

ONLINE APPENDIX

for

Systemic risk: New evidence from alternative financial systems

This is the online appendix for the manuscript titled “Systemic risk: New evidence from alternative financial systems”.

It contains details of the robustness tests and analyses mentioned in the main paper, and for brevity, are placed here. In particular:

- Section A1 presents and discusses estimation results for the systemic risk using the dynamic conditional correlations (DCC)-GARCH models.
- Section A2 presents and discusses estimation results for the systemic risk using the CoRisk measure that is based on credit default swap (CDS) spreads.

A1. Systemic risk estimated using DCC-GARCH models

In this robustness check, we estimate systemic risk using a multivariate dynamic conditional correlation (DCC)-GARCH model, a widely recognized method for capturing and analyzing volatility in financial contexts such as risk analysis, portfolio optimization, and derivative pricing (Bollerslev, 1986; Brownlees & Engle, 2012; Füss, Kaiser, & Adams, 2016). DCC-GARCH models, first introduced by Engle (2002), are particularly useful as they enable the analysis of asset portfolios, allowing for the examination of cross-dependencies among portfolio assets; thereby making them well-suited for systemic risk modeling.

Let $\mathbf{r}_t = (r_{1t}, r_{2t}, \dots, r_{Nt})$ represent the vector of asset returns at time t . The conditional covariance matrix of $\mathbf{r}_t$ is defined as $\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$, where $\mathbf{D}_t = \text{diag}(h_{1t}^{0.5}, h_{2t}^{0.5}, \dots, h_{Nt}^{0.5})$ is a matrix of standard deviations (volatility) typically obtained from univariate GARCH specifications, which may include functions of other exogenous variables; and $\mathbf{R}_t$ is the time-varying conditional correlation matrix.

We model each asset's volatility (h_{it}) as a GARCH(1,1) process:

$$h_{it} = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} \quad (\text{A1})$$

where $\omega_i, \alpha_i, \beta_i$ are parameters to be estimated subject to the usual stationarity conditions, and ε_{it-1}^2 are lagged residuals.

The time-varying correlation matrix $\mathbf{R}_t$ is constructed from the dynamic covariance matrix $\mathbf{Q}_t$:

$$\mathbf{R}_t = \text{diag}(\mathbf{Q}_t)^{-0.5} \mathbf{Q}_t \text{diag}(\mathbf{Q}_t)^{-0.5} \quad (\text{A2})$$

where

$$\mathbf{Q}_t = (1 - \gamma - \delta) \mathbf{Q} + \gamma (\mathbf{z}_{t-1} \mathbf{z}_{t-1}') + \delta \mathbf{Q}_{t-1} \quad (\text{A3})$$

and $\mathbf{z}_t$ are standardized returns computed as r_{it}/h_{it} ; γ, δ parameters to be estimated; and $\mathbf{Q}$ is viewed as a long-run average (i.e., unconditional) correlation. DCC-GARCH models are estimated using maximum likelihood in two steps. First, the univariate GARCH parameters are estimated. Second, the dynamic correlations are estimated.¹

¹ DCC-GARCH models are well-suited for multiple assets, offering easier estimation compared to BEKK models. Equation A3 can be simplified with exponential smoothing dynamics or correlation targeting, reducing parameters and improving convergence, especially for large portfolios, see Engle (2002) for more details.

Following the DCC-GARCH estimation, systemic risk is assessed using established methodologies (see [Adrian & Brunnermeier, 2016](#); [Girardi & Ergün, 2013](#); [Choi & Shin, 2019](#) for details).

We define the conditional probability of the financial system (FS) return (X_t^{FS}) given that the individual asset i 's return (X_t^i) is less than or equal to its VaR, namely:

$$\Pr(X_t^{FS} | X_t^i \leq VaR_{q,t}^i) = q\% \quad (A4)$$

where $VaR_{q,t}^i = \Phi^{-1}(q\%)h_t^i$ represents the value-at-risk at the $q\%$ quantile for asset i , and Φ^{-1} is the inverse cumulative normal function.

Given the conditional volatility h_t^i of asset i and h_t^{FS} of the financial system, the CoVaR for asset i at the $q\%$ quantile can be expressed as:

$$CoVaR_{q,t}^i = \Phi^{-1}(q\%) \left(h_t^i \sqrt{1 - (\rho_{i,t}^{FS})^2} + \rho_{i,t}^{FS} h_t^{FS} \right) \quad (A5)$$

where $\rho_{i,t}^{FS}$ is the conditional correlation between asset i and the financial system at time t .

For the median state (i.e., $q = 50\%$ and $\Phi^{-1}(50\%) = 0$), the contribution from individual asset volatility is diminished, hence:

$$CoVaR_{50,t}^i = \rho_{i,t}^{FS} h_t^{FS} \quad (A6)$$

Finally, the systemic risk measure $\Delta CoVaR_{q,t}^i$ at quantile $q\%$ is given by:

$$\Delta CoVaR_{q,t}^i = \Phi^{-1}(q\%) \rho_{i,t}^{FS} h_t^{FS} \quad (A7)$$

Table A1 compares systemic risk estimates from DCC-GARCH and quantile regression models for the aggregate sector, as well as for Islamic and conventional financial institutions separately.² In all cases, the differences between the two methods are not statistically significant confirming the robustness and consistency of our main results.

² [Adrian and Brunnermeier \(2016\)](#) report that GARCH models converge for only 56% of firms, due to missing or extreme values (see Footnote 14 of their paper). In our analysis, GARCH models converge for 74% of the financial institutions in the sample. To allow for a meaningful comparison, we re-estimate the quantile regression models using only the sub-sample of institutions for which the GARCH models converged. Consequently, the systemic risk estimates from this robustness check differ from those reported in the main paper, which are based on the full sample where quantile regression models converged for all financial institutions.

Figure A1 shows mean systemic risk estimates over time for the aggregate sector, while Figures A2 presents similar comparisons for randomly selected medium-sized (Panel A) and small (bottom 5%) financial institutions (Panel B) (based on 2007 market capitalization). Notably, the smallest institutions, often local financial entities, have shown systemic importance similar to or even exceeding that of larger institutions, as they share common risk profiles and are highly interconnected (Fong et al., 2009). Visual inspection reveals comparable systemic risk patterns across methods, further supporting our main findings.

A2. Systemic risk estimated using CDS spreads

In this robustness check, we estimate systemic risk using an alternative approach based on CDS spreads, known as CoRisk. CoRisk, introduced in the IMF's 2009 Global Financial Stability Review (IMF, 2009), is part of a broader array of systemic risk measures available before the development of newer techniques such as ΔCoVaR (Adrian and Brunnermeier, 2016). Common data sources for estimating co-movement in the credit risk of financial institutions include CDS spreads, Moody's KMV expected default frequencies, corporate bond spreads, distance-to-default measures, and the VaR of trading portfolios (IMF, 2009). The co-movement of CDS spreads reflects both direct and indirect linkages among financial institutions. When CDS spreads reach their 95th quantile (the right tail of the distribution), it signals the onset of a distress regime (Bisias, Flood, Lo, and Valavanis, 2012).

Following IMF (2009), CDS spreads of the financial system as of time t are given as:

$$CDS_{FS,t} = \alpha_q^{FS} + \sum_{m=1}^M \beta_{q,m}^{FS} R_{m,t} + \beta_{q,i}^{FS} CDS_{i,t} + \varepsilon_{FS,t} \quad (\text{A8})$$

where $CDS_{FS,t}$ denotes the CDS spread of the full financial system at time t ; $CDS_{i,t}$ is the CDS spread of financial institution i at time t ; $R_{m,t}$ represents the risk factors m at time t ; q denotes the quantile; $\beta_{q,i}^{FS}$ measures how institution i affects the risk of the financial system at the q -th quantile; $\beta_{q,m}^{FS}$ measures the contribution of each risk factor on the financial system risk at the q -th quantile; $\varepsilon_{FS,t}$ is the stochastic error term.

We use the following risk factors: (i) Equity market volatility (computed as the 22-day rolling standard deviation of daily equity market returns); (ii) Equity risk premium (computed as the return of the equity market over the risk-free rate, proxied by the 3-month T-bills rate); (iii) the

Short-term liquidity risk (measured by the TED spread, the difference between LIBOR and the 3-month T-bills rate); (iv) the 3-month T-bills yield change (calculated as the change in the 3-month T-bills yield from the previous period). We obtain monthly CDS data for our sample of financial institutions from Bloomberg for the period 2005-2019.³ The data for the risk factors are collected from Bloomberg and DataStream.

Following from Eq.A8 estimation⁴, the conditional CoRisk measure is obtained as:

$$CoRisk_t^{FS|i} = 100 \times \left(\frac{\alpha_q^{FS} + \sum_{m=1}^M \beta_{q,m}^{FS} R_{m,t} + \beta_{q,i}^{FS} CDS_{i,t}(q)}{CDS_{FS}(q)} - 1 \right) \quad (A9)$$

where $CoRisk_t^{FS|i}$ denotes the systemic risk contribution from institution i to the financial system; $CDS_{sys}(q)$ is the CDS spread of the financial system corresponding to the q -th percentile of its empirical distribution. In our analysis we set $q = 95\%$.

Table A2 presents summary statistics of systemic risk for all financial institutions, including Islamic and conventional institutions, based on the CoRisk measure. It indicates that the mean and median CoRisk measures for conventional institutions are significantly higher than those for Islamic institutions. The logarithmic difference indicates that the CoRisk of Islamic institutions is, on average, 5.15% lower than that of conventional institutions in our sample. Furthermore, the highest CoRisk among conventional institutions is about 39.13% higher than that of Islamic institutions. These results corroborate our findings using the $\Delta CoVaR$ measure, further supporting the observed differences between Islamic and conventional institutions.

Figure A3 displays the time evolution of systemic risk as measured by CoRisk, while Figure A4 compares CoRisk-based systemic risk between Islamic and conventional financial institutions (Panel A) and the $\Delta CoVaR$ measure used in the main paper. Notably, the maximum spillover in CoRisk occurred during the 2008 Global Financial Crisis. Finally, the systemic risk dynamics exhibited by CoRisk and $\Delta CoVaR$ are comparable over time.

³ The data for CDS spread of our sample financial institutions was only available for this time period.

⁴ See IMF (2009) for more details on the quantile regression methodology used to estimate systemic risk in this study.

References

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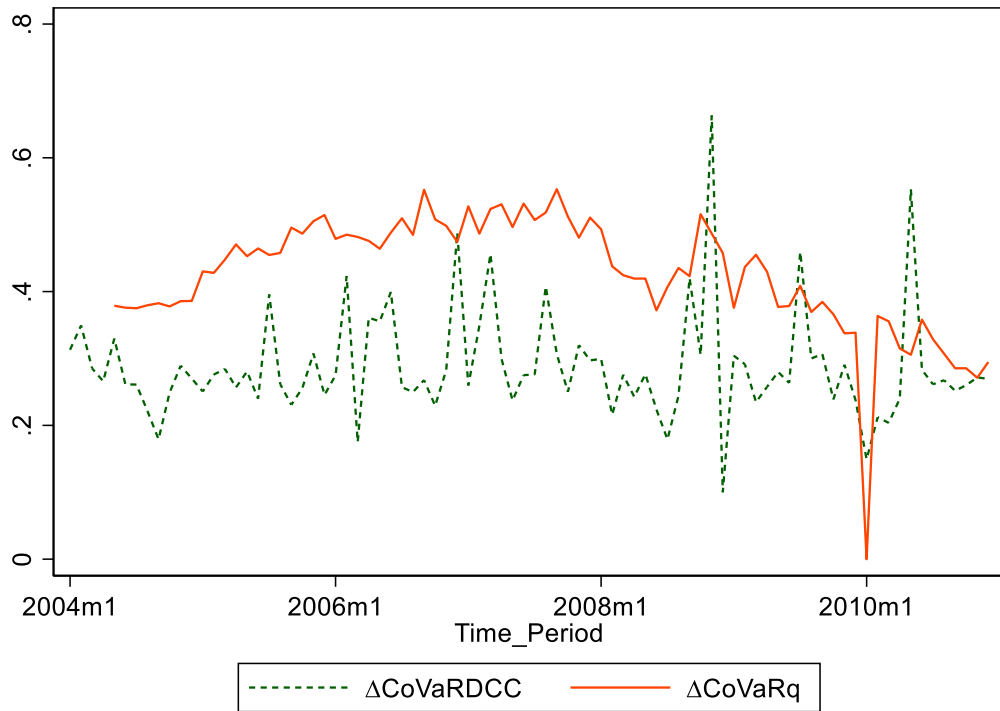
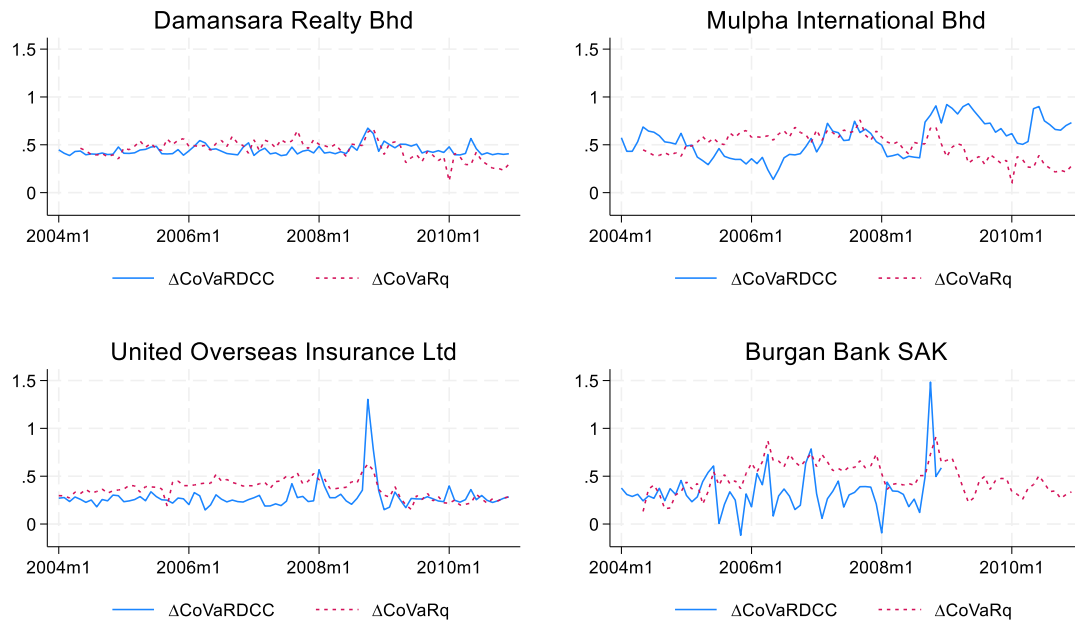


Figure A1: Comparison of mean systemic risk estimates from DCC-GARCH and quantile regression

Panel A: Average-sized financial institutions



Panel B: Small financial institutions

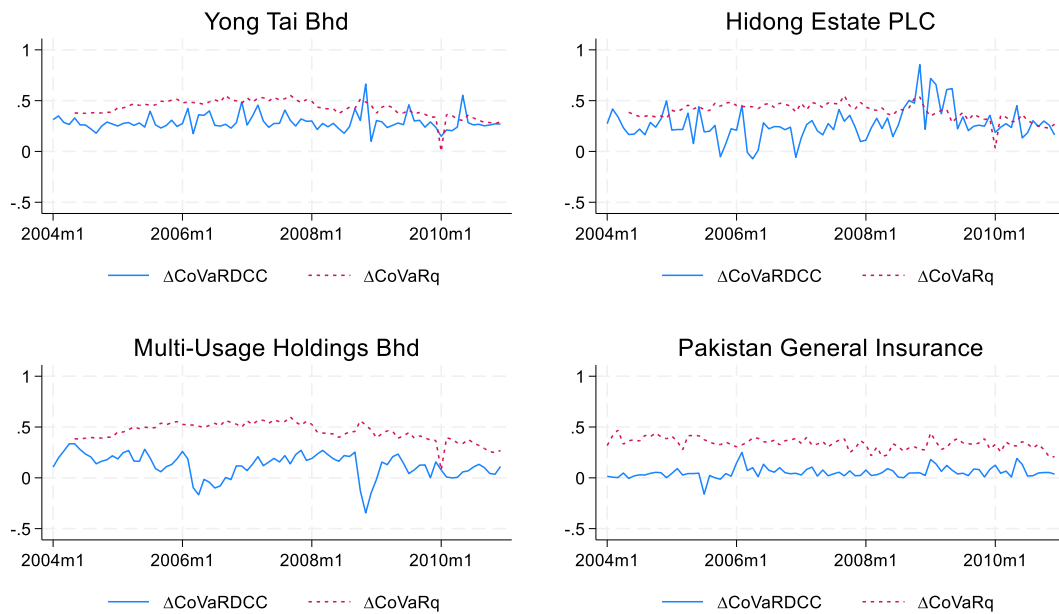


Figure A2: Comparison of mean systemic risk estimates from DCC-GARCH and quantile regression for average-sized and small financial institutions

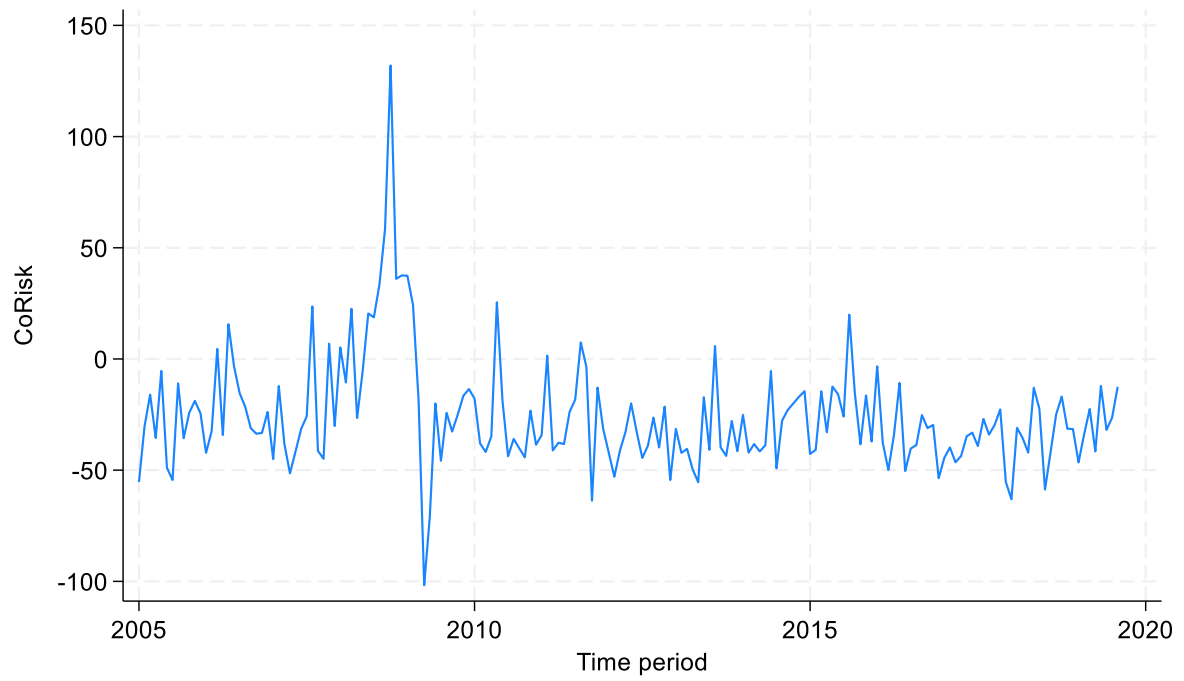
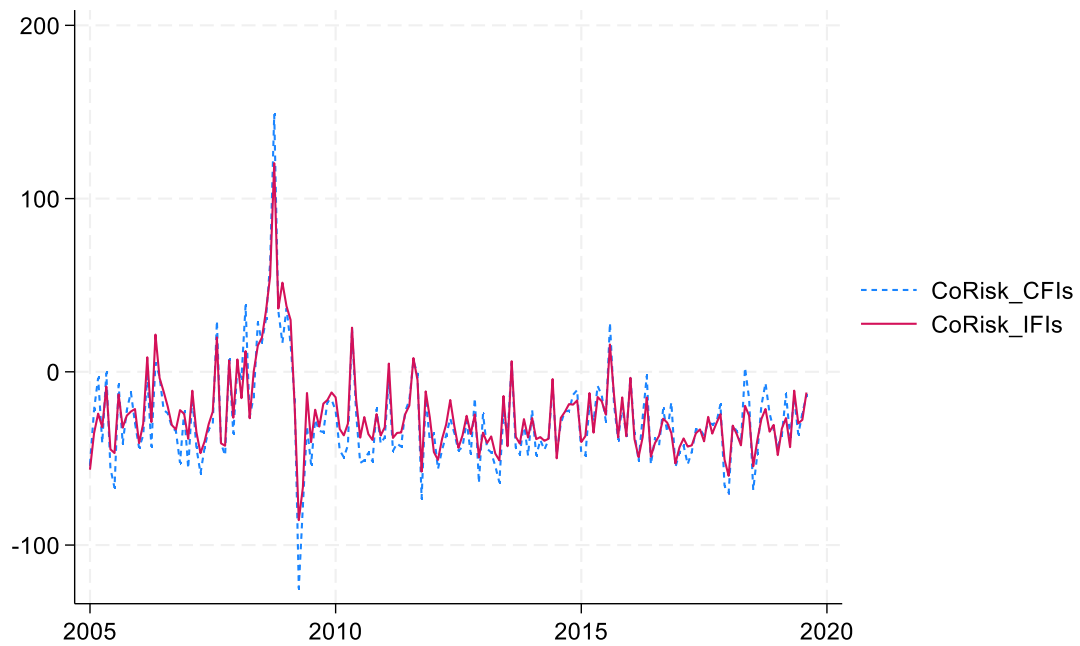


Figure A3: Evolution of systemic risk based on the CoRisk measure

Panel A: Islamic (IFIs) and conventional (CFIs) financial institutions



Panel B: ΔCoVaR and CoRisk

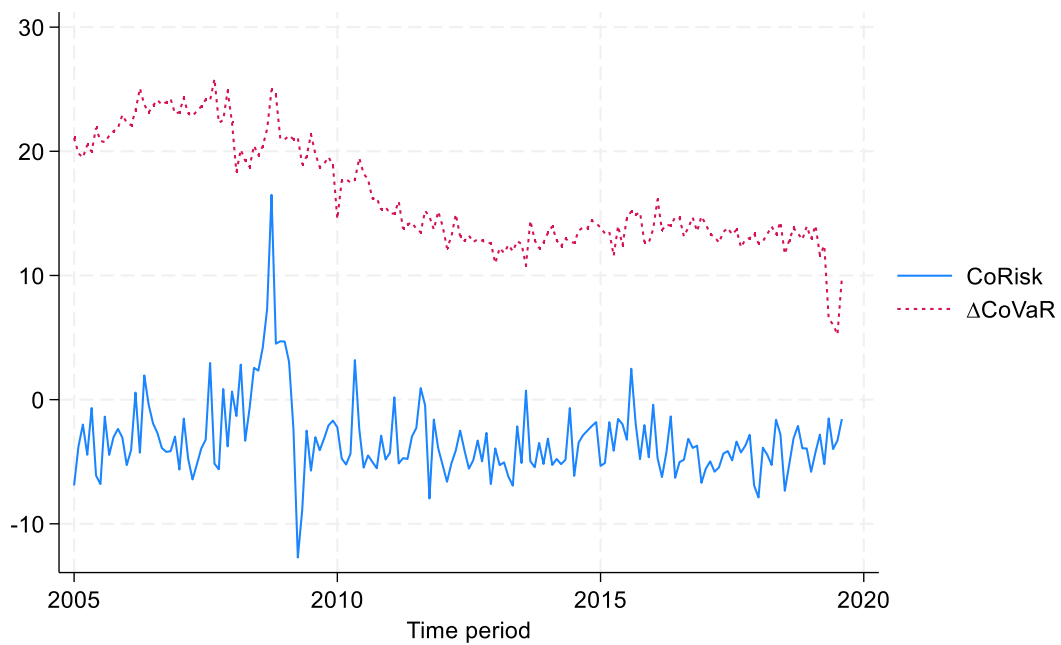


Figure A4: Comparison of systemic risk estimates over time by institution type (Islamic vs conventional) and risk measure (ΔCoVaR vs CoRisk)

Table A1. Systemic risk estimates from DCC-GARCH and quantile regression models.

	<u>Mean</u>	<u>Std. Dev.</u>	<u>Min</u>	<u>Max</u>
$\Delta\text{CoVaR}_{\text{DCC}}$	0.390	0.402	-0.527	4.613
$\Delta\text{CoVaR}_{\text{QREG}}$	0.393	0.122	-0.023	1.152
$\Delta\text{CoVaR}_{\text{DCC}} - \Delta\text{CoVaR}_{\text{QREG}}$	-0.002 [0.67]			
$\Delta\text{CoVaR}_{\text{DCC}}^{\text{IFI}}$	0.397	0.203	-0.163	3.514
$\Delta\text{CoVaR}_{\text{QREG}}^{\text{IFI}}$	0.394	0.064	-0.185	1.804
$\Delta\text{CoVaR}_{\text{DCC}}^{\text{IFI}} - \Delta\text{CoVaR}_{\text{QREG}}^{\text{IFI}}$	0.003 [1.20]			
$\Delta\text{CoVaR}_{\text{DCC}}^{\text{CFI}}$	0.367	0.407	-0.527	4.613
$\Delta\text{CoVaR}_{\text{QREG}}^{\text{CFI}}$	0.385	0.114	-0.023	1.152
$\Delta\text{CoVaR}_{\text{DCC}}^{\text{CFI}} - \Delta\text{CoVaR}_{\text{QREG}}^{\text{CFI}}$	-0.018 [1.50]			

Notes: The table summarizes systemic risk estimates derived from DCC-GARCH (DCC) and Quantile Regression (QREG) models. Estimates for Islamic and conventional financial institutions are denoted by superscripts IFI and CFI, respectively. For rows presenting the mean difference between DCC and QREG estimates, t-statistics are reported in brackets.

Table A2. Summary statistics of systemic risk measured using the CDS spread-based CoRisk

	<u>Mean</u>	<u>Median</u>	<u>Std. Dev.</u>	<u>Min</u>	<u>Max</u>	<u>Obs</u>
CoRisk	-27.053	-30.833	37.112	-199.973	339.562	39,863
CoRisk ^{IFI}	-27.966	-31.602	38.515	-199.973	229.571	13,978
CoRisk ^{CFI}	-26.561	-30.512	36.324	-199.973	339.562	25,885
CoRisk ^{CFI} – CoRisk ^{IFI}	1.405*** [3.60]	1.09*** [2.79]				

Notes: The table presents summary statistics of systemic risk for all financial institutions, Islamic (IFI) and conventional (CFI) institutions, using the CoRisk measure. The difference in means is tested using a t-test and a two-sample Wilcoxon rank-sum (Mann-Whitney) test is used to check the significance of the median difference. t-statistics are reported in brackets. *** represents significance at the 1% level.