 trading days). Further, we modify the DY method to our research requirements by introducing two groups – conventional and Islamic, which we denote as $g \in [0,1]$. Hence total *group* directional spillovers, net total *group* directional spillovers and total *group* spillover indices are defined as $C_{i_g \leftarrow \bullet, \mathrm{t-w:t}}^{H}$, $C_{\bullet \leftarrow \mathrm{j}_g, \mathrm{t-w:t}}^{H}$, $C_{i_g, \mathrm{t-w:t}}^{H}$ and $C_{g, \mathrm{t-w:t}}^{H}$.[25]

Figure 5, Panel A presents the *net total group directional spillovers* estimates for the full sample and by business sector.[26] On average, the results suggest that Islamic investments reduce spillovers in the financial system; conventional ones increase them. Focusing on individual sectors reveals interesting features. Approximately half of the business sectors are spillover transmitters, the rest being spillover absorbers. Within the spillover transmitters, the Islamic ones record a lower estimate. Among spillover absorbers, Islamic investments bear a higher estimate. For example, the Industrials estimate is -26.8 compared to -22.3, while the Utilities estimate is 8.2 compared to 31.4 for the conventional and Islamic, respectively. Two noteworthy cases are the Financials and the Oil & Gas sectors: the former for being a spillover transmitter under conventional investments, but a spillover absorber for the Islamic ones. Besides, Financials bears the largest differential between the two groups, which is plausible given the financial restrictions of Islamic investments being most apparent here. The latter is the only sector where Islamic investments are inferior to conventional ones, confirming their

[25] In our analysis we focus on daily conditional volatility spillovers using a second-order VAR in the generalised variance decomposition framework of Koop et al. (1996) and Pesaran and Shin (1998). Conditional correlations are estimated via GJR-GARCH(1,1,1) models akin to the univariate analysis of the main paper. For robustness we also conduct the same analysis with logarithmic returns (Diebold & Yilmaz, 2009) and the results remain qualitatively similar. Data limitations prohibit us from using realised volatility as in Diebold and Yilmaz (2014). Our choice of forecast horizon is set to H=10 days, and we also run robustness with horizons between 2 and 14 days. In the dynamic analysis we opt for a three-year rolling estimation window to allow sufficient smoothing in the connectedness process, which we roll by a day. We have also experimented with a 2-year window, a 4-year window and a different stepping period; while these results are not presented for brevity, we confirm that they are qualitatively similar.

[26] The connectedness table is available in the online appendix.

"Achilleas heal" status documented in the main paper. Our findings are in line with Hkiri et al. (2017) who find Islamic indices to be recipients of volatility spillovers during major crises.

Figure 5, Panel B plots the *total group spillover index* over a 3-year rolling-sample window for conventional and Islamic investments; thus allows for a dynamic evaluation of spillover intensity. A cursory inspection reveals that around the dotcom crisis the conventional index drops from a high of 82% to a low of 62%. In the period leading to the 2008 global financial crisis the index moves upwards, reaching 80% at the time of the Lehman collapse; thus confirming the earlier findings (Diebold & Yilmaz, 2014). In the following years the connectedness increases further and stabilises, only to drop following the 2014-15 Oil crisis. From a high of 87% the total group spillover index drops to around 72% until the Covid-19 outbreak when it jumps up to 86%. The Islamic total spillover index shows similar dynamics to the conventional but with a clear convergence evidenced across time. Specifically, around the dotcom crisis the distance between the two indices is approximately 15 percentage points, with the gap narrowing towards the more recent past. Our results concur with Yarovaya et al. (2021) study who document a comparable effect upon volatility spillovers for Islamic and conventional stock markets during the pandemic. Hence the dynamic spillover analysis here corroborates our convergence results documented in the main paper.

[Figure 5 around here]

6. Conclusion

The superiority of the unrestricted portfolio of investment in finance has been challenged by the appeal of ethical, environmental, sustainable and faith-based investments over the past couple of decades. Superior return, lower risk, resilience during financial crises, reputation management and peace of mind are some of the reasons that have made investors accept restrictions in their portfolio allocation process. Islamic finance, perhaps the most restrictive and well-defined forms of such investments, has been growing at a considerable pace, largely unaffected by financial crises, for more than twenty years. Islamic financial institutions are established in an increasing number of countries, while the range of financial products on offer constantly expands. Convergence between Islamic and conventional investments may be expected for a variety of reasons, such as the ongoing financial integration and global presence of financial institutions, aided by trade, regulatory and monetary unions; the competition between conventional and Islamic financial institutions for investors/depositors, which may manifest in product replication; the increased awareness of ethical behaviour that the public/investors may require from firms, which may be aided by the increased use of technology (e.g., social media).

The aim of this paper is to empirically examine evidence of convergence between Islamic and conventional investments and assess whether this has been detrimental to their relative performance. We focus on sectoral equity indices and five episodes of endogenous and exogenous crises during the 1996 – 2020 period. A multivariate framework is used to provide time-dependent estimates of correlation between the two types of investments. To model convergence dynamics we deploy beta and sigma-convergence models within a difference-in-difference (DiD) framework, which allows us to compare and contrast convergence rates across investment types, business sectors and episodes of crises.

Our main findings are suggestive of a strong convergence between Islamic and conventional investments across time. During episodes of crises Islamic investments show significantly decreased convergence rates. Sectoral evidence suggests that during crises investors can identify the conventional sectors hit the hardest and take appropriate action. By contrast, our sectoral convergence results within Islamic investments suggest that these are viewed as a single entity.

We proceed to examine how the convergence process affects the comparative performance of Islamic and conventional investments using a mean-variance portfolio allocation. We find that on average Islamic investments offer around 7% risk reduction when incorporated in a portfolio, which translates to a monthly performance fee of 64 basis points. Using a decomposition technique, we show that the documented convergence decreases the risk diversification benefit and increases the performance fee. For example, during the most recent Covid-19 exogenous shock a risk-averse investor would be willing to pay 466 basis points.

We also examine the varying extent to which Islamic investments behave as a transmitting channel of shocks using the financial contagion framework. We conduct a series of five financial contagion analyses spanning from the dotcom to the recent Covid-19 crisis. Our results show that Islamic investments are progressively less insulated from financial crises. In regard to the Covid-19 crisis financial contagion is verified, however Islamic investments are significantly less affected than their conventional counterparts.

The convergence results are reflective of worldwide financial integration in market practices and regulation policies as well as the competition between Islamic and non-Islamic financial institutions. Evolving customer needs require Islamic financial institutions to introduce new financial products, which may strain their capabilities, and potentially dilute their operational focus. For instance, demographics of Mulsim population are suggestive of an upcoming young and tech-literate generation that uses technology to communicate, purchase and invest (Kettani, 2010; World Bank, 2020). Fintech has great potential impact both conventional and Islamic finance industries (Ali et al., 2019). To remain competitive, Islamic institutions should react fast; yet this could be at the expense of increased convergence. Furthermore, it appears that the Islamic characteristic dominates sectoral characteristics; thus creating a "single entity" effect, which may be viewed as a form of psychological accounting. [27]

Our results will be primarily useful for policy makers and investors. Investors will be able to better understand the dynamics between Islamic and conventional investments as these would affect the diversification benefits of their portfolios. Policy makers would be able to design regulatory policies that would affect both markets. For example, the recent EU Sustainable Finance policy (EU, 2019a) could consider the characteristics of Islamic finance. Future research could focus on the microstructure characteristics of Islamic investments, such as investor type (e.g., private vs institutional), trading patterns (e.g., short-term vs long-term investments), and investor qualitative characteristics. The cross-country and time evolution of such characteristics could shed more light to the changing Islamic investment dynamics.

[27] Psychological (or mental) *accounting* attempts to describe the process whereby people code, categorize and evaluate economic outcomes, see Zhang and Sussman (2018) for more information.

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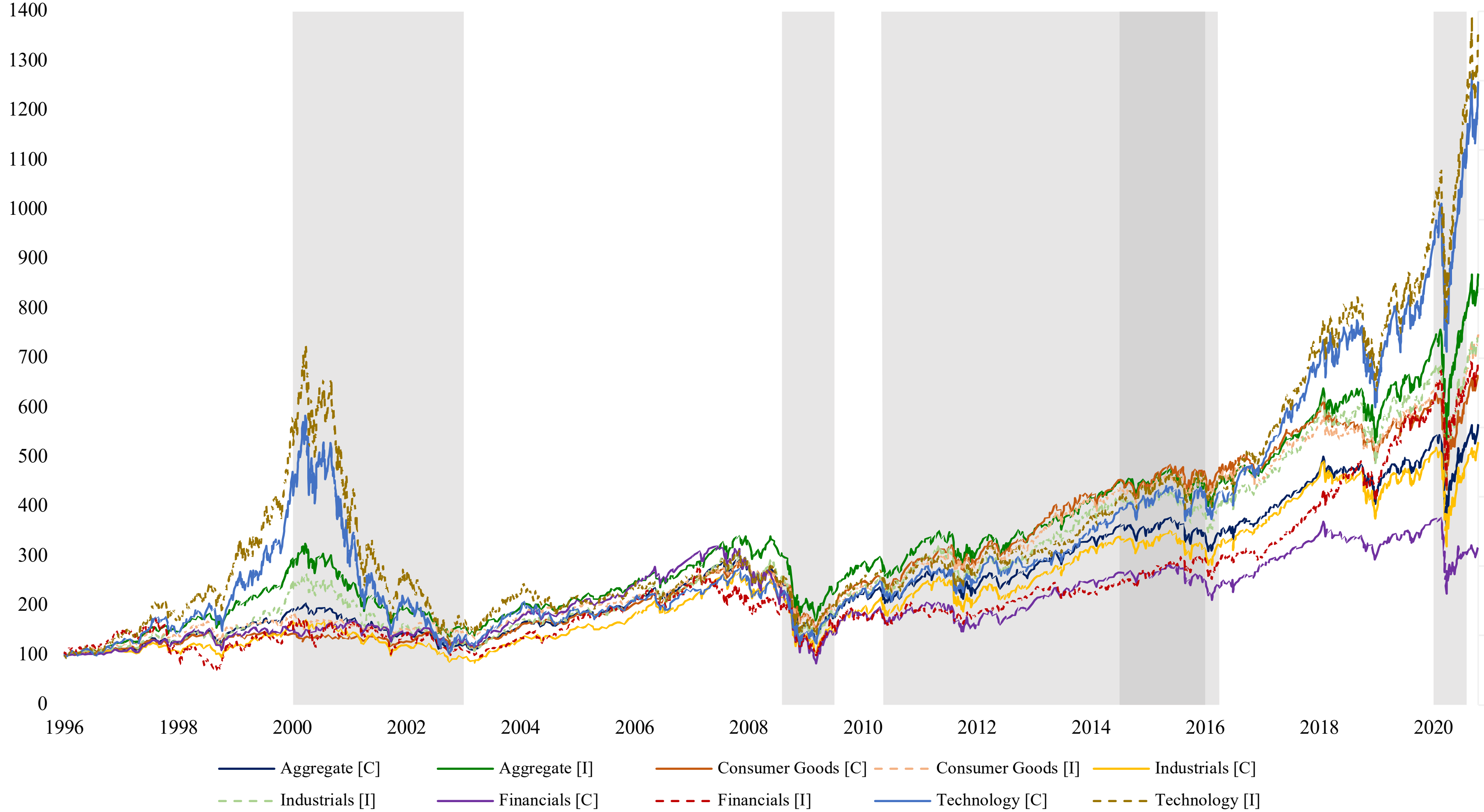
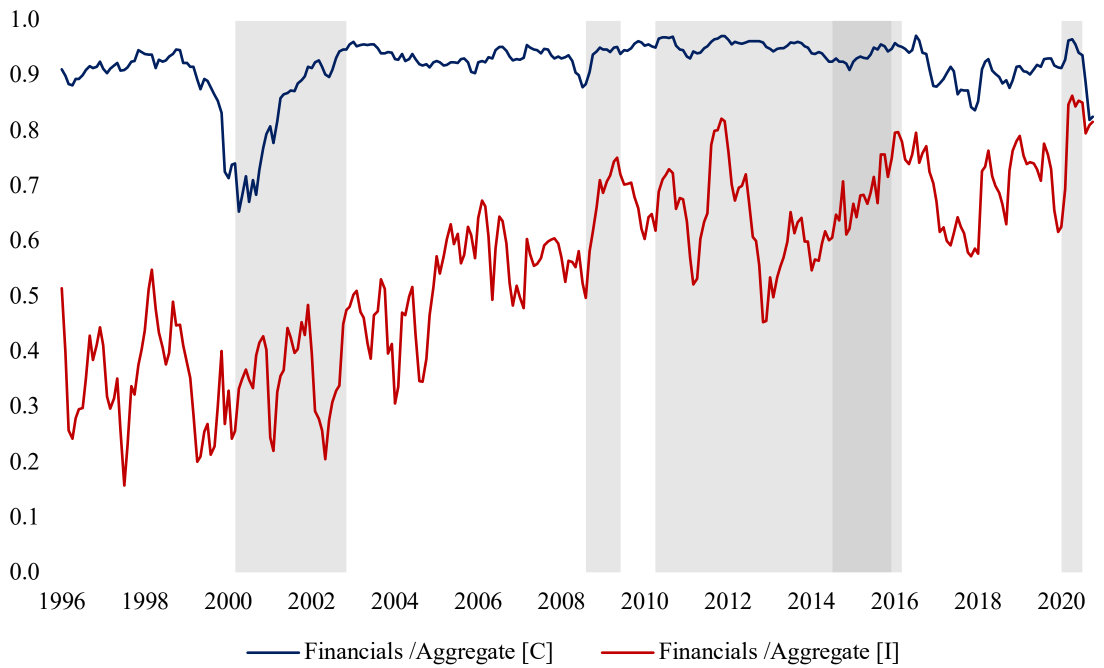
Figure 1. Line plots of sectoral equity indices



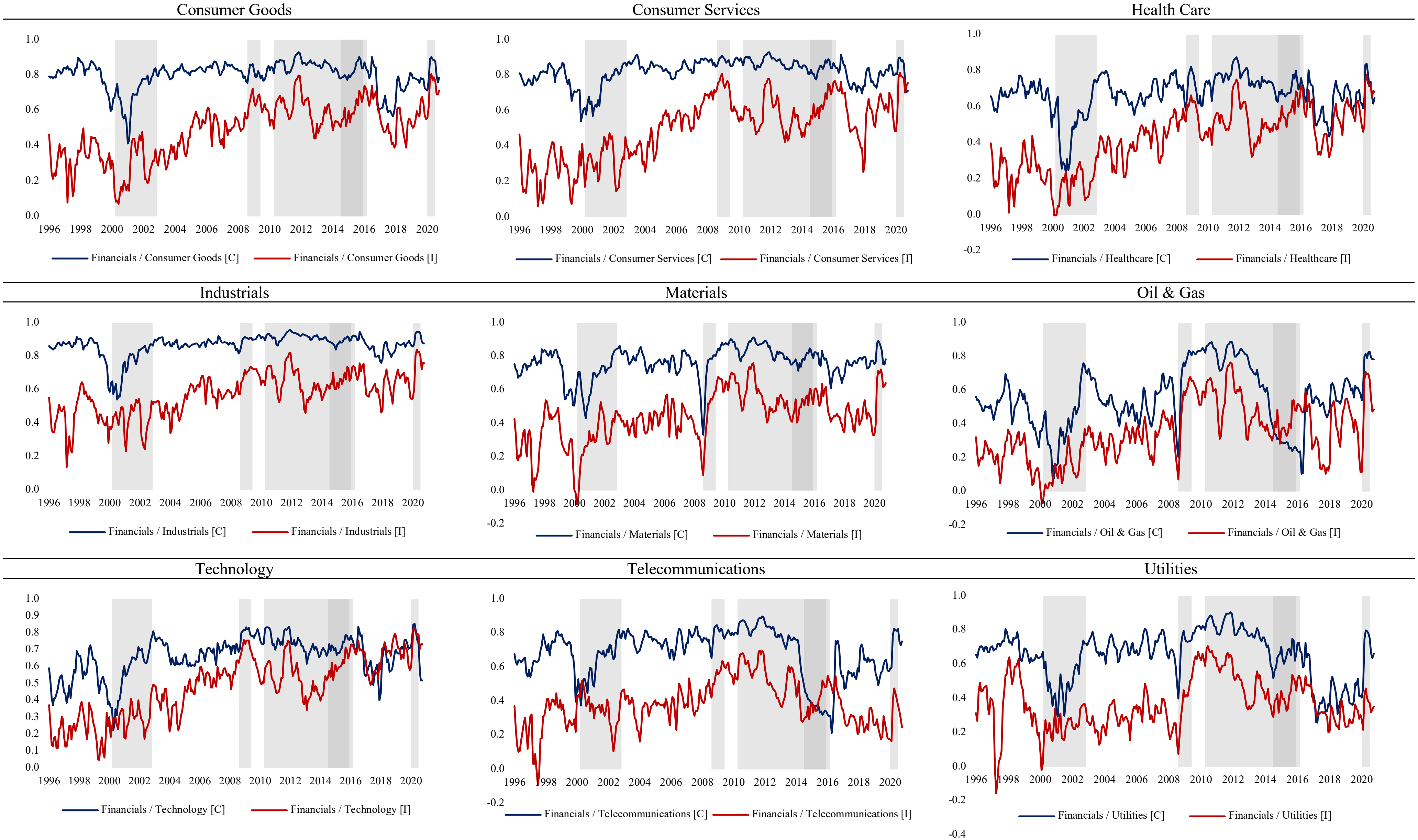
Notes: The graph depicts indicative conventional and Islamic equity indices rebased at 100. Grey shaded areas represent the crisis periods under examination in our study.

Figure 2. Financials / Aggregate indices conditional correlation



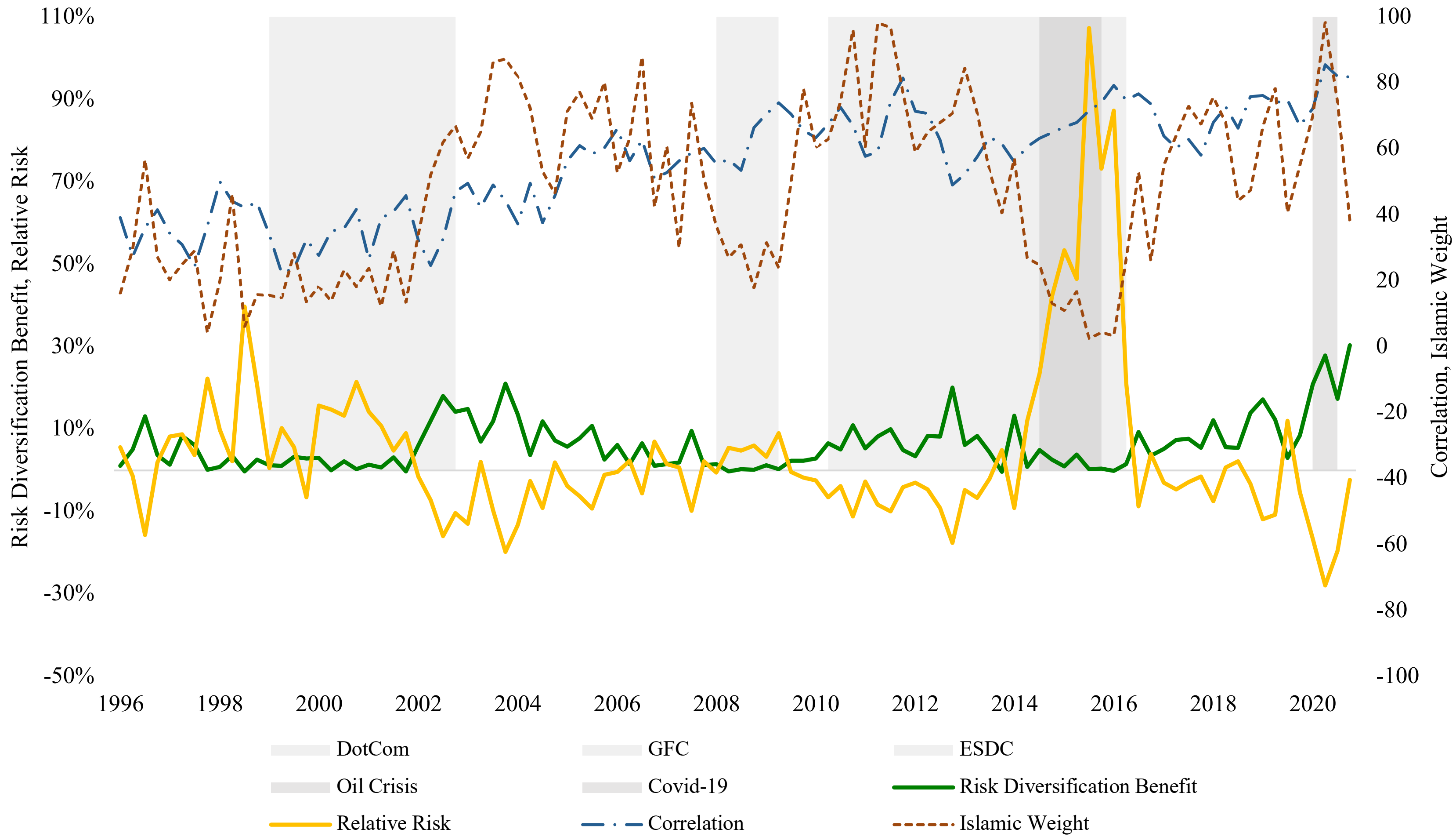
Notes: The graph depicts conditional correlation estimates for the Financials / Aggregate index pairs of conventional (blue line) and Islamic (red line) equity indices respectively. Grey shaded areas represent the crisis periods under examination in our study.

Figure 3. Conditional correlation plots



Notes: The graphs depict conditional correlation estimates for the Financials vis-à-vis against each other sector for conventional (blue line) and Islamic (red line) equity indices respectively. Grey shaded areas represent the crisis periods under examination in our study.

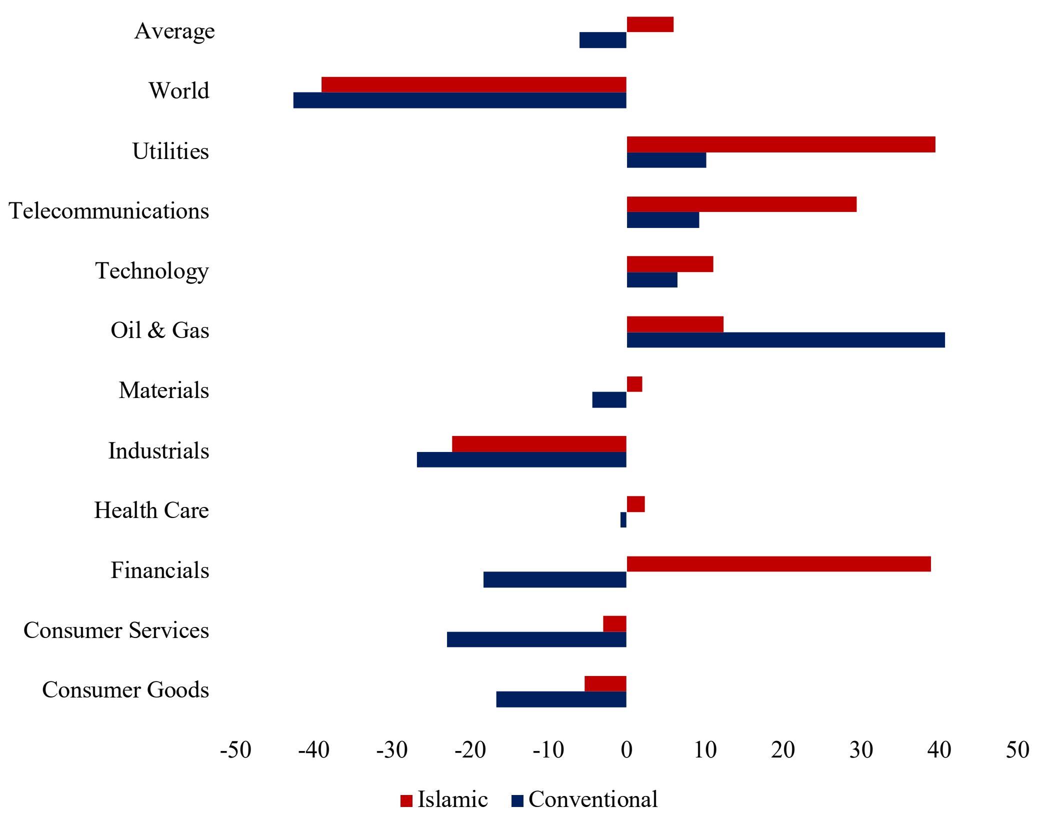
Figure 4. Relative risk across time



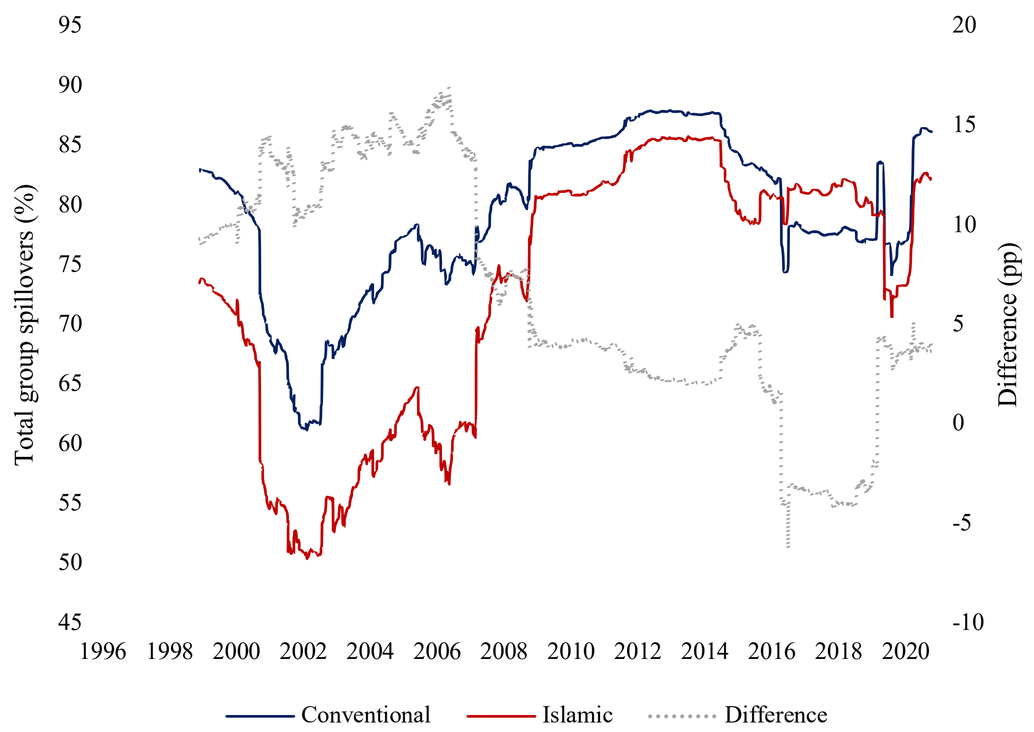
Notes: All, CB and IB refer to the three strategies used, where All invests in both conventional and Islamic equity indices, CB (IB) only in (Islamic) conventional. The Δlog(All/CB) and Δlog(IB/CB) columns report the percentage gain in risk reduction of the All strategy compared to the IB and between the IB and CB strategies respectively (left-axis). A positive value indicates that the All and IB strategies exhibit higher risk respectively. Correlation refers to the average correlation between the Islamic and conventional indices (right-axis). The IB weight shows the composition of Islamic investments in the All strategy (right-axis).

Figure 5. Volatility spillover results

Panel A: Net total group directional spillovers



Panel B: Total group spillover plots



Notes: Panel A: The figure plots the average net total group directional spillovers as well as across business sectors and world aggregate for conventional and Islamic investments. Positive (negative) values indicate a spillover absorber (transmitter), respectively. Panel B: The figure plots the total group spillover indices for conventional and Islamic investments (left axis) and their difference in percentage points is given on the right axis. The rolling estimation window is 3 years.

Table 1. Descriptive statistics

Index	Sector	Mean (%)	Rank	Annualised Volatility (%)	Rank	Min	Max	Skewness	Kurtosis
Conventional	Consumer Goods	0.029	4	12.41	11	-9.38	8.94	-0.51	14.11
Conventional	Consumer Services	0.032	3	15.43	8	-9.99	7.36	-0.57	11.25
Conventional	Financials	0.018	11	18.98	4	-11.41	10.68	-0.47	15.58
Conventional	Health Care	0.037	2	14.83	9	-8.26	9.86	-0.38	10.73
Conventional	Industrials	0.026	6	16.34	5	-10.05	9.08	-0.60	11.91
Conventional	Materials	0.022	8	19.18	3	-10.76	9.35	-0.61	13.02
Conventional	Oil & Gas	0.018	10	22.17	2	-31.71	13.56	-2.67	57.87
Conventional	Technology	0.039	1	23.44	1	-12.04	10.67	-0.10	8.62
Conventional	Telecommunications	0.020	9	16.03	6	-8.36	9.90	-0.18	10.11
Conventional	Utilities	0.025	7	13.37	10	-11.73	11.77	-0.57	23.88
Conventional	World	0.027	5	15.48	7	-9.95	8.66	-0.66	13.67
Islamic	Consumer Goods	0.031	6	13.24	11	-9.33	7.86	-0.59	13.04
Islamic	Consumer Services	0.040	2	17.24	5	-12.89	9.12	-0.49	13.08
Islamic	Financials	0.030	7	24.69	2	-16.98	17.28	0.11	18.84
Islamic	Health Care	0.037	3	15.16	10	-7.88	9.78	-0.33	9.84
Islamic	Industrials	0.031	5	17.10	6	-9.56	9.08	-0.50	10.85
Islamic	Materials	0.027	8	20.02	4	-11.14	9.87	-0.58	12.96
Islamic	Oil & Gas	0.016	11	23.38	3	-18.85	13.61	-0.85	17.75
Islamic	Technology	0.040	1	24.75	1	-12.45	11.72	-0.05	8.54
Islamic	Telecommunications	0.022	9	16.80	7	-8.07	9.96	-0.12	8.72
Islamic	Utilities	0.020	10	16.50	8	-11.78	14.67	-0.16	23.22
Islamic	World	0.034	4	16.19	9	-9.64	9.78	-0.53	12.33

Notes: The table reports descriptive statistics for the sectoral indices used in the analysis over the full sample period. The Rank columns provide ranking positions of each index relatively to the mean return and annualised volatility.

Table 2. Univariate estimation results

	World	Consumer Goods	Consumer Services	Financials	Health Care	Industrials	Materials	Oli & Gas	Technology	Telecommunications	Utilities
Panel A. Conventional Equity Indices											
θ_0	0.0003***	0.0003***	0.0003***	0.0003**	0.0003***	0.0003***	0.0002	-0.0001	0.0005***	0.0002***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0001)	(0.0001)	(0.0001)
φ_1	0.1786***	0.1587***	0.1518***	0.1948***	0.0981***	0.2096***	0.2387***	0.1352***	0.1158***	0.1358***	0.0998***
	(0.0146)	(0.0141)	(0.0133)	(0.0150)	(0.0136)	(0.0138)	(0.0133)	(0.0159)	(0.0135)	(0.0141)	(0.0136)
ω_0	0.0106***	0.0110***	0.0117***	0.0105***	0.0151***	0.0111***	0.0094***	0.0932	0.0175***	0.0090	0.0151***
	(0.0018)	(0.0016)	(0.0020)	(0.0015)	(0.0026)	(0.0016)	(0.0018)	(0.0652)	(0.0036)	(0.0082)	(0.0021)
α_1	0.0087	0.0152	0.0186*	0.0159	0.0168	0.0128	0.0285***	0.0007	0.0308***	0.0408***	0.0389***
	(0.0112)	(0.0111)	(0.0108)	(0.0098)	(0.0102)	(0.0145)	(0.0099)	(0.0609)	(0.0116)	(0.0114)	(0.0111)
β_1	0.9087***	0.9042***	0.9020***	0.9069***	0.9055***	0.9094***	0.9239***	0.8881***	0.9095***	0.9127***	0.8843***
	(0.0089)	(0.0092)	(0.0092)	(0.0073)	(0.0117)	(0.0096)	(0.0074)	(0.0177)	(0.0086)	(0.0123)	(0.0107)
γ_1	0.1343***	0.1159***	0.1276***	0.1355***	0.1144***	0.1275***	0.0810***	0.1073***	0.0991***	0.0746***	0.0935***
	(0.0181)	(0.0160)	(0.0180)	(0.0142)	(0.0165)	(0.0166)	(0.0145)	(0.0396)	(0.0171)	(0.0164)	(0.0172)
AIC	-6.934	-7.213	-6.878	-6.675	-6.832	-6.806	-6.478	-6.016	-6.072	-6.842	-7.150
BIC	-6.928	-7.207	-6.871	-6.669	-6.825	-6.800	-6.472	-6.010	-6.065	-6.836	-7.144
T	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465
Panel B. Islamic Equity Indices											
θ_0	0.0004***	0.0003***	0.0004***	0.0005***	0.0003***	0.0004***	0.0003**	0.0003*	0.0005***	0.0002**	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
φ_1	0.1367***	0.1215***	0.0999***	0.0648***	0.0947***	0.1913***	0.2144***	0.1086***	0.0860***	0.1282***	0.0590***
	(0.0144)	(0.0150)	(0.0132)	(0.0134)	(0.0136)	(0.0152)	(0.0153)	(0.0133)	(0.0135)	(0.0129)	(0.0144)
ω_0	0.0123***	0.0118***	0.0155***	0.0124***	0.0139***	0.0128***	0.0146***	0.0214***	0.0184***	0.0080***	0.0144***
	(0.0023)	(0.0019)	(0.0029)	(0.0024)	(0.0023)	(0.0026)	(0.0038)	(0.0034)	(0.0039)	(0.0020)	(0.0031)
α_1	0.0161	0.0189*	0.0256**	0.0449***	0.0182**	0.0133	0.0336***	0.0251***	0.0311***	0.0375***	0.0386

	(0.0154)	(0.0111)	(0.0107)	(0.0089)	(0.0092)	(0.0212)	(0.0116)	(0.0088)	(0.0117)	(0.0085)	(0.0235)
β_1	0.9078***	0.8972***	0.8985***	0.9030***	0.9092***	0.9120***	0.9152***	0.9216***	0.9109***	0.9244***	0.8948***
	(0.0105)	(0.0105)	(0.0096)	(0.0076)	(0.0100)	(0.0114)	(0.0111)	(0.0080)	(0.0083)	(0.0073)	(0.0127)
γ_1	0.1210***	0.1266***	0.1219***	0.0945***	0.1105***	0.1205***	0.0820***	0.0790***	0.0971***	0.0625***	0.1040***
	(0.0233)	(0.0190)	(0.0169)	(0.0146)	(0.0154)	(0.0243)	(0.0156)	(0.0146)	(0.0171)	(0.0132)	(0.0366)
AIC	-6.791	-7.124	-6.629	-6.200	-6.782	-6.686	-6.353	-6.042	-5.965	-6.636	-6.786
BIC	-6.785	-7.118	-6.623	-6.194	-6.776	-6.680	-6.346	-6.035	-5.959	-6.629	-6.779
T	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465	6,465

Notes: The table reports estimated coefficients and Bollerslev and Wooldrige (1992) robust standard errors in brackets for the univariate GJR-GARCH models of Eq.3 & 4. AIC and BIC denote the Akaike and Schwartz information criteria respectively. ***, **, * denote statistical significance at the 1, 5 and 10% significance level respectively. ω_0 is scaled by 10^4.

Table 3. Multivariate estimation results

a	0.0134***
	(0.0016)
b	0.9784***
	(0.0058)
g	0.0072**
	0.0035)
AIC	-191.400
BIC	-190.973
T	6,465

Notes: The table reports estimated coefficients and robust standard errors in brackets for the multivariate ADCC-GARCH model of Eq.9. AIC and BIC denote the Akaike and Schwartz information criteria respectively. ***, **, * denote statistical significance at the 1, 5 and 10% significance level respectively.

Table 4. Beta-convergence estimation results

	Random effects						System-GMM					
Model	I	II	III	IV	V	VI	I	II	III	IV	V	VI
a	-0.0285***	-0.0148***	-0.0164**	-0.0188***	-0.0721	-0.1080**	-0.0208**	-0.0146***	-0.0159**	-0.0184**	-0.0371***	-0.0542***
	(0.0072)	(0.0037)	(0.0068)	(0.0059)	(0.0452)	(0.0462)	(0.009)	(0.005)	(0.008)	(0.008)	(0.011)	(0.017)
β_0	-0.0498***	-0.0439***	-0.0115	-0.0418***	-0.0482***	-0.1160***	-0.0439***	-0.0489***	-0.0182	-0.0509***	-0.0526**	-0.0966**
	(0.0081)	(0.0051)	(0.0143)	(0.0133)	(0.0184)	(0.0281)	(0.010)	(0.008)	(0.014)	(0.019)	(0.022)	(0.049)
β_1	—	-0.0517***	—	-0.0175	-0.0135	-0.0002		-0.0534***		-0.0291	-0.0374*	0.0299
		(0.0143)		(0.0161)	(0.0160)	(0.0160)		(0.015)		(0.020)	(0.020)	(0.084)
β_2	—	-0.0375***	—	0.0156	0.0245	0.0592		-0.0340**		0.0091	-0.0021	0.0876
		(0.0141)		(0.0255)	(0.0307)	(0.0387)		(0.014)		(0.031)	(0.033)	(0.106)
γ_1	—	—	-0.0206	0.0100*	0.0607	0.0957*			-0.0089	0.0094	0.0064	0.0506
			(0.0129)	(0.0056)	(0.0502)	(0.0532)			(0.010)	(0.007)	(0.009)	(0.041)
γ_2	—	—	-0.0779***	-0.0033	-0.0222	-0.0047			-0.0533**	0.0051	0.0004	0.0759
			(0.0270)	(0.0210)	(0.0311)	(0.0373)			(0.023)	(0.027)	(0.037)	(0.083)
δ_0	—	—	—	-0.0578**	-0.0733***	-0.0718***				-0.0410*	-0.0376*	-0.1655
				(0.0281)	(0.0274)	(0.0276)				(0.021)	(0.022)	(0.147)
δ_1	—	—	—	-0.102**	-0.110**	-0.1200**				-0.0845**	-0.0771*	-0.2318
				(0.0453)	(0.0491)	(0.0536)				(0.041)	(0.045)	(0.180)
ρ							0.2087***	0.2215***	0.1989***	0.2088***	0.2098***	0.2059***
							(0.023)	(0.024)	(0.023)	(0.023)	(0.029)	(0.025)
R-squared	0.0218	0.0325	0.0416	0.0535	0.3001	0.3104						
Time Fixed Effects	NO	NO	NO	NO	YES	YES	NO	NO	NO	NO	YES	YES
Sector Fixed Effects	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO	YES
Observations	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466
Wald statistic							97.6***	259.6***	190.2***	549.0***	418.2***	371.6***
Arellano-Bond AR1 (p-value)							0.002	0.002	0.002	0.002	0.002	0.002
Arellano-Bond AR2 (p-value)							0.011	0.011	0.010	0.010	0.010	0.009
Hansen test (p-value)							0.185	0.195	0.163	0.194	0.192	0.306
Kleibergen-Paap LM test (p-value)							0.008	0.008	0.007	0.007	0.007	0.007
Kleibergen-Paap Wald statistic							533.6***	545.3***	532.0***	535.7***	541.1***	544.5***

Notes: The table reports estimated coefficients and robust standard errors in parentheses for the beta-convergence models outlined in section 3.2 (Eq.11). In particular, the following equation is estimated: $\Delta\rho_{ij,t} = a + \beta_0(\ln\rho_{ij,t-1}) + \beta_1 ISL + \beta_2 ISL \times \ln(\rho_{ij,t-1}) + \gamma_1 CR + \gamma_2 CR \times \ln(\rho_{ij,t-1}) + \delta_0 ISL \times CR + \delta_1 ISL \times CR \times \ln(\rho_{ij,t-1}) + \rho\Delta\rho_{ij,t-1} + \varepsilon_{i,t}$. ISL is a binary variable that takes the value of 1 for equity indices that abide by the Shariah rules, zero otherwise. CR is a binary variable that takes the value of 1 for periods of turmoil, as identified in section 2.2, zero otherwise. The Arellano-Bond AR1 and AR2 report the p-values for the of first- and second order autocorrelation in the system-GMM model, respectively. The Hansen test p-value is for the test of over-identifying restrictions relevant to the system-GMM. The Kleibergen-Paap LM test reports the p-value for the under-identification test. The Kleibergen-Paap Wald statistic reports the test statistic for the weak instrument test and the asterisks here correspond to rejection of the null hypothesis against the Stock and Yogo (2005) critical values. ***, **, * denote statistical significance at the 1, 5 and 10% significance level.

Table 5. Sigma-convergence estimation results

	Random effects						System-GMM					
Model	I	II	III	IV	V	VI	I	II	III	IV	V	VI
a	-0.0028	-0.0009	-0.0037	-0.0010	0.0474	0.0469	0.0003	0.0007	-0.0013	0.0010	-0.0024	-0.0044
	(0.0035)	(0.0022)	(0.0030)	(0.0024)	(0.0638)	(0.0585)	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.010)
σ_0	-0.0809***	-0.0398***	-0.0204	-0.0332***	-0.0335**	-0.0840***	-0.0765***	-0.0442***	-0.0339**	-0.0403**	-0.0406**	-0.0413**
	(0.0143)	(0.0059)	(0.0142)	(0.0129)	(0.0137)	(0.0166)	(0.016)	(0.009)	(0.017)	(0.018)	(0.018)	(0.018)
σ_1	—	-0.0038	—	-0.0055	-0.0055	0.0232***		-0.0029		-0.0063	-0.0062	-0.0074
		(0.0071)		(0.0059)	(0.0062)	(0.0058)		(0.010)		(0.008)	(0.008)	(0.016)
σ_2	—	-0.0624***	—	0.0181	0.0167	0.0104		-0.0620**		0.0072	0.0074	0.0089
		(0.0182)		(0.0227)	(0.0221)	(0.0273)		(0.028)		(0.031)	(0.031)	(0.032)
γ_1	—	—	0.0025	0.0002	-0.0525	-0.0480			0.0031	-0.0007	-0.0010	-0.0010
			(0.0041)	(0.0017)	(0.0630)	(0.0589)			(0.005)	(0.002)	(0.002)	(0.002)
γ_2	—	—	-0.0280	0.0900***	0.0860***	0.0900***			-0.0892**	-0.0056	-0.0053	-0.0045
			(0.0390)	(0.0330)	(0.0310)	(0.0310)			(0.041)	(0.029)	(0.029)	(0.027)
δ_0	—	—	—	0.0053	0.0054	0.0060				0.0071	0.0071	0.0074
				(0.0073)	(0.0076)	(0.0075)				(0.009)	(0.009)	(0.009)
δ_1	—	—	—	-0.1740***	-0.1730***	-0.1750***				-0.1590***	-0.1595***	-0.1611***
				(0.0423)	(0.0408)	(0.0446)				(0.042)	(0.042)	(0.042)
ρ							0.1907***	0.1964***	0.1809***	0.1834***	0.1837***	0.1897***
							(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.038)
R-squared	0.0325	0.0369	0.0523	0.0666	0.1003	0.1186						
Time Fixed Effects	NO	NO	NO	NO	YES	YES	NO	NO	NO	NO	YES	YES
Sector Fixed Effects	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO	YES
Observations	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466	5,466
Wald statistic							98.47***	186.5***	119.6***	333.4***	729.1***	697.4***
Arellano-Bond AR1 (p-							0.009	0.009	0.008	0.007	0.007	0.007
Arellano-Bond AR2 (p-							0.017	0.017	0.017	0.017	0.017	0.018
Hansen test (p-value)							0.184	0.198	0.162	0.189	0.19	0.194
Kleibergen-Paap LM test							0.008	0.009	0.007	0.007	0.007	0.007
Kleibergen-Paap Wald							455.9***	458.3***	465.1***	487.2***	487.0***	493.0***

Notes: The table reports estimated coefficients and robust standard errors in parentheses for the sigma-convergence models outlined in section 3.2 (Eq.13). In particular, the following equation is estimated: $\Delta E_{ij,t} = a + \sigma_0 E_{ij,t} + \sigma_1 ISL + \sigma_2 ISL \times E_{ij,t} + \gamma_1 CR + \gamma_2 CR \times E_{ij,t} + \delta_0 ISL \times CR + \delta_1 ISL \times CR \times E_{ij,t} + \varepsilon_{i,t}$. ISL is a binary variable that takes the value of 1 for equity indices that abide by the Shariah rules, zero otherwise. CR is a binary variable that takes the value of 1 for periods of turmoil, as identified in section 2.2, zero otherwise. The Arellano-Bond AR1 and AR2 report the p-values for the of first- and second order autocorrelation in the system-GMM model, respectively. The Hansen test p-value is for the test of over-identifying restrictions relevant to the system-GMM. The Kleibergen-Paap LM test reports the p-value for the under-identification test. The Kleibergen-Paap Wald statistic reports the test statistic for the weak instrument test and the asterisks here correspond to rejection of the null hypothesis against the Stock and Yogo (2005) critical values. ***, **, * denote statistical significance at the 1, 5 and 10% significance level.

Table 6. Beta-/sigma-convergence estimation results by crisis

	Beta-convergence					Sigma-convergence				
	DTCM	GFC	ESDC	OIL	COVID-19	DTCM	GFC	ESDC	OIL	COVID-19
a	-0.1200***	-0.1180**	-0.0883***	-0.1130**	-0.1160**	0.0455	0.0432	0.0459	0.0443	0.0438
	(0.0466)	(0.0468)	(0.0129)	(0.0469)	(0.0467)	(0.0585)	(0.0591)	(0.0365)	(0.0592)	(0.0592)
β_0 $\{\sigma_0\}$	-0.1300***	-0.1220***	-0.1000***	-0.1160***	-0.1210***	-0.1110***	-0.0984***	-0.0788***	-0.0912***	-0.0983***
	(0.0351)	(0.0360)	(0.0295)	(0.0368)	(0.0364)	(0.0247)	(0.0254)	(0.0208)	(0.0275)	(0.0257)
β_1 $\{\sigma_1\}$	0.0031	0.0029	-0.0020	0.0008	0.0025	0.0227***	0.0200***	0.0166***	0.0190***	0.0196***
	(0.0185)	(0.0200)	(0.0179)	(0.0195)	(0.0198)	(0.0071)	(0.0048)	(0.0048)	(0.0057)	(0.0056)
β_2 $\{\sigma_2\}$	0.0625	0.0620	0.0471	0.0565	0.0606	0.0362	0.0321	0.0204	0.0261	0.0327
	(0.0465)	(0.0488)	(0.0428)	(0.0488)	(0.0492)	(0.0374)	(0.0365)	(0.0312)	(0.0385)	(0.0373)
γ_1	0.2170***	0.0318	0.0704***	0.1120**	0.0291	-0.0404	-0.0496	-0.0453	-0.0487	-0.0490
	(0.0710)	(0.0481)	(0.0167)	(0.0495)	(0.0480)	(0.0590)	(0.0579)	(0.0381)	(0.0576)	(0.0569)
γ_2	0.0140	-0.3120***	0.0729**	0.0943***	-0.2070***	-0.0079	-0.3350***	0.0521*	0.0771***	-0.2830***
	(0.0272)	(0.0375)	(0.0360)	(0.0317)	(0.0504)	(0.0207)	(0.0215)	(0.0284)	(0.0267)	(0.0264)
δ_0	-0.2340***	-0.0967***	-0.0345**	-0.0566**	-0.0169	0.0039	0.0116	0.0056	0.0070	0.0044
	(0.0778)	(0.0354)	(0.0172)	(0.0228)	(0.0400)	(0.0203)	(0.0162)	(0.0055)	(0.0071)	(0.0236)
δ_1	-0.1970***	-0.0715	-0.1260***	-0.1990***	-0.0441	-0.1510**	-0.0390	-0.1300***	-0.1620***	0.0625
	(0.0728)	(0.0630)	(0.0427)	(0.0514)	(0.106)	(0.0636)	(0.0588)	(0.0336)	(0.0379)	(0.133)
R-squared	0.2867	0.3071	0.2676	0.2634	0.2843	0.1016	0.1155	0.0591	0.0617	0.0717
Time FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,766	3,276	4,216	3,496	3,256	3,766	3,276	4,216	3,496	3,256

Notes: The table reports estimated coefficients and robust standard errors in parentheses for the beta-/sigma-convergence models outlined in section 3.2 (Eq.11) and (Eq.13). For beta-convergence the following equation is estimated: $\Delta\rho_{ij,t} = a + \beta_0(\ln\rho_{ij,t-1}) + \beta_1 ISL + \beta_2 ISL \times \ln(\rho_{ij,t-1}) + \gamma_1 CR + \gamma_2 CR \times \ln(\rho_{ij,t-1}) + \delta_0 ISL \times CR + \delta_1 ISL \times CR \times \ln(\rho_{ij,t-1}) + \varepsilon_{i,t}$. For sigma-convergence the following equation is estimated: $\Delta E_{ij,t} = a + \sigma_0 E_{ij,t} + \sigma_1 ISL + \sigma_2 ISL \times E_{ij,t} + \gamma_1 CR + \gamma_2 CR \times E_{ij,t} + \delta_0 ISL \times CR + \delta_1 ISL \times CR \times E_{ij,t} + \varepsilon_{i,t}$ ISL is a binary variable that takes the value of 1 for equity indices that abide by the Shariah rules, zero otherwise. CR is a binary variable that takes the value of 1 for periods of turmoil, as identified in section 2.2, zero otherwise. ***, **, * denote statistical significance at the 1, 5 and 10% significance level.

Table 7. Portfolio analysis results

		Return			VaR 95%					
Year	Islamic weight	Combined	Conv'al	Islamic	Combined	Conv'al	Islamic	Risk diversification benefit %	Relative risk %	Correlation
1996	32.44	0.0561	0.0459	0.0771	0.6433	0.6822	0.6690	5.87	-1.95	36.04
1997	19.60	0.0772	0.0744	0.0863	0.8089	0.8334	0.9529	2.99	13.40	31.61
1998	22.06	0.0980	0.0966	0.1069	0.8695	0.8837	1.0830	1.62	20.34	45.06
1999	18.06	0.0205	0.0134	0.0885	0.8745	0.8922	0.9222	2.01	3.30	28.17
2000	18.45	0.0323	0.0345	0.0075	0.9016	0.9139	1.0794	1.35	16.65	35.17
2001	19.65	-0.0308	-0.0318	-0.0291	1.0534	1.0657	1.1741	1.16	9.68	38.06
2002	53.84	-0.0043	-0.0226	-0.0066	1.0553	1.2156	1.0919	14.14	-10.73	34.19
2003	73.96	0.0953	0.1048	0.0831	0.7351	0.8450	0.7649	13.93	-9.96	46.32
2004	63.50	0.0947	0.0859	0.0911	0.6957	0.7574	0.7160	8.49	-5.62	42.56
2005	74.56	0.0515	0.0493	0.0477	0.6760	0.7210	0.6875	6.45	-4.76	59.05
2006	61.59	0.0948	0.0988	0.0820	0.7256	0.7528	0.7573	3.68	0.60	59.06
2007	53.97	0.0683	0.0633	0.0665	0.8653	0.9006	0.8863	4.00	-1.61	57.09
2008	28.13	-0.1380	-0.1383	-0.1330	1.9875	1.9965	2.0790	0.45	4.05	58.05
2009	45.94	0.0726	0.0775	0.0675	1.2779	1.2960	1.3372	1.41	3.13	70.17
2010	73.47	0.0595	0.0481	0.0620	1.0578	1.1290	1.0611	6.52	-6.21	67.64
2011	83.13	0.0100	0.0193	0.0064	1.3122	1.4194	1.3220	7.85	-7.11	68.15
2012	65.71	0.0738	0.0686	0.0791	0.8107	0.8930	0.8226	9.67	-8.21	63.47
2013	62.33	0.0586	0.0900	0.0509	0.7776	0.8122	0.7962	4.36	-1.99	58.75
2014	30.47	0.0269	0.0245	0.0535	0.5564	0.5905	0.6994	5.94	16.93	61.20
2015	8.68	0.0070	0.0057	0.0067	0.5054	0.5124	1.0880	1.38	75.29	70.11
2016	27.22	0.0391	0.0285	0.0310	0.7793	0.8137	1.0406	4.32	24.60	76.12
2017	64.95	0.0798	0.0889	0.0757	0.5058	0.5397	0.5235	6.49	-3.05	61.32
2018	58.85	0.0103	0.0014	-0.0013	0.7926	0.8788	0.8533	10.32	-2.95	70.78
2019	60.20	0.0803	0.0879	0.0712	0.6107	0.6755	0.6574	10.09	-2.72	73.00
2020	76.64	0.0702	0.0568	0.0763	1.2606	1.7049	1.2784	30.19	-28.79	80.14
Average	**47.90**	**0.0442**	**0.0429**	**0.0459**	**0.8855**	**0.9490**	**0.9737**	**6.92**	**2.57**	**55.65**

Notes: The table reports the results of the portfolio diversification exercise. Combined, conventional and Islamic refer to the three strategies used, where "Combined" invests in both conventional and Islamic equity indices, conventional and Islamic only in the respective indices. Portfolio returns and 95% value at risk are reported. The Islamic Weight column shows the composition of Islamic investments in the combined strategy. The Risk diversification benefit is defined as Δlog(Conventional/Combined) and the relative risk as Δlog(Islamic/Conventional), both expressed as percentages. A positive value indicates that the combined and conventional strategies exhibit higher risk respectively. The Correlation column reports the average correlation between the Islamic and conventional indices.

Table 8. Investment strategies and performance fees

	γ=2		γ=6		γ=10	
Periods	Combined	Islamic	Combined	Islamic	Combined	Islamic
Full sample (1996-2020)	18	-9	64	-42	109	-71
	(23.25)	(14.55)	(32.44)	(25.47)	(31.62)	(25.98)
First (1996-2004)	15	-7	54	-53	91	-93
	(4.87)	(1.25)	(16.16)	(23.12)	(16.05)	(22.32)
Second (2005-2013)	17	7	57	31	96	53
	(9.60)	(17.22)	(21.44)	(40.83)	(21.23)	(40.40)
Third (2014-2020)	22	-34	87	-122	149	-207
	(9.05)	(10.65)	(9.85)	(15.05)	(9.74)	(15.13)

Notes: The table reports the economic gains of switching from the conventional strategy (benchmark) to the combined and Islamic strategies in basis points (rounded to the nearest integer) under risk aversion levels of γ=2, 6, and 10. Numbers in parentheses are t-statistics for the Giacomini and White (2006) test, where the null hypothesis assumes that the mean economic gain equals zero.

Table 9. Drivers of risk diversification benefit

Model	(I)	(II)	(III)	(IV)
Constant	0.106***	0.116***	0.020***	0.146***
	(0.013)	(0.013)	(0.004)	(0.029)
Relative risk	-0.243***	-0.261***	-0.772***	-0.158**
	(0.070)	(0.067)	(0.046)	(0.068)
ρ_{ij}	-0.106***	-0.136***	0.038***	-0.156**
	(0.030)	(0.039)	(0.014)	(0.064)
AR1	0.579***	0.003	0.291**	0.497***
	(0.061)	(0.136)	(0.125)	(0.085)
R-squared	0.540	0.642	0.894	0.500
Period	1996-2020	1996-2004	2005-2013	2014-2020
Observations	297	107	108	82

Notes: The table presents estimated coefficients and robust standard errors in parentheses pertaining to Eq.20. The dependent variable is the *risk diversification benefit*, defined as the logarithmic difference between the combined and the conventional strategy. Relative risk is defined as the logarithmic difference between the Islamic and the conventional strategy, where high values indicate a riskier Islamic strategy; ρ_{ij} is the conditional correlation between the Islamic and the conventional equity indices. AR1 denotes the autoregressive coefficient of order one. ***, **, * denote statistical significance at the 1, 5 and 10% significance level.

Table 10. Financial contagion estimates by crisis

Dotcom (Source: TECH)			GFC (Source: FIN)			ESDC (Source: FIN)			Oil Crisis (Source: OIL&GAS)			Covid-19 (Source: WORLD)		
Target	**DTCM**	**t-stat**	**Target**	**GFC**	**t-stat**	**Target**	**ESDC**	**t-stat**	**Target**	**OILCR**	**t-stat**	**Target**	**COVID**	**t-stat**
						Panel A. Conventional								
MAT	-0.135	-9.120	MAT	-0.163	-7.719	MAT	0.034	6.533	MAT	-0.162	-9.010	MAT	0.034	3.152
CGDS	-0.204	-14.07	CGDS	-0.035	-5.023	CGDS	0.041	9.131	CGDS	-0.163	-10.30	CGDS	0.028	3.607
CSVS	-0.047	-4.747	CSVS	-0.026	-6.188	CSVS	0.014	4.128	CSVS	-0.200	-10.99	CSVS	-0.001	-0.131
HCARE	-0.297	-17.43	HCARE	-0.043	-3.595	HCARE	0.077	11.11	HCARE	-0.193	-11.86	HCARE	0.018	1.407
IND	0.084	9.726	IND	-0.030	-6.522	IND	0.028	11.39	IND	-0.184	-10.11	IND	0.018	4.625
OIL&GAS	-0.242	-17.67	OIL&GAS	-0.185	-7.924	OIL&GAS	0.085	4.367	FIN	-0.187	-9.865	OIL&GAS	0.051	2.458
FIN	-0.071	-5.200	TECH	-0.050	-6.543	TECH	0.032	5.656	TECH	-0.171	-10.48	FIN	0.051	5.102
TELECM	0.023	2.465	TELECM	-0.037	-3.150	TELECM	0.005	0.301	TELECM	-0.027	-0.987	TECH	0.029	3.640
UTI	-0.159	-11.29	UTI	-0.119	-6.691	UTI	0.066	7.904	UTI	-0.189	-11.19	TELECM	0.101	3.625
WORLD	0.076	10.66	WORLD	-0.026	-7.721	WORLD	0.014	9.385	WORLD	-0.185	-9.782	UTI	0.121	3.563
Average	**-0.097**	**-5.667**		**-0.071**	**-6.108**		**0.032**	**5.533**		**-0.166**	**-9.457**		**0.045**	**3.105**
						Panel B. Islamic								
MAT	-0.146	-9.104	MAT	-0.183	-8.071	MAT	0.037	6.379	MAT	-0.150	-8.610	MAT	0.054	3.870
CGDS	-0.211	-12.87	CGDS	-0.024	-3.933	CGDS	0.045	9.328	CGDS	-0.176	-10.87	CGDS	0.021	1.522
CSVS	-0.075	-6.191	CSVS	-0.032	-4.173	CSVS	0.037	6.515	CSVS	-0.187	-11.16	CSVS	0.018	2.273
HCARE	-0.275	-15.94	HCARE	-0.043	-3.318	HCARE	0.084	11.71	HCARE	-0.187	-11.96	HCARE	0.011	0.980
IND	0.129	11.92	IND	-0.033	-8.058	IND	0.033	11.63	IND	-0.193	-10.49	IND	0.024	7.930
OIL&GAS	-0.243	-17.29	OIL&GAS	-0.194	-9.007	OIL&GAS	0.115	10.00	FIN	-0.168	-11.00	OIL&GAS	0.045	1.922
FIN	-0.004	-0.327	TECH	-0.054	-6.255	TECH	0.037	5.870	TECH	-0.169	-10.66	FIN	-0.021	-1.179
TELECM	0.031	2.570	TELECM	-0.039	-4.245	TELECM	0.023	3.092	TELECM	-0.141	-10.45	TECH	0.030	3.337
UTI	0.050	5.828	UTI	-0.171	-7.678	UTI	0.098	5.879	UTI	-0.143	-8.728	TELECM	0.057	2.959
WORLD	0.062	13.20	WORLD	-0.075	-8.726	WORLD	0.032	9.665	WORLD	-0.191	-10.32	UTI	0.025	1.622
Average	**-0.068**	**-2.821**		**-0.085**	**-6.346**		**0.054**	**8.006**		**-0.171**	**-10.42**		**0.026**	**2.523**
Change	**-35.52**			**18.00**			**52.32**			**2.97**			**-54.86**	

Notes: Notes: The table reports estimated coefficients and t-statistics for Eq.19. The full sample is split in three seven-year periods, which are characterised in turn by the Dotcom crisis, the GFC and ESDC crises, and the Oil Crisis. The source of contagion is the Technology, Financials and Oil & Gas sectors for each of the periods respectively. Further control variables (not shown in the table): the logarithmic change in the interest rate (yield) spread, proxied by the 10-Year US Government bond rate minus the 3-Month US Treasury bill rate; the logarithmic change in the corporate bond yield spread, proxied by the AAA Corporate bond yield minus the BAA Corporate bond yield; the logarithmic changes in the MSCI World Index, the S&P GSCI Commodity Index and the DJ REIT Index respectively; the logarithm of the US TED Spread, the logarithm of the Economic Policy Uncertainty (EPU) index, and the CBOE VIX. The coefficients show the average change in the pairwise conditional correlations defined as the Source/Target pair. Panel A examines financial contagion within conventional indices; Panel B assumes that the source of contagion is the respective conventional index but the target is an Islamic index. The Average shows the average change in conditional correlation during each crisis, while the Change shows the percentage logarithmic difference (in percentage points) between the average value of Panel A to Panel B.

Table 11. Gamma convergence

All	0.418
	(0.067)
	[6.271]
Conventional	0.293
	(0.038)
	[7.626]
Islamic	0.928
	(0.282)
	[3.290]
Period	1996 – 2020

Notes: The table reports estimated γ coefficients, standard errors in parentheses and t-statistics in square brackets for the log-t regression of Eq.24. We run separate regressions for the full sample of conditional correlations (All), only the conditional correlations between conventional (Conventional) and Islamic (Islamic) indices.

Table 12. Endogenous structural breakpoint results

Crisis	Period	Conventional %	Islamic %	Islamic Lead/Lag
DTCM	11/3/2000 – 9/10/2002	100	100	-7.12
GFC	1/8/2007 – 31/3/2009	60	60	36.29
ESDC	23/4/2010 – 28/3/2016	100	100	-7.36
OIL	01/7/2014 – 31/12/2015	90	100	1.28
COVID-19	1/2/2020 – 31/7/2020	80	90	0.05

Notes: The table shows the percentage of conventional and Islamic index correlation pairs that exhibit a structural break during each identified crisis in the sample. The Bai and Perron (2003) is used to identify structural break points. The Lead/Lag column reports the average lead/lag between the breakpoints of conventional and Islamic indices; a positive (negative) number indicates that Islamic indices exhibit a structural breakpoint earlier (later) to the respective conventional.

Technical Appendix

We assume a risk-averse investor that splits his/her funds between a risk-free asset and one of our investment strategies, namely All/Conventional/Islamic, to evaluate the economic value that the investor obtains. The investor wishes to maximise his/her economic utility by optimising:

$$\max_{w_t} U_t[E_t(r_{p,t}), Var_t(r_{p,t})] \tag{1}$$

where $E_t(r_{p,t})$ is the conditional expected portfolio return, $Var_t(r_{p,t})$ is the conditional variance of the portfolio return and w_t is the portfolio weight of the risky asset. The portfolio return is a weighted average of the return of the particular investment strategy and the risk free asset, and is given as: $E_t(r_{p,t}) = w_t E_t(r_{m,t}) + (1 - w_t) r_{f,t}$ and the portfolio variance is given as: $Var_t(r_{p,t}) = w_t^2 Var_t(r_{m,t})$. The risk-free asset is proxied by the 3-month US Treasury bill, and the conditional variance for the investment strategy is obtained from the ADCC-GARCH step.

The mean-variance utility function is given by:

$$U_t[E_t(r_{p,t}), Var_t(r_{p,t})] = E_t(r_{p,t}) - \frac{\gamma}{2} Var_t(r_{p,t}) \tag{2}$$

where γ is the risk-aversion parameter. Substituting and taking FOC w.r.t w_{t+1} we obtain the optimal portfolio weight as:

$$w_t = \frac{E_t(r_{m,t}) - r_{f,t}}{\gamma Var_t(r_{m,t})} \tag{3}$$

We constraint the portfolio so that short-selling and borrowing are not allowed, hence $0 \leq w_t \leq 1$.

We use a volatility timing-based portfolio allocation strategy to estimate the economic value associated with each investment strategy. We rely on the average realised utility and compare the *All* and *Islamic* investment strategies to the *Conventional* one, which we consider as the benchmark. We consider three different risk aversion levels $\gamma = \{2,6,10\}$ in line with Fleming et al. (2003), Marquering and Verbeek (2004), Nolte and Xu (2015).

The sample averaged realised utility for a given strategy may be interpreted as the certain return that provides the same utility to the investor as the risky investment strategy, and is given as:

$$\overline{U}(R_p) = T^{-1} \sum_{t=0}^{T-1} \left[r_{p,t} - \frac{\gamma}{2} Var_t(r_{p,t}) \right] \tag{4}$$

With each of the three investment strategies corresponding to a different sample averaged realised utility, we can consider the performance fee that an investor may be willing to pay to switch strategies. Considering the *Conventional* as the benchmark strategy, the performance fee denoted in basis points would then represent the economic value of the *All* and *Islamic* investment strategies. The performance fee, denoted as Δ_γ may be obtained by equating the sample averaged realised utility of the candidate strategy to the benchmark and solving for the performance fee, namely:

$$T^{-1} \sum_{t=0}^{T-1} \left[(r_{p,t} - \Delta_\gamma) - \frac{\gamma}{2} Var_t(r_{p,t}) \right] = T^{-1} \sum_{t=0}^{T-1} \left[r_{bm,t} - \frac{\gamma}{2} Var_t(r_{bm,t}) \right] \tag{5}$$

Table OA1. Volatility spillover connectedness table

	Consumer Goods [C]	Consumer Services [C]	Financials [C]	Health Care [C]	Industrials [C]	Materials [C]	Oil & Gas [C]	Technology [C]	Telecommunications [C]	Utilities [C]	World [C]	Consumer Goods [I]	Consumer Services [I]	Financials [I]	Health Care [I]	Industrials [I]	Materials [I]	Oil & Gas [I]	Technology [I]	Telecommunications [I]	Utilities [I]	World [I]	**FROM**
Consumer Goods [C]	9.0	5.7	5.9	4.6	6.5	5.2	1.5	3.1	3.7	4.8	7.0	6.9	4.2	1.9	4.1	5.5	4.2	3.2	2.9	2.4	1.8	6.1	**91.0**
Consumer Services [C]	5.2	8.9	5.7	4.8	6.5	3.9	1.2	4.9	3.6	3.2	7.2	4.3	7.3	2.3	4.3	5.8	3.2	2.8	4.6	2.1	1.2	6.9	**91.1**
Financials [C]	5.8	6.0	9.2	4.1	6.7	4.9	1.8	3.5	3.7	4.1	7.8	4.5	4.4	2.8	3.6	5.6	4.0	3.9	3.2	2.3	1.7	6.3	**90.8**
Health Care [C]	5.3	6.0	4.9	11.1	5.0	3.1	1.3	3.8	3.2	3.8	6.5	4.9	5.0	1.9	10.4	4.4	2.7	2.9	3.7	1.8	1.4	6.8	**88.9**
Industrials [C]	5.8	6.3	6.2	3.8	8.4	5.3	1.6	4.3	3.4	3.4	7.4	4.3	4.6	2.2	3.3	7.5	4.3	3.5	4.0	2.2	1.5	6.8	**91.6**
Materials [C]	6.0	4.7	5.6	3.1	6.5	10.2	2.3	2.6	3.4	4.4	6.6	4.1	3.3	1.8	2.8	5.7	8.8	5.1	2.3	2.4	2.5	5.9	**89.8**
Oil & Gas [C]	3.8	3.3	4.6	2.8	4.4	5.0	23.5	2.0	5.5	3.5	5.2	3.0	2.5	1.7	2.5	3.8	4.3	9.0	1.8	1.4	1.6	4.9	**76.5**
Technology [C]	3.8	6.4	4.4	4.0	5.9	2.9	1.0	11.6	3.3	2.2	6.8	3.3	5.2	2.3	3.5	6.0	2.5	2.4	11.5	2.0	0.8	8.1	**88.4**
Telecommunications [C]	5.2	5.2	4.9	3.8	5.1	4.1	2.9	3.5	12.1	4.3	6.2	4.2	4.0	1.6	3.5	4.8	3.5	2.8	3.3	7.2	1.8	6.0	**87.9**
Utilities [C]	6.6	4.8	5.7	4.6	5.1	5.1	1.9	2.3	4.2	12.2	6.3	5.1	3.6	2.0	4.1	4.3	4.2	4.1	2.1	2.5	3.6	5.5	**87.8**
World [C]	5.7	6.3	6.4	4.5	6.7	4.8	1.7	4.5	3.7	3.8	7.6	4.5	4.7	2.2	4.0	6.0	4.0	3.7	4.2	2.3	1.5	7.2	**92.4**
Consumer Goods [I]	7.9	5.2	5.2	4.8	5.5	4.1	1.3	3.0	3.3	4.2	6.3	10.2	4.6	2.0	5.3	5.6	4.4	2.9	2.8	2.8	2.8	5.8	**89.8**
Consumer Services [I]	4.6	8.8	5.1	4.8	5.8	3.2	1.1	4.9	3.3	2.9	6.6	4.6	10.8	2.5	4.7	5.8	3.2	2.5	4.7	2.2	1.4	6.6	**89.2**
Financials [I]	4.0	5.6	5.9	4.0	5.0	3.3	1.4	4.1	2.5	3.1	5.9	3.9	5.2	18.3	3.6	4.9	2.8	3.5	3.9	1.8	1.7	5.8	**81.7**
Health Care [I]	5.0	5.5	4.5	10.9	4.6	2.9	1.2	3.5	3.0	3.6	6.0	5.8	5.0	1.8	11.6	4.7	3.2	2.7	3.4	2.3	2.3	6.4	**88.4**
Industrials [I]	5.1	5.9	5.5	3.6	7.8	4.8	1.4	4.6	3.3	3.0	7.0	4.7	4.9	2.2	3.7	8.8	4.7	3.2	4.2	2.7	2.2	6.7	**91.2**
Materials [I]	5.3	4.2	4.9	2.9	5.8	9.5	2.1	2.3	3.1	4.0	5.9	4.9	3.5	1.7	3.3	6.0	11.1	4.8	2.1	3.1	3.9	5.5	**88.9**
Oil & Gas [I]	4.6	4.3	5.6	3.6	5.3	6.3	5.1	2.7	2.9	4.4	6.5	3.8	3.3	2.3	3.2	4.7	5.4	13.2	2.5	2.0	2.0	6.3	**86.8**
Technology [I]	3.7	6.3	4.3	4.1	5.7	2.7	1.0	12.1	3.2	2.1	6.7	3.3	5.3	2.3	3.6	5.8	2.4	2.3	12.3	2.0	0.8	8.2	**87.7**
Telecommunications [I]	4.6	4.2	4.2	3.0	4.4	3.9	1.0	2.9	9.5	3.5	5.3	4.8	3.6	1.5	3.6	5.2	4.6	2.5	2.6	15.6	4.1	5.2	**84.4**
Utilities [I]	4.5	3.1	4.1	3.0	3.9	4.9	1.4	1.6	3.2	6.0	4.6	5.8	3.1	1.9	4.5	5.4	6.9	3.0	1.5	5.1	18.4	4.1	**81.6**
World [I]	5.1	6.2	5.4	4.9	6.3	4.4	1.6	5.5	3.6	3.4	7.4	4.4	4.9	2.2	4.4	6.0	3.8	3.8	5.3	2.3	1.4	7.9	**92.1**
TO	**107.7**	**114.1**	**109.1**	**89.7**	**118.4**	**94.2**	**35.8**	**81.9**	**78.6**	**77.6**	**135.0**	**95.2**	**92.2**	**42.8**	**86.1**	**113.5**	**86.9**	**74.4**	**76.6**	**55.0**	**42.1**	**131.1**	**88.10%**
TO (Islamic)	**54.4**	**59.3**	**54.7**	**49.6**	**60.1**	**50**	**18.6**	**47.2**	**40.9**	**40.2**	**68.2**	—	—	—	—	—	—	—	—	—	—	—	**46.59%**
TO (Conventional)	—	—	—	—	—	—	—	—	—	—	—	**49.1**	**48.8**	**22.7**	**46.1**	**59.4**	**45.7**	**43.4**	**43.6**	**28.6**	**19.4**	**70.5**	**46.16%**
NET	**-16.7**	**-23.0**	**-18.3**	**-0.8**	**-26.8**	**-4.4**	**40.7**	**6.5**	**9.3**	**10.2**	**-42.6**	**-5.4**	**-3.0**	**38.9**	**2.3**	**-22.3**	**2.0**	**12.4**	**11.1**	**29.4**	**39.5**	**-39.0**	

Notes: The connectedness table presents the full-sample directional conditional volatility spillovers, the total directional spillovers (FROM/TO), the total group directional spillovers (TO Islamic, TO Conventional) and the net total directional spillovers (NET). Conditional volatility is estimated via a GJR-GARCH(1,1,1). For the connectedness we have used a second order VAR with generalised variance decomposition, horizon is set to 10 days. [C] and [I] denote a conventional and an Islamic equity index respectively.

Appendix A1 - Financial contagion

At the global level, financial markets have become increasingly integrated as a result of deregulation and globalisation. At the country level, financial markets are catalytic to the prosperity and stability of the economy. During turmoil the phenomenon of financial contagion is observed, which in broad strokes may be defined as an increase in financial market correlation dynamics due to a financial shock in a particular market. On the one hand there are profound implications of financial contagion for asset allocation and geographical/sectoral diversification, market efficiency and the firm cost of capital. On the other hand, the relationship between financial contagion and macro-economic or industry-specific dynamics (e.g., capital outflows, liquidity shocks – see Gkillas et al. (2019) and references therein) is highly asymmetrical. Financial contagion is only partially explained by the said macro-economic or industry-specific shocks. Contrarily financial contagion may be regarded as an irrational phenomenon, subjected to the rules of "herd behaviour" or "mass hysteria" akin to the case of bank runs (Chari & Kehoe, 2003; Chen, 1999; Gorton, 1988). Information cascades can boost the contagious effect across financial markets irrespective of their underlying financial soundness.[28] However, macro-economic or industry-specific conditions can be significantly affected by the intensity and duration of financial contagion. Hence, both the behaviour of financial markets and the dynamics of financial contagion is of great importance.

A large body of literature has also analysed financial contagion as the phenomenon in which a financial crisis spreads across countries, stock market indices, sectors and other asset classes. No uniformly accepted definition exists for financial contagion, apart from the fact that financial contagion may be perceived as the negative side of financial integration. Nevertheless, we may say that financial contagion is the phenomenon in which a financial crisis spreads across countries, sectors and between stock market indices. This area of research on shock transition started with the work of King and Wadhwani (1990) and has received a certain focus over the past two decades on theory (Allen & Gale, 2000; Dungey et al., 2005; Karolyi, 2003) as well as on empirical tests (Bekaert et al., 2014). Most of the empirical work typically follows the Forbes and Rigobon (2002) and/or the Bekaert et al. (2005) seminal papers. One of the key distinctions in these two approaches is that the former, also dubbed as "shift-contagion", examines for a significant increase in the cross-market correlation following a crisis event, see for example Gravelle et al. (2006). By contrast, the latter emphasizes the role of (economic) fundamentals as transmission channels by attributing the characterisation of contagion only when correlations significantly increase over and above what fundamentals can explain, building on the work of Calvo et al. (1996) and Kaminsky and Reinhart (2000) among others. The "shift-contagion" approach became quite popular following the innovation of multivariate GARCH models (e.g. ADCC-GARCH) that were capable of producing conditional correlation estimates, while handling a large number of assets (Cappiello et al., 2006; Engle, 2002).

The vast majority of empirical studies on financial contagion is focused on conventional stock market indices, however there are studies which use exchange rates, credit default swaps, implied market volatility indices or bond market data, see for example Chiang et al. (2007), Claeys and Vašíček (2014), Kenourgios (2014), Pappas et al. (2016) and references therein. Even rarer are applications pertaining to sectoral equity data with some notable exceptions which provide evidence on sector-specific contagion. For example, (Bekaert et al., 2014) focus on 55 countries and 415 country-sector equity portfolios. Kenourgios and Dimitriou (2015) use sectoral equity indices for six geographical

[28] There is a voluminous literature on the impact of non-financial information (e.g. word-of-mouth, geographical concentration, cultural differences, peer choices, social interactions, inhibition) on financial decision making (Duflo & Saez, 2002; Feng & Seasholes, 2004; Hirshleifer & Teoh, 2009; Karlsson et al., 2009; Madrian & Shea, 2001; Ng & Wu, 2010; Shiller, 1995; Shiller & Pound, 1989).

regions (e.g., Developed Pacific, Emerging Asia). In terms of crisis focus, in the Phylaktis and Xia (2009) the data span covers most of the 1990s and early 2000s crises. By contrast, Baur (2012), Bekaert et al. (2014), Kenourgios and Dimitriou (2015) and Alexakis and Pappas (2018) focus on the GFC and/or the ESDC crises.

Regarding the contagion between Islamic and conventional indices during financial crisis episodes, there is an increasing number of studies after the global financial crisis. The dynamic dependence of Islamic and conventional equity indices suggest that Islamic equity indices are less likely to augment financial contagion following crises events (Ajmi et al., 2014; Hammoudeh et al., 2014) and even decouple from their conventional counterparts (Hkiri et al., 2017; Kenourgios et al., 2016). The reduced financial contagion evidence on Islamic indices is in part attributed to the low volatility spillovers between conventional and Islamic equity markets (Majdoub & Mansour, 2014; Rizvi et al., 2014).

Despite some evidence that the Islamic equity indices have become increasingly integrated with the conventional system (Yilmaz et al., 2015), there is no empirical investigation focusing on the convergence of the two types of indices. Convergence models may follow the beta and sigma-convergence models that are borrowed from the economic growth literature. Alternative specifications that build on dynamic (latent) factor models also exist. They have been used in banking (efficiency, profitability, risk, productivity), equity markets, interest rates, prices, business cycles, current account balances, technology and economic growth (Apergis et al., 2014; Cozzi & Davenport, 2017; Inklaar & Diewert, 2016; Méjean & Schwellnus, 2009; Olson & Zoubi, 2017; Phillips & Sul, 2009; Walheer, 2016).