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# HOW ASEAN4 CONVENTIONAL, ISLAMIC, AND ESG INDICES REACT TO TWITTER MARKET UNCERTAINTY?

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## ABSTRACT

We investigate the time varying return spillover of ASEAN4 asset classes from four countries including Thailand, Philippines, Malaysia and Indonesia, and Twitter based market uncertainty measure, using daily data from 01-Sep-2014 to 21-Apr-2023. The estimations are performed using TVP-VAR approach. The results reveal that the dynamic connectedness of ASEAN4 markets fluctuates significantly. It peaked during bearish periods (2015-2016 and 2020) and remained low during market booms (2017-2018 and 2022). Islamic and ESG indices exhibit patterns similar to conventional indices. Indonesia and Malaysia emerge as net shock transmitters until the pandemic, with Thailand becoming a net transmitter post-COVID. Thailand's role shifts between receiver and transmitter based on economic conditions relative to other ASEAN countries. Twitter Market Uncertainty Index (TMUENG) primarily remains a receiver, with limited impact on ASEAN4 Conventional, Islamic, and ESG indices. The findings are robust to a battery of robustness tests and carry important policy implications for investors and policymakers.

*Keywords: ASEAN4; Twitter market uncertainty; Islamic finance; ESG investments.*
**JEL classifications: G15; G32; G41**.

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## I. INTRODUCTION

Financial markets are prone to uncertainty arising from various channels including global events, macroeconomic conditions, political instability (to name a few), and may lead to heightened stock price volatility and excessive risk aversion among investors (Mezghani et al., 2024). According to the Efficient Market Hypothesis (Fama, 1970, 1991, 1998), which posits that financial markets are "informationally efficient" and asset prices fully reflect all available information at any given time, the influence of market uncertainty should be quickly reflected in the prices of financial assets.

However, behavioral finance challenges this hypothesis and incorporates psychological and emotional factors into the analysis of financial markets (Shiller, 2003). The premise of behavioral finance theories is that investors do not always act rationally as they are influenced by cognitive biases, emotions, and social factors, leading to market anomalies and inefficiencies (H. K. Baker & Nofsinger, 2010). Following this argument, and also documented by contemporary literature, uncertainty may affect different asset classes in distinct ways.

To begin, whenever spiked by uncertainty, broad market indices experience substantial volatility prompting widespread selloffs and shifts in risk appetite (Engle & Rangel, 2008). However, Islamic financial assets might be less volatile during turbulent times due to their distinguished features like risk-sharing, prohibition of interest, and prohibition of speculative transactions that contribute to greater stability and lower risk exposure (Khattak & Khan, 2023; Mansoor Khan & Ishaq Bhatti, 2008). Moreover, Environmental, Social, and Governance (ESG) assets might also show resilience during uncertain periods due to growing preference for sustainability and corporate responsibility among investors, making ESG investments more attractive even amid market turmoil, potentially making them immune to severe impacts of uncertainty (Nofsinger & Varma, 2014; Tekin & Güçlü, 2023).

Nevertheless, we come across plethora of studies arguing that all asset classes including commodities, cryptocurrencies, Islamic indices, ESG indices exhibit volatility spillover during periods of heightened uncertainty i.e., crises situations (El Khoury, Alshater & Alqaralleh, 2024; Billah et al., 2024; El Khoury, Nasrallah, Hussainey & Assaf, 2023; Rehman et al., 2020) or no clear patterns, i.e. divergences within the sample (Loang, 2024). The theoretical foundations of this argument are based on financial contagion theory (Gilkeson, 2002; Pericoli & Sbracia, 2003). It suggests that market disturbances including volatility or crashes, spread from one market to another, leading to increased interconnectedness and systemic risk. This phenomenon is particularly relevant in a globalized world where markets are highly interconnected through trade, investment, and financial channels. Moreover, investors often mimic actions of others leading to herd behavior, which can amplify market trends and contribute to asset price bubbles or market crashes (Bikhchandani et al., 1992; Scharfstein & Stein, 1990).

To sum up, we are aware that uncertainty affects global markets and influences asset prices, but it is still unresolved whether uncertainty affects different asset classes differently or the financial markets form contagions in response to uncertainty. This study aims to contribute to this debate for Association of South East Asian Countries (ASEAN) market. We contend that for our study, ASEAN region offers ideal settings owing to several reasons.

First, Developing East Asia and Pacific is growing faster than the rest of the world, set to record 4.5% regional growth driven mostly by investment (WorldBank, 2024). Hence, this market is still attractive for global investors and due to its substantial reliance on investments, it is extremely important to assess how uncertainty affects different asset categories related to this region. Second, ASEAN holds diverse economic landscape and divergent levels of market development among member countries. Since member countries are currently undergoing different levels of economic maturity and exposure to global uncertainties, ASEAN offers a rich context for investigating how uncertainty affects various asset classes. Third, these countries are host to divergent regulatory environments and investment climates. This economic heterogeneity can enhance the generalizability of findings and allows for testing of our hypotheses across different economic conditions.

Here, a question arises: can we measure market uncertainty? Taking a cue from behavioral economics and finance (Nofsinger, 2005; Smith, 2007; Tetlock, 2007), we utilize Twitter Market Uncertainty Index (TMUENG) of Baker et al. (2021). This index captures total number of daily English-language tweets containing "Uncertainty" and "Economy" terms. TMUENG is a novel way to quantify the effects of uncertainty by analyzing social media sentiment and measures how public perceptions of uncertainty influence different asset classes. TMUENG represents global sentiments and considering exogenous impact of global investors' perception on domestic markets, it is suitable for our analysis of the impact of uncertainty on ASEAN markets (Bollen et al., 2011). TMUENG is superior to market-based uncertainty measures like Value-at-Risk, Volatility and others, which rely upon financial or market performance data. TMUENG accounts for investor behaviors and biases that are acknowledged as one of key determinants of investors' decision-making processes (Shiller, 2003).

We argue that Twitter Based measure are suitable in ASEAN context. These economies are often influenced by global economic uncertainties and exhibit relatively high sensitivity to policy decisions due to factors like foreign investments, trade policies, and political stability. Twitter provides real-time data on public sentiment and perceptions of uncertainty. As of August 2024, Twitter's user base in the ASEAN-4 countries included Indonesia (27.1 million users), Thailand (14.6 million users), Philippines (11.1 million users) and Malaysia (4.45 million users). As Twitter is among the widely used social media platforms across ASEAN-4 countries, it serves as a suitable proxy for public sentiment on economic policy due to its use in news sharing and opinion dissemination.

In addition, there exists a theoretical relationship between ESG factors and TMUENG, rooted in the role of social media as a real-time proxy for market sentiment and its influence on ESG investments. TMUENG captures economic and policy discussions on topics, among others, climate policies, labor rights, and governance reforms - key areas that directly affect ESG-focused firms. ESG investments are sensitive to public sentiment, as they rely on reputation, stakeholder trust, and ethical considerations. Twitter, as a fast-moving platform, amplifies discussions on policy uncertainty, shaping market perceptions of ESG investments. For instance, heightened uncertainty about environmental regulations or labor reforms reflected on Twitter could increase volatility in ESG stock performance. Conversely, positive sentiment on green policies or social justice initiatives may benefit ESG investments by boosting investor confidence. Nevertheless, we do not find empirical exploration of the linkage between Twitter-based uncertainty and ESG stock performance and how sentiment-driven shifts on Twitter align with ESG market trends.

Having decided our research questions, finalized sample and identified suitable uncertainty measure, we look for most suitable empirical approach for our research. We are aware that capital markets are dynamic, characterized by shifting economic conditions, structural breaks, and evolving market dynamics (Bodie et al., 2014). Evidently, the linkage between uncertainty and asset classes is subject to change over time. Consequently, we employ Time-Varying Parameters Vector Autoregression (TVP-VAR) approach of Antonakakis et al. (2020). This approach is valuable for analyzing complex systems where the effects of shocks or uncertainties are not static but vary with the economic cycle or external factors (Gabauer & Gupta, 2018). In addition, it allows for the parameters governing the relationships between variables to adjust to newly available information (Negro & Primiceri, 2010). By using TVP-VAR framework, our analysis can capture temporal variations within ASEAN economies as well as several asset classes including conventional stocks, Islamic assets, and ESG investments. Therefore, TVP-VAR is the most suitable framework to perform our analysis.

In line with this motivation, we investigate the time varying return spillover of ASEAN asset classes from four countries, namely Thailand, Philippines, Malaysia and Indonesia, and Twitter based market uncertainty measure, for a sample period from 01-Sep-2014 to 21-Apr-2023. The analysis reveals that the dynamic connectedness of ASEAN4 markets fluctuates significantly. It peaked during bearish periods (2015-2016 and 2020) and remained low during market booms (2017-2018 and 2022). Islamic and ESG indices exhibit patterns similar to conventional indices. Indonesia and Malaysia emerge as net shock transmitters until the pandemic, with Thailand becoming a net transmitter post-COVID. Thailand's role shifts between receiver and transmitter based on economic conditions relative to other ASEAN countries. TMUENG primarily remains a receiver, with limited impact on ASEAN4 Conventional, Islamic, and ESG indices.

We add to the literature on market efficiency, financial contagions, and uncertainty. In contemporary literature, we come across plethora of studies exploring the linkage of uncertainty with various asset classes including, stock markets (Behera & Rath, 2022; J. Chen et al., 2017; Coskun & Taspinar, 2024; Karnizova & Li, 2014; Lu & Lang, 2023; Yıldırım-Karaman, 2018), Islamic markets (Hammoudeh et al., 2016), Oil volatility (Lu et al., 2022) and Cryptocurrency returns (Aharon et al., 2022; Wu et al., 2021), to name a few. Nevertheless, no study has explored linkage of twitter uncertainty with multiple ASEAN indices. Our study fills this important gap. Our findings are robust to a battery of robustness tests. The results carry important policy implications for investors and policymakers.

The rest of the work is organized as follows: Section 2 summarizes the theoretical and empirical literature. Section explains data and methodology. Section 4 reports results and discussions. Section 5 concludes the study.

## II. LITERATURE REVIEW

### 2.1. Theoretical Foundations

The linkage between financial markets and uncertainty is widely explored in contemporary literature. As *Efficient Market Hypothesis* (EMH) posits, a market is considered 'efficient' in relation to an information set if the price fully reflects that information set and if the information set is revealed to all market participants, the price would be unaffected (Kliger & Gurevich, 2015; Schwartz, 1970). However, macroeconomic and market uncertainty can disrupt how markets incorporate information into prices and in reality, uncertainty can lead to delayed reactions or incorrect pricing, as market participants may interpret the same information differently (Shiller, 2021). To understand this difference, we need to revert to Knight (1921), who distinguishes between risk (where probabilities are known) and uncertainty (where probabilities are unknown). The EMH primarily operates in the context of *risk*, whereas financial markets often operate in environments of *uncertainty*.

In respect of alternate theories, Lo (2004) forwards the *Adaptive Market Hypothesis* (AMH), arguing that markets are not always perfectly efficient, but their efficiency can adapt over time based on level of uncertainty, the number of informed versus uninformed traders, and the changing dynamics of the marketplace. Moreover, the *prospect theory* (Kahneman & Tversky, 2013) asserts that investors often make irrational decisions under uncertainty, leading prices to deviate from their true value. Hence, markets may not always be efficient, especially during times of significant uncertainty. Furthermore, Investors often exhibit *herd behavior*, following the actions of others in uncertain environments, which can further distance actual market prices from the theoretical EMH (Scharfstein & Stein, 1990). Also, *Behavioral finance* challenges the EMH by incorporating psychological and emotional factors into market analysis, highlighting that investors often act irrationally due to biases and emotions (H. K. Baker & Nofsinger, 2010; Shiller, 2003). Their irrational behaviors can lead to market inefficiencies and anomalies, particularly in uncertain market conditions.

Behavioral finance also points towards faith-based investing styles (like Shariah Compliant Investment and Socially Responsible Investment styles). Hence, the available market portfolio becomes less diversified compared to the actual market portfolio (Xu & Malkiel, 2005). It is probable that uncertainty affects these portfolios differently compared to market portfolio.

The plot thickens when we take into account the interconnectedness of global markets. According to the *Meteor Shower Hypothesis* (Ito et al., 1992), volatility in financial market arises from common external shocks affecting multiple markets simultaneously, similar to a meteor shower impacting various locations at once. Therefore, financial crises or shocks in one country or market spread to others, causing instability across regions or sectors (Bavister & Squirrell, 2000). The *Financial Contagion Theory* further asserts that this spread can occur due to both fundamental linkages, such as shared economic vulnerabilities, or through irrational factors, like panic and herd behavior among investors. For example, during the 1997 Asian financial crisis and the 2008 global financial crisis, problems in one country rapidly affected other markets.

### 2.2. Empirical Evidence

We come across rich literature that provides empirical evidence of financial contagions (Baruník et al., 2017; Baur & Lucey, 2010; Chatziantoniou et al., 2022; R. Chen et al., 2021; Mensi et al., 2021; Rehman et al., 2021; Tiwari et al., 2020; Yousaf et al., 2022).

For example, Baur & Lucey (2010) find that gold has hedging properties (normal-) and safe haven properties (crisis-situations) against stocks. Baruník et al. (2017) examine the impact of good and bad volatility on forex market, highlighting the presence of asymmetric volatility connectedness. Chen et al. (2021) show that speculative sentiment is stronger than hedging sentiment in generating greater market fluctuations in the energy futures markets. Mensi et al. (2021) show negative and positive average dependencies between energy assets (crude oil, natural gas, and gasoline) and most MENA stock markets in the short term, both before and after the oil crash. Rehman et al. (2021) highlight high dependence among US metals and mining stocks and no dependence among these companies based in Italy, the UK and Poland. Chatziantoniou et al. (2022) observe that heating oil and kerosene remain persistent net transmitters of shocks to network of Brent, WTI, gasoline, heating oil, jet fuel and propane.

There is also a large number of studies that have utilized TVP-VAR technique to study various financial and real assets in network context (Ha & Nham, 2022; He, 2023; Huang et al., 2022, 2023; Liu, 2021; Yousaf & Yarovaya, 2022).

Moving forward, several recent studies offer heterogenous results on the linkage of Twitter uncertainty measures and different asset classes. Aharon et al. (2022) show that there is a strong causal link between Twitter uncertainty measures and cryptocurrency returns. Behera & Rath (2022) show that Twitter market uncertainty, S&P 500 index, and G7 average returns are net receivers of shocks while DAX index (Germany) is a major transmitter of shocks. Nevertheless, Coskun & Taspinar (2024) show the existence of feedback hypothesis between G7 stock returns and Twitter Uncertainty. Also, Polat et al. (2025) find Twitter uncertainty as net transmitter for a network comprising green bonds and the S&P 500 Composite Index. Nyakurukwa & Seetharam (2024) highlight that Twitter Uncertainty leads South African returns during crises periods. Similarly, Lu & Lang (2023) find that Twitter uncertainty indices can predict Chinese stock market volatility. Ma et al. (2025) also validate predictive power of these measures for twenty international markets.

However, to the best of our knowledge, no study has yet explored the dynamic linkage of ASEAN4 asset classes including conventional, Islamic and ESG indices and Twitter Market Uncertainty. The current study fills this gap.

## III. METHODOLOGY

### 3.1. Data

Our research objective is to assess how uncertainty affects various asset classes related to ASEAN region. The sample includes three families of Morgan Stanely Capital International (MSCI) indices including Conventional, Islamic and ESG indices. MSCI is the only index provider for ASEAN countries for all the three asset classes. The sample includes four ASEAN countries (hereinafter referred to as ASEAN4) namely Indonesia, Malaysia, Philippines, and Thailand. The indices include MSCI THAILAND U$ - PRICE INDEX (THAI), MSCI PHILIPPINES U$ - PRICE INDEX (PHIL), MSCI MALAYSIA U$ - PRICE INDEX (MAL), MSCI INDONESIA $ - PRICE INDEX (IND), MSCI THAILAND ISLAMIC IMI $ - PRICE INDEX (THAI_ISL), MSCI PHILIPPINES ISLAMIC IMI $ - PRICE INDEX (PHIL_ISL), MSCI INDONESIA ISLAMIC IMI $ - PRICE INDEX (IND_ISL), MSCI MALAYSIA ISLAMIC IMI $ - PRICE INDEX (MAL_ISL), MSCI THAILAND ESG LEADERS $ - PRICE INDEX (THAI_ESG), MSCI PHILIPPINES ESG UNIVERSAL $ - PRICE INDEX (PHIL_ESG), MSCI INDONESIA ESG LEADERS $ - PRICE INDEX (IND_ESG), MSCI MALAYSIA COUNTRY ESG LEADERS $ - PRICE INDEX (MAL_ESG), And TWITTER MARKET UNCERTAINTY – ENG (TMUENG). There are 2254 observations in total.

The selection of ASEAN4 countries is based on data availability as MSCI offers all three sets of indices for only these four countries. To proxy market uncertainty, we utilize Twitter Market Uncertainty Index-ENG developed by Baker et al. (2021). It is widely used in recent literature as a measure of market uncertainty (Bollen et al., 2011; Coskun & Taspinar, 2024; Lu & Lang, 2023). TMUENG is a text-based measure and constructed by using keywords ‘uncertain’, and ‘equity markets’ used in tweets on Twitter.

We utilize daily returns of sampled indices, sourced from Datastream. TMUENG data is downloaded from the website https://policyuncertainty.com/index.html. The sample period starts from 01 Sep 2014 and this selection is based on the data availability of returns of sampled indices. The sample period ends on 21 Apr 2023 due to discontinuation of research data availability by Twitter after the said date.

**Table 1.**
**Summary Statistics**
**This table reports the summary statistics for the sampled firms.**

| Symbol | Mean | P50 | SD | P25 | P75 | Max | Min | Skew | Kurt | ADF (D1) |
|---|---|---|---|---|---|---|---|---|---|---|
| THAI | -0.01 | 0.00 | 1.16 | -0.53 | 0.53 | 8.26 | -11.88 | -1.07 | 19.36 | -27.836*** |
| PHIL | -0.01 | 0.00 | 1.31 | -0.69 | 0.65 | 7.99 | -14.51 | -1.07 | 15.04 | -27.336*** |
| MAL | -0.03 | 0.00 | 0.93 | -0.50 | 0.44 | 7.33 | -6.42 | -0.06 | 9.71 | -23.269*** |
| IND | -0.01 | 0.00 | 1.52 | -0.77 | 0.76 | 15.16 | -11.36 | -0.07 | 12.62 | -26.167*** |
| THAI_ISL | 0.00 | 0.00 | 1.37 | -0.64 | 0.64 | 9.70 | -15.34 | -1.07 | 19.01 | -25.78*** |
| PHIL_ISL | -0.02 | 0.00 | 1.36 | -0.72 | 0.69 | 6.27 | -17.53 | -1.62 | 21.58 | -28.196*** |
| MAL_ISL | -0.02 | 0.00 | 0.92 | -0.50 | 0.40 | 5.88 | -5.82 | 0.11 | 7.85 | -23.938*** |
| IND_ISL | -0.02 | 0.00 | 1.45 | -0.74 | 0.72 | 14.28 | -11.06 | -0.15 | 12.74 | -25.912*** |
| THAI_ESG | -0.01 | 0.00 | 1.12 | -0.52 | 0.52 | 7.57 | -11.46 | -1.06 | 18.96 | -28.248*** |
| PHIL_ESG | -0.01 | 0.00 | 1.32 | -0.68 | 0.68 | 8.46 | -13.79 | -0.94 | 13.83 | -27.309*** |
| MAL_ESG | -0.03 | 0.00 | 0.85 | -0.44 | 0.39 | 6.03 | -5.62 | 0.01 | 8.35 | -22.776*** |
| IND_ESG | 0.00 | 0.00 | 1.50 | -0.69 | 0.71 | 16.39 | -11.57 | -0.01 | 15.74 | -24.109*** |
| TMUENG | 0.04 | -0.71 | 33.64 | -19.26 | 17.05 | 154.34 | -171.38 | 0.30 | 5.48 | -36.518*** |

***, **, * represent significance level at 10%, 5% and 1% respectively.

We report the details and summary statistics for sampled indices in Table 1. MSCI Indonesian indices appear most volatile, while MSCI Malaysian indices are least volatile. We observe that all return series have zero (or close to zero) means and medians. All the series are stationary at first difference and meet the requirement of applying TVP-VAR.

We also show historical movements of prices (Figure 1) and returns (Figure 2), and observe interesting trends. [1] First, within each country, there is not much difference in historical trends between all three categories of indices. Second, ASEAN4 markets generally experienced collapse in 2015-2016 that was (among others) an outcome US interest rate hikes and resulting capital outflows. Third, we observe boom conditions for ASEAN4 stock markets around 2017--2018, driven mainly by strong economic growth, rising foreign direct investment, and increase in global liquidity that made ASEAN4 markets attractive investment destinations. Fourth, ASEAN4 markets collapsed in 2020 at the onset of COVID19. Fourth, ASEAN4 economies recorded recovery in 2022 owing to resumption of tourism activity, technology sector growth, and geopolitical stability in the region.

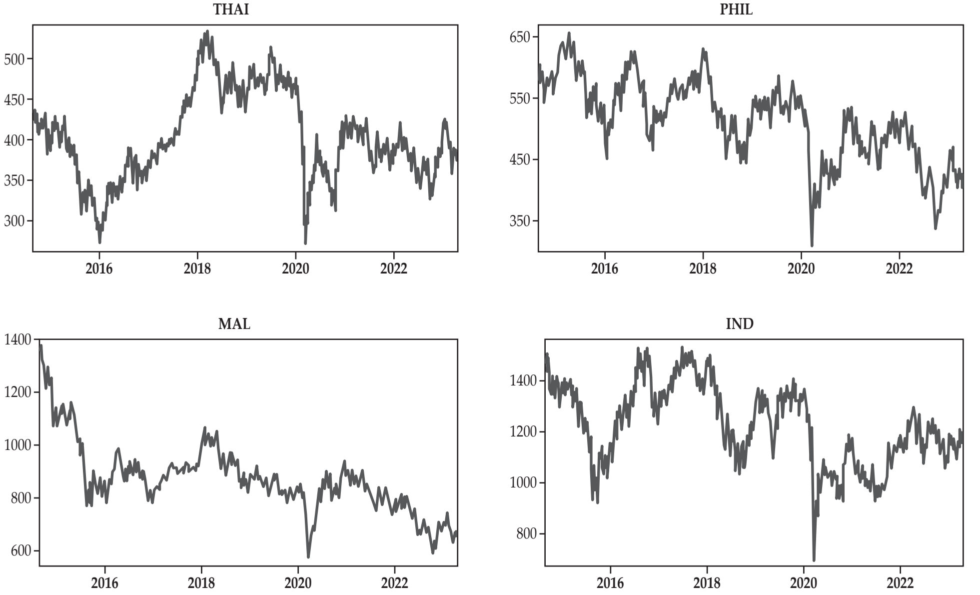


**Figure 1.**
**Historical Trend (Prices)**

1. For discussions in this section as well as section 4 (results and analysis), we rely upon the news articles and other online information sources.

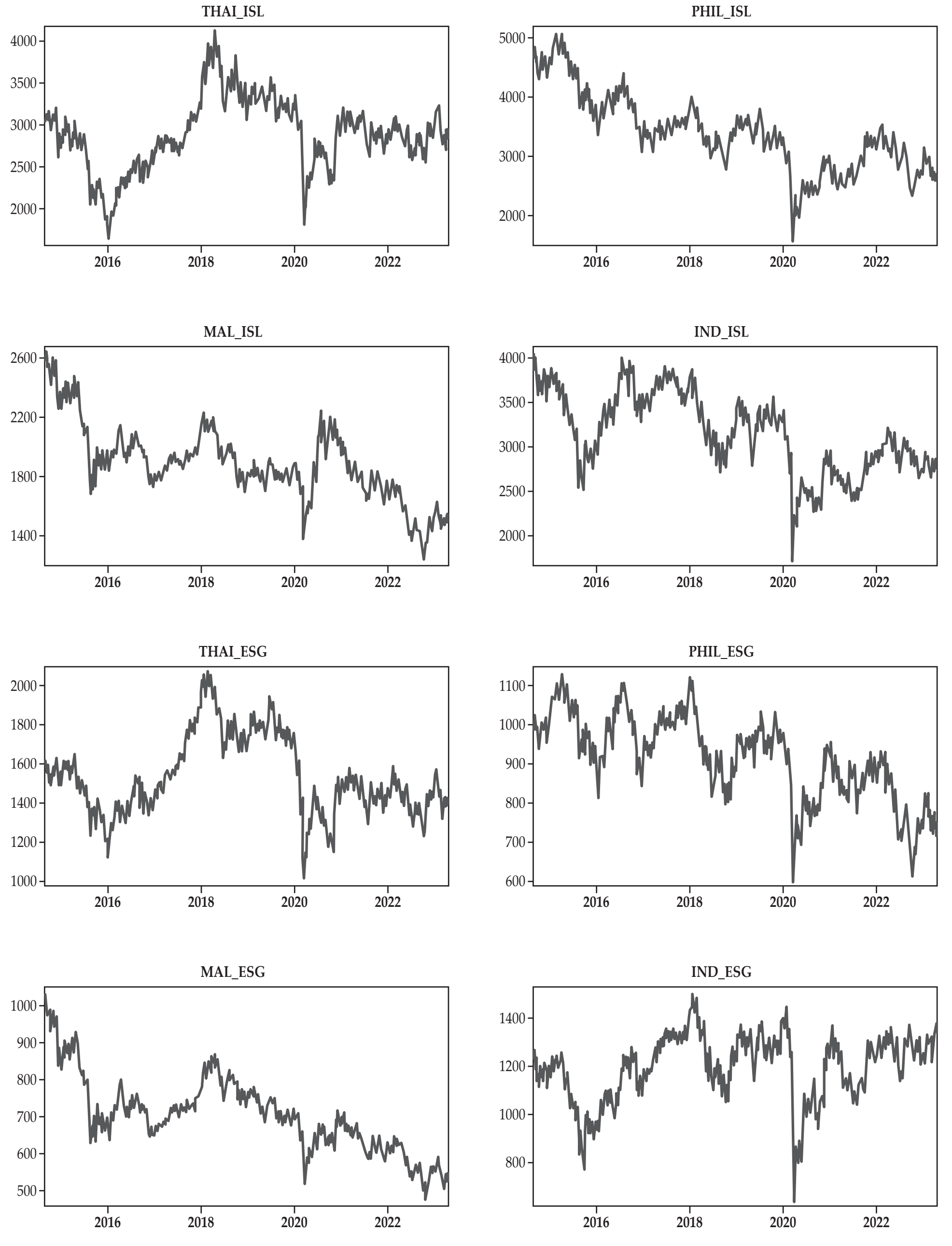


**Figure 1.**
**Historical Trend (Prices) (Continued)**

This figure shows the historical trends of prices of ASEAN4 Indices over the sample period.

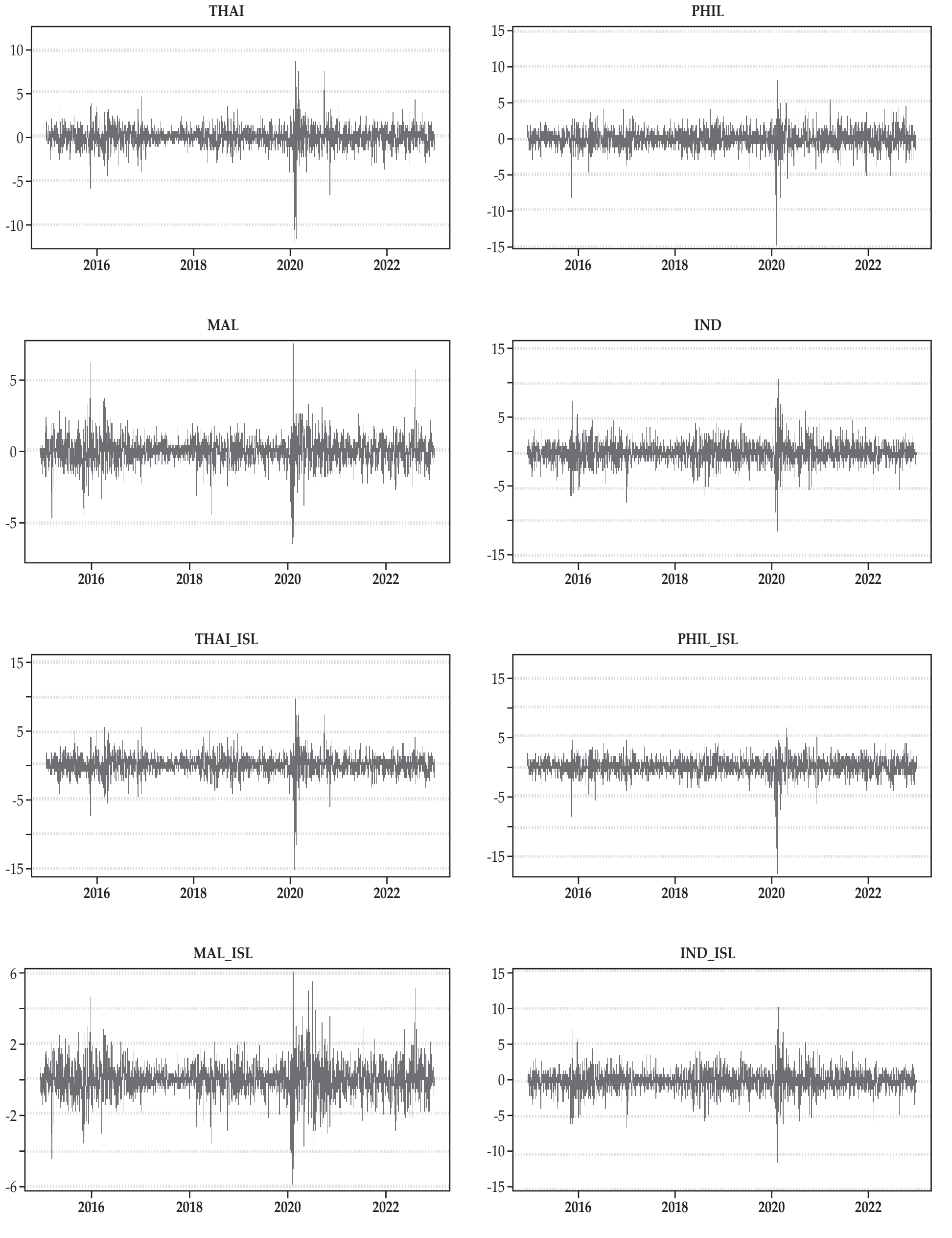


**Figure 2.**
**Historical Trend (Returns)**

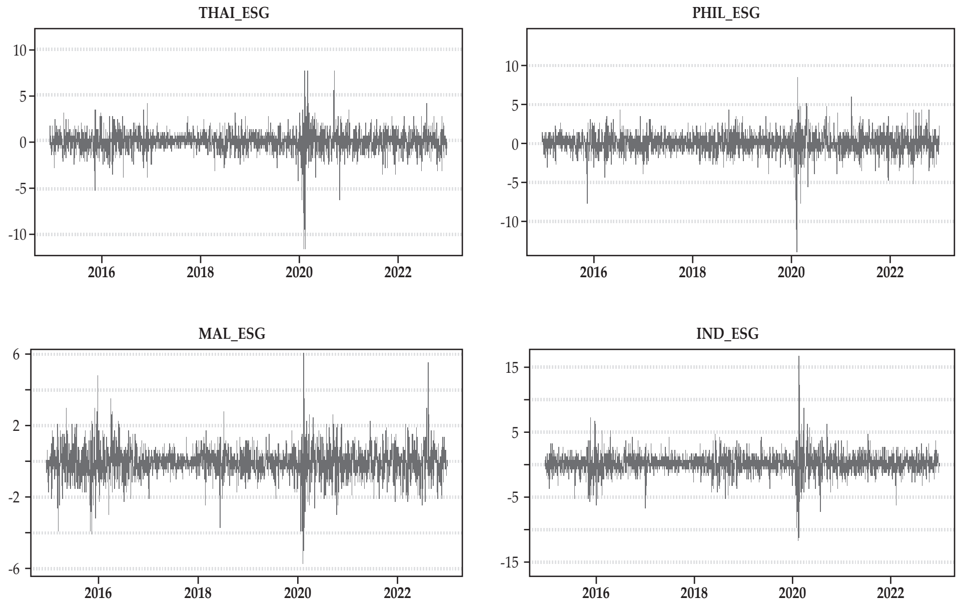


**Figure 2.**
**Historical Trend (Returns) (Continued)**

This figure shows the historical trends of returns of ASEAN4 Indices over the sample period.

Figures 3-5 show distribution of variables on the diagonal, the bivariate scatter plots with a fitted line on the bottom of the diagonal and the value of the correlation plus the significance level as stars on the top of the diagonal for conventional, Islamic, and ESG indices families. The figures reveal that MSCI indices generally exhibit symmetric distributions, while TMUENG indicates the presence of outliers or non-normal behavior. ASEAN indices and TMUENG exhibit significant negative correlation.

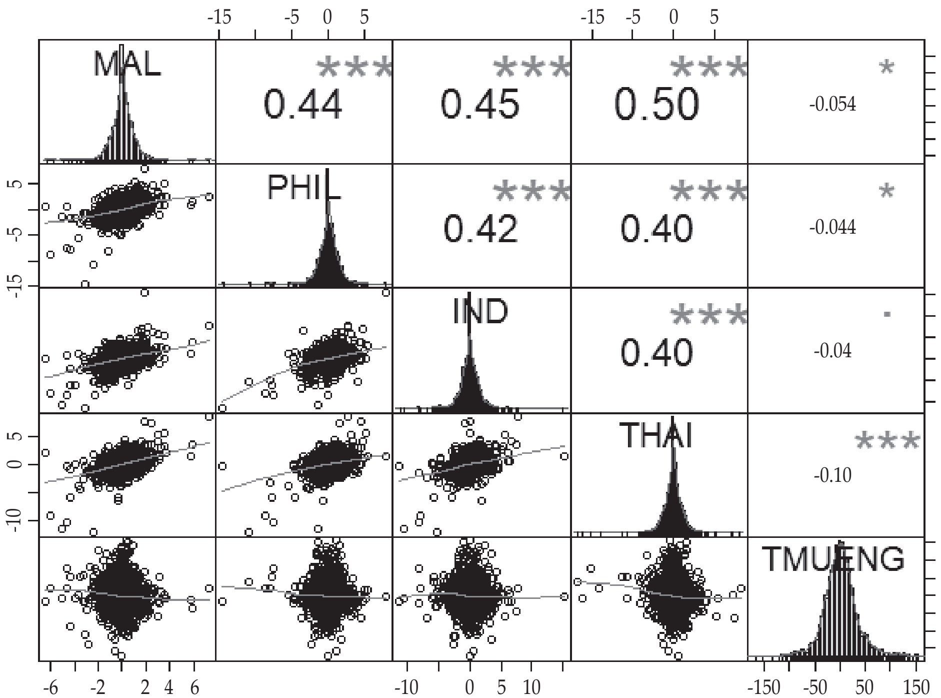


**Figure 3.**
**Distribution Types and Correlation Heatmap (ASEAN4 Conventional)**

This figure shows value of the correlation plus the significance level for ASEAN4 Conventional Indices as stars on the top of the diagonal. "***", "**", "*", "." represent significance of correlations at 0.001, 0.01, 0.05, 0.1 levels respectively. The distribution of each index is shown on the diagonal. The bivariate scatter plots with a fitted line are shown on the bottom of the diagonal.

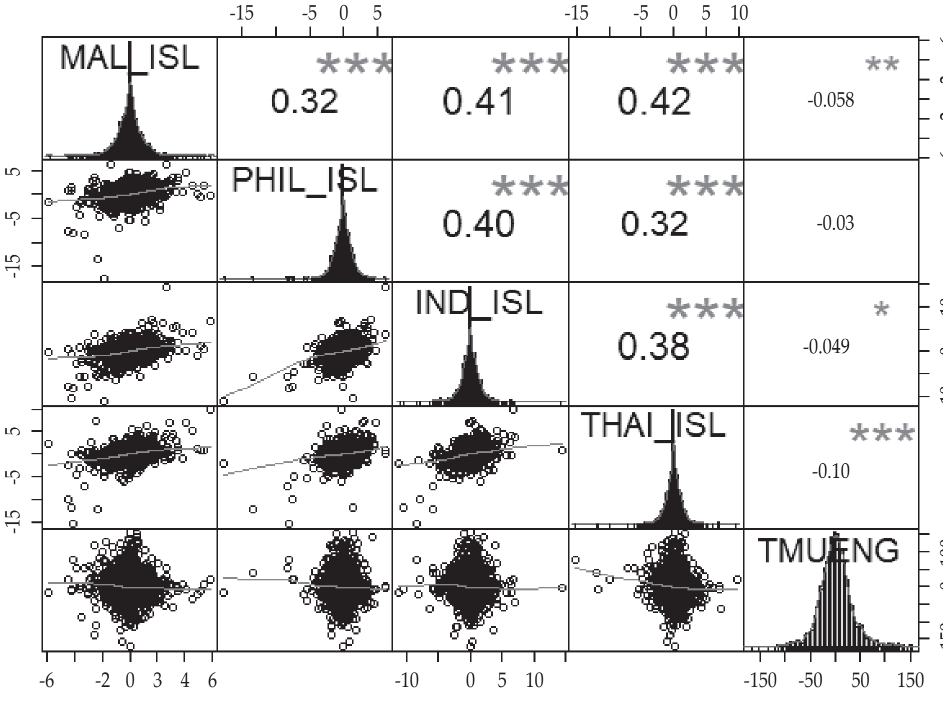


**Figure 4.**
**Distribution Types and Correlation Heatmap (ASEAN4 Islamic)**

This figure shows value of the correlation plus the significance level for ASEAN4 Islamic Indices as stars on the top of the diagonal. "***", "**", "*", "." represent significance of correlations at 0.001, 0.01, 0.05, 0.1 levels respectively. The distribution of each index is shown on the diagonal. The bivariate scatter plots with a fitted line are shown on the bottom of the diagonal.

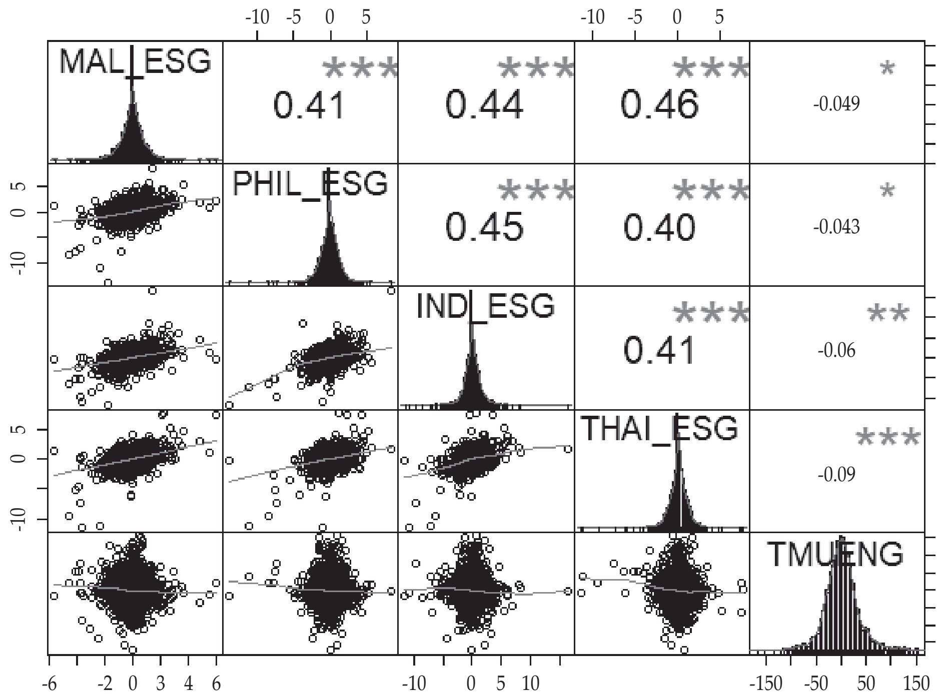


**Figure 5.**
**Distribution Types and Correlation Heatmap (ASEAN4 ESG)**

This figure shows value of the correlation plus the significance level for ASEAN4 ESG Indices as stars on the top of the diagonal. "***", "**", "*", "." represent significance of correlations at 0.001, 0.01, 0.05, 0.1 levels respectively. The distribution of each index is shown on the diagonal. The bivariate scatter plots with a fitted line are shown on the bottom of the diagonal.

Here, we find preliminary answers to our research questions. First, regardless of the category asset classes, ASEAN4 markets behave alike in the times of market booms/busts. Second, ASEAN4 stocks move opposite TMUENG, and hence are affected by market uncertainty.

### 3.2. Model Development and Methodology

Our empirical model is engrained in theoretical foundations of our study. As widely documented, ASEAN4 markets are not frictionless and inflicted with information asymmetry, transaction costs, and behavioral biases leading to market inefficiencies, where asset prices do not fully reflect all available information (Munir et al., 2012; Shabri Abd Majid et al., 2009). In such scenarios, investor sentiments play a crucial role in market dynamics. By incorporating behavioral biases into our analysis, we acknowledge that market participants may react to uncertainty in ways that are not fully rational, leading to time-varying relationships between conventional, Islamic, and ESG indices in the ASEAN4 region (Ali et al., 2023).

Moreover, ASEAN4 region is deeply integrated both economically and financially, making them susceptible to financial contagion. More precisely, a shock in one country's stock market, driven by domestic or global factors, can quickly spread to other ASEAN4 markets through various channels, including investor sentiment and capital flows. The interconnectedness of conventional, Islamic, and ESG stocks across these countries implies that financial contagion can manifest in both expected and unexpected ways (Rahman & Ermawati, 2020).

In line with this theoretical background, we deem the Time-Varying Parameter Vector Autoregression (TVP-VAR) technique suitable as it allows for the exploration of time-varying connectedness within MSCI indices, providing insights into how financial contagion might operate within ASEAN4 conventional, Islamic and ESG markets. The inclusion of TMUENG also adds a layer of complexity, as it captures real-time shifts in investor sentiment that could trigger or exacerbate contagion effects. We will first perform a static timeseries network analysis, based on a vector autoregressive (VAR) model (Sims, 1980). We then estimate dynamics employing a rolling-window VAR framework based on the TVP-VAR (Antonakakis et al., 2020). This approach is insensitive to the size of rolling window and outliers, and also ensures no loss of observation. Moreover, the TVP-VAR can capture the dynamic interactions between stock indices and market uncertainty, which are likely to change in response to various factors like economic conditions, investor sentiment, and external shocks. This approach also enables the study of impulse responses and variance decompositions over time, providing insights into how shocks to one variable, such as a sudden increase in Twitter-based market uncertainty affects the other variables in the system. This allows for better understanding of the interconnectedness between conventional, Islamic, and ESG stocks and the role of market uncertainty in shaping these relationships.

To estimate the TVP-VAR(1) model. We first define Bayesian Information Criterion (BIC) in the following manner: -

$$z_t = \boldsymbol{B}_t z_{t-1} + u_t \qquad u_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{1}$$

$$\text{vec}(\boldsymbol{B}_t) = \text{vec}(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(0, \boldsymbol{R}_t) \tag{2}$$

Here, $z_t, z_{t-1}$, and $u_t$ are vectors of *k x 1* dimension and $B_t$ and $S_t$ are matrices of *k x k* dimensions. Also, $vec(B_t)$ and $v_t$ are vectors of $k^2$ x 1 dimension and $R_t$ is a matrix of $k^2$ x $k^2$ dimensions.

Now, following Koop et al. (1996) and Pesaran & Shin (1995), we calculate H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD). To utilize GFEVD spillover framework, we transform the estimated TVP-VAR model into a Time-Varying Parameter Vector Moving Average (TVP-VMA) process using following equality:

$$\boldsymbol{z}_t = \sum_{x=1}^{p} \boldsymbol{B}_{x\,t}\boldsymbol{z}_{t-x} + \boldsymbol{u}_t = \sum_{y=0}^{\infty} \boldsymbol{A}_{y\,t}\boldsymbol{u}_{t-y} \tag{3}$$

The (scaled) GFEVD standardizes the (unscaled) GFEVD, $\phi^{g}_{x\,y,t}(H)$ making the sum of every row equal to 1. Hence, $\tilde{\phi}^{g}_{x\,y,t}(H)$ expresses the effect of variable $x$ on variable $y$ in respect of its forecast error variance share. It can be termed as the *pairwise directional connectedness* from $y$ to x.

$$\phi^{g}_{x\,y,t}(H) = \frac{S^{-1}_{x\,x,t}\sum_{t=1}^{H-1}\left(\boldsymbol{l}'_x\boldsymbol{A}_t\boldsymbol{S}_t\boldsymbol{l}_y\right)^2}{\sum_{y=1}^{k}\ \sum_{t=1}^{H-1}(\boldsymbol{l}_x\boldsymbol{A}_t\boldsymbol{S}_t\boldsymbol{A}'_t\boldsymbol{l}_x)} \qquad \tilde{\phi}^{g}_{x\,y,t}(H) = \frac{\phi^{g}_{x\,y,t}(H)}{\sum_{y=1}^{k}\ \phi^{g}_{x\,y,t}(H)} \tag{4}$$

Here, $\sum_{y=1}^{k}\ \tilde{\phi}^{g}_{x\,y,t}(H) = 1$, $\sum_{x,y=1}^{k}\ \tilde{\phi}^{g}_{x\,y,t}(H) = k$, and $l_x$ represent a selection vector having $x = 1$ and '0' otherwise

For our estimations, we utilize five connectedness measures developed by Diebold & Yilmaz (2012), based upon the GFEVD:

*Total Connectedness Index (TCI)* highlights average impact variable $y$ has on all *others*. It can be represented as

$$TCI_t = k^{-1}\sum_{y=1}^{k} TO_{y\,t} \equiv k^{-1}\sum_{y=1}^{k} FROM_{y\,t} \tag{1}$$

*Total Directional Connectedness to Others (TO)* captures aggregated impact that a shock in variable $y$ has on all *others* variables.

$$TO_{y\,t} = \sum_{x=1,x\neq y}^{k} \tilde{\phi}^{g}_{x\,y,t}(H) \tag{2}$$

*Total Directional Connectedness from Others (FROM)* represents the aggregated influence of all *other* variables on variable $y$.

$$FROM_{y\,t} = \sum_{x=1,x\neq y}^{k} \tilde{\phi}^{g}_{y\,i,t}(H) \tag{3}$$

*Net Total Directional Connectedness (NTDC)* shows whether a variable $y$ is a net receiver or a net transmitter of shocks.

$$NTDC_{y\,t} = TO_{y\,t} - FROM_{y\,t} \tag{4}$$

*Net Pairwise Directional Connectedness (NPDC)* captures bivariate relationship of two variables $y$ and $x$, and portrays whether variable $x$ is driving variable $y$ or vice versa.

$$NPDC_{x\,y,t} = \tilde{\phi}_{x\,y,t}(H) - \tilde{\phi}_{y\,x,t}(H) \tag{5}$$

# IV. RESULTS AND ANALYSIS

## 4.1. Average and Dynamic Total Connectedness Measures

We start our analysis by discussing averaged connectedness measures for ASEAN4 conventional indices (Table 2). The main diagonal shows own-variance shares of shocks, whereas off diagonal elements highlight the interaction of sampled indices. We first observe moderate connectedness between conventional indices and TMUENG i.e., 25.86% implying that on average, 27.2% of the forecast error variance in one variable can be attributed to the innovations in all others. We also observe that although Thailand emerges as net transmitter of shocks for the full sample period, TMUENG remains the main transmitter of shocks (7.34) for our network of ASEAN4 conventional indices. For Islamic (Table 3) and ESG (Table 4) indices, we observe much bigger role of TMUENG as net transmitter of shocks. Hence, these markets appear to be more affected by market uncertainty. This finding is intuitive because these indices are subsets of market portfolios and more exposed to market risk (Merton, 1987).

**Table 2.**
**Average Connectedness (ASEAN4 Conventional)**

| | THAI | PHIL | MAL | IND | TMUENG | FROM others |
|---|---|---|---|---|---|---|
| THAI | 62.61 | 11.48 | 17.9 | 6.19 | 1.82 | 37.39 |
| PHIL | 13.44 | 71.56 | 9.78 | 3.14 | 2.08 | 28.44 |
| MAL | 18 | 9.57 | 61.41 | 5.51 | 5.51 | 38.59 |
| IND | 7.7 | 3.51 | 7.01 | 79.49 | 2.29 | 20.51 |
| TMUENG | 0.41 | 1.76 | 1.86 | 0.33 | 95.64 | 4.36 |
| TO others | 39.56 | 26.32 | 36.55 | 15.17 | 11.7 | 129.3 |
| Inc. own | 102.16 | 97.88 | 97.96 | 94.66 | 107.34 | TCI |
| NET | 2.16 | -2.12 | -2.04 | -5.34 | 7.34 | 25.86 |
| NPDC | 1 | 3 | 2 | 4 | 0 | |

This table reports the average connectedness among ASEAN4 Conventional Indices for the whole sample period (01 Sep 2014 to 21 Apr 2023).

**Table 3.**
**Average Connectedness (ASEAN4 Islamic)**

| | THAI_ISL | PHIL_ISL | MAL_ISL | IND_ISL | TMUENG | FROM others |
|---|---|---|---|---|---|---|
| THAI_ISL | 68.57 | 4.64 | 16.7 | 8.9 | 1.19 | 31.43 |
| PHIL_ISL | 5.69 | 83.94 | 5.62 | 3.33 | 1.42 | 16.06 |
| MAL_ISL | 15.92 | 6.57 | 64.21 | 6.97 | 6.34 | 35.79 |
| IND_ISL | 9.84 | 3.34 | 8.27 | 76.67 | 1.87 | 23.33 |
| TMUENG | 0.1 | 0.85 | 1.74 | 0.09 | 97.22 | 2.78 |
| TO others | 31.55 | 15.4 | 32.33 | 19.29 | 10.82 | 109.39 |
| Inc. own | 100.12 | 99.34 | 96.54 | 95.96 | 108.04 | TCI |
| NET | 0.12 | -0.66 | -3.46 | -4.04 | 8.04 | 21.88 |
| NPDC | 2 | 2 | 2 | 4 | 0 | |

This table reports the average connectedness among ASEAN4 Islamic Indices for the whole sample period (01 Sep 2014 to 21 Apr 2023).

**Table 4.**
**Average Connectedness (ASEAN4 ESG)**

| | THAI_ESG | PHIL_ESG | MAL_ESG | IND_ESG | TMUENG | FROM others |
|---|---|---|---|---|---|---|
| THAI_ESG | 64.12 | 11.68 | 16.09 | 6.83 | 1.27 | 35.88 |
| PHIL_ESG | 13.51 | 71.32 | 9.07 | 4.03 | 2.07 | 28.68 |
| MAL_ESG | 16.13 | 8.87 | 63.8 | 6.41 | 4.78 | 36.2 |
| IND_ESG | 6.86 | 4.44 | 7.86 | 79.16 | 1.69 | 20.84 |
| TMUENG | 0.16 | 1.83 | 2.06 | 0.35 | 95.6 | 4.4 |
| TO others | 36.66 | 26.83 | 35.07 | 17.63 | 9.81 | 126 |
| Inc. own | 100.78 | 98.15 | 98.87 | 96.79 | 105.41 | TCI |
| NET | 0.78 | -1.85 | -1.13 | -3.21 | 5.41 | 25.2 |
| NPDC | 1 | 3 | 2 | 4 | 0 | |

This table reports the average connectedness among ASEAN4 ESG Indices for the whole sample period (01 Sep 2014 to 21 Apr 2023).

However, the results presented in Tables 2-4 are aggregate results and account for the period of study in its entirety. They may ignore specific periods contributing to notable deviations from the average TCI values for ASEAN4 indices. We, therefore, adopt a dynamic approach to identify specific episodes affecting connectedness across ASEAN4 indices over time.

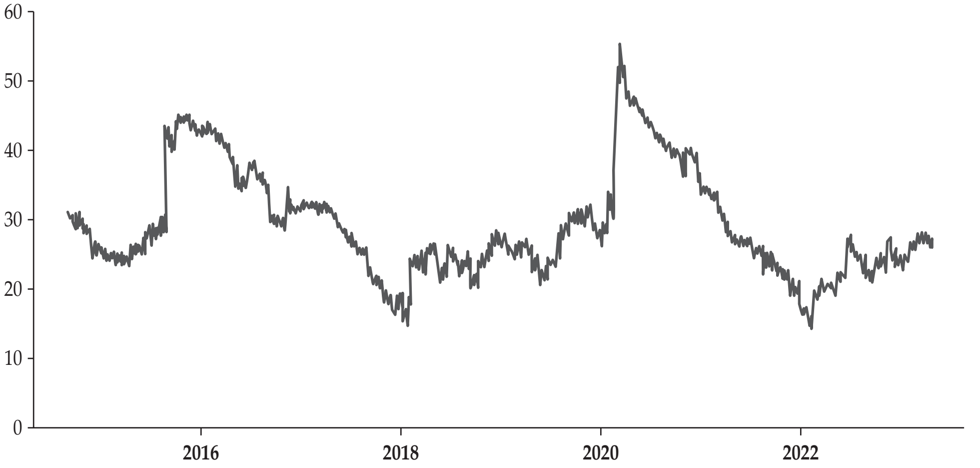


**Figure 6.**
**Total Connectedness Index (ASEAN4 Conventional)**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG.

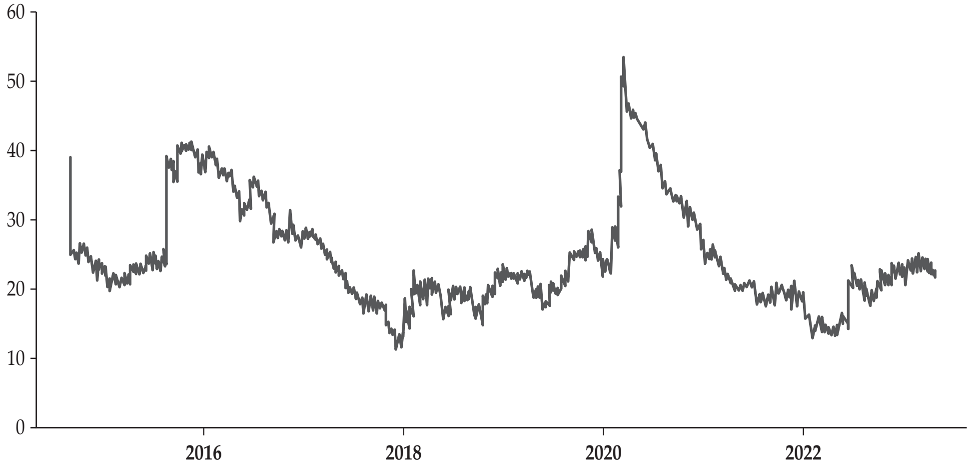


**Figure 7.**
**Total Connectedness Index (ASEAN 4 Islamic)**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 Islamic Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG.

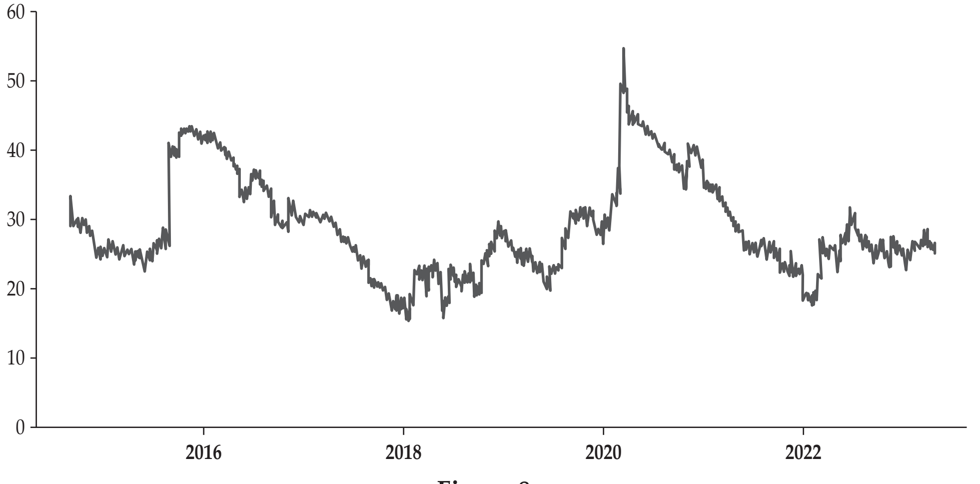


**Figure 8.**
**Total Connectedness Index (ASEAN 4 ESG)**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 ESG Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG.

We start the analysis with conventional indices (Figure 6). We notice that the dynamic connectedness of our network fluctuates considerably over time. The total connectedness peaks during 2015-2016 and 2020. If we recall, during both periods, ASEAN markets experienced bearish markets. During 2017-2018 and 2022 (market booms), we observe extremely low connectedness. We observe similar results for Islamic (Figure 7) and ESG (Figure 8) indices. Since Islamic and ESG indices are often influenced by the same macroeconomic and geopolitical factors as conventional indices, the shock transmission patterns for ASEAN4 markets are similar.

Therefore, we draw inference that all categories of ASEAN4 indices exhibit interconnectedness during bearish periods. However, during favorable environment, ASEAN4 markets perform independently of each other.

**4.2. Net Total Directional Connectedness (NTDC)**

NTDC shows the net impact (transmission minus receiving of shocks) of every ASEAN4 index on the entire network. Here, positive values in the shaded area indicate periods when an index acts as a net transmitter, while negative values reflect times when the index is a net receiver from others. We are primarily interested in observing how uncertainty (TMUENG) transmits / receives shocks to / from ASEAN4 markets. Nevertheless, we will also identify net impact ASEAN4 economies in network context.

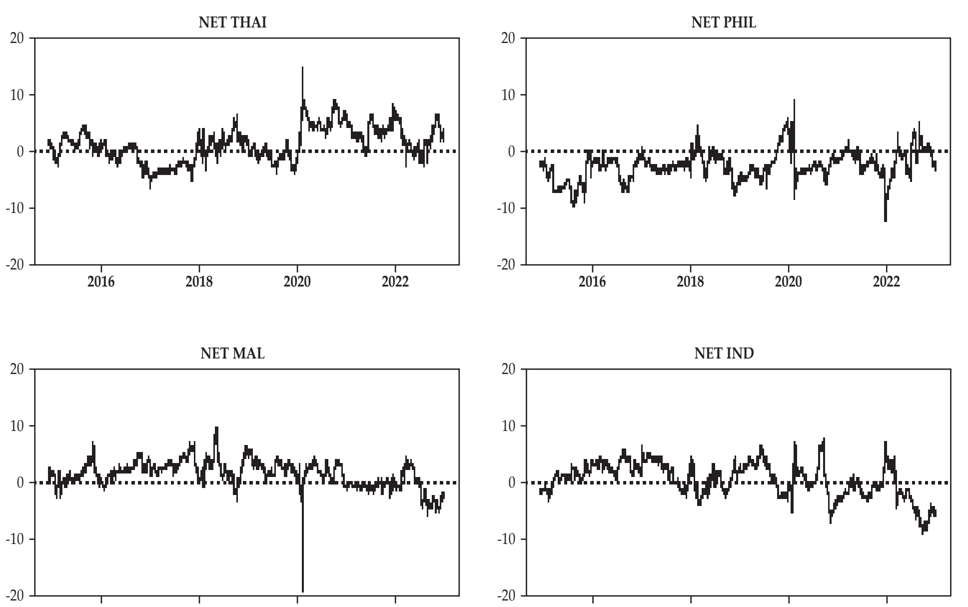


**Figure 9.**
**Net Total Directional Connectedness (ASEAN4 Conventional)**

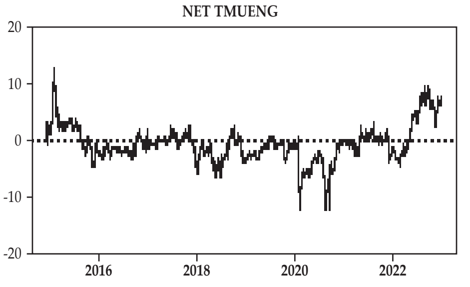


**Figure 9.**
**Net Total Directional Connectedness (ASEAN4 Conventional) (Continued)**

Figure 9 offers interesting insights. We observe that Indonesia and Malaysia remained net transmitters of shocks for most of the sample period i.e., up to pandemic. Both countries possess stable macroeconomic fundamentals and more developed financial markets. Their position in ASEAN is strengthened by virtue of their roles as key exporters of commodities making them influential financial centers. This allows them to transmit shocks to other economies, particularly during periods of global commodity price fluctuations or external financial crises.

This figure shows Net Total Directional based on a TVP-VAR model for a network of ASEAN4 Conventional Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. Here, positive values in the shaded area indicate periods when an index acts as a net transmitter, while negative values reflect times when the index is a net receiver from others.

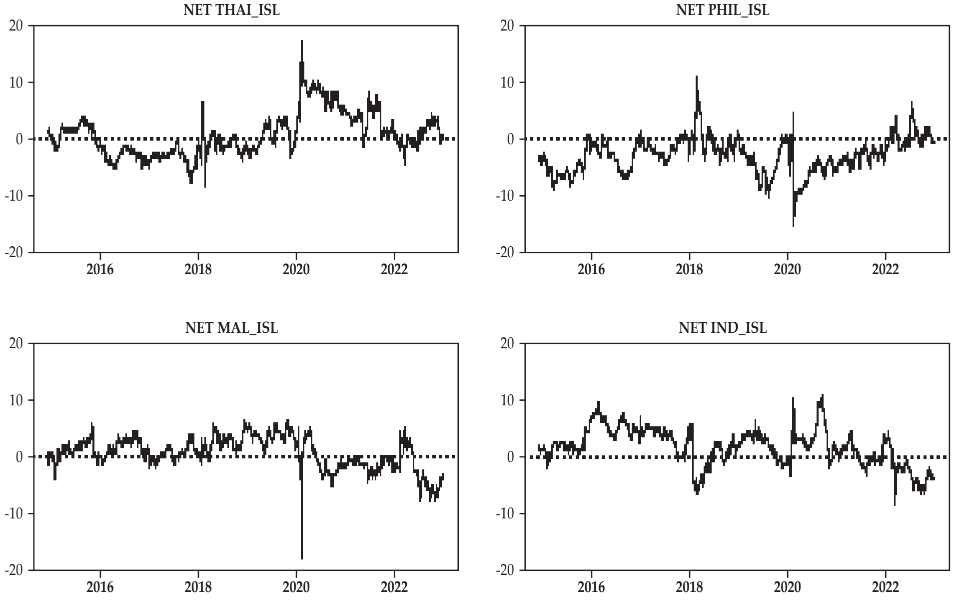


**Figure 10.**
**Net Total Directional Connectedness (ASEAN4 Islamic)**

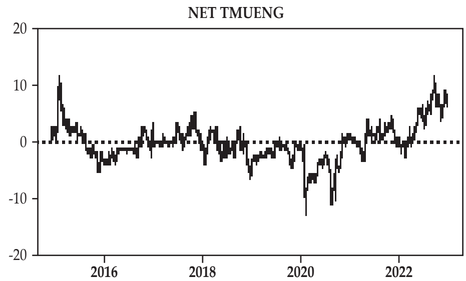


**Figure 10.**
**Net Total Directional Connectedness (ASEAN4 Islamic) (Continued)**

This figure shows Net Total Directional based on a TVP-VAR model for a network of ASEAN4 Islamic Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. Here, positive values in the shaded area indicate periods when an index acts as a net transmitter, while negative values reflect times when the index is a net receiver from others.

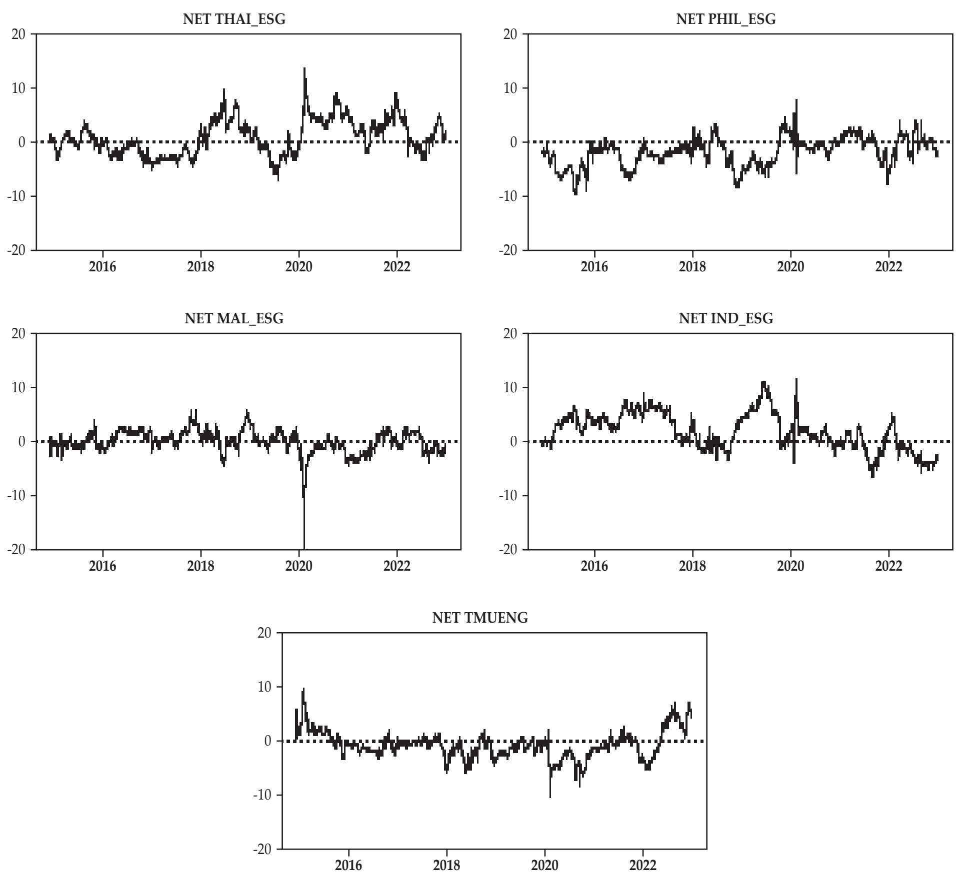


**Figure 11.**
**Net Total Directional Connectedness (ASEAN4 ESG)**

This figure shows Net Total Directional based on a TVP-VAR model for a network of ASEAN4 ESG Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. Here, positive values in the shaded area indicate periods when an index acts as a net transmitter, while negative values reflect times when the index is a net receiver from others.

In post-COVID period, Thailand emerges as a net transmitter of shocks to the network due to relatively rapid recovery, driven by factors such as tourism rebound, manufacturing exports, and government policies. As Thailand's economy rebounded, its financial market gained influence within the network, allowing it to transmit shocks to others.

Interestingly, TMUENG remained a receiver except for a very small period of time (2023). We argue that social media platforms like Twitter may not have enough direct impact on traditional financial systems to become net transmitters, more so on informationally inefficient markets like ASEAN4. Although they can reflect uncertainty, their role in actually driving market movements appears limited in case of ASEAN4.

We observe the similar patterns for Islamic (Figure 10) and ESG (Figures 11) indices. We contend that financial structures and dependencies in the ASEAN4 region mirror across different asset classes. More specifically, for ESG indices, the similar patterns among ASEAN4 are likely due to harmonized sustainability policies under ASEAN agreements, such as the ASEAN Green Bond Standards, and adherence to international frameworks like the UN SDGs that create a similar regulatory environment, influencing ESG practices across the region. In addition, geographical proximity and shared environmental vulnerabilities contribute to similar ESG performance. Additionally, global investors often view ASEAN-4 markets collectively, leading to synchronized responses to global narratives like climate change or renewable energy adoption. Finaly, market sentiment and informational spillovers also play a role, as events in one country like policy shifts or environmental crises may influence neighboring countries due to interconnected economies and similar socio-economic contexts.

**4.3. Net Pairwise Directional Connectedness (NPDC)**

NTDC may not reveal interesting relationships between sampled indices and TMUENG. We now focus on pairs of variables to describe the dynamic linkages over time.

We start our analysis of conventional indices (Figure 12) by looking at how Thailand interacts with other countries. For THAI-PHIL, Thailand becomes a receiver of shocks after 2022. We argue that Philippines may have experienced stronger economic recovery compared to Thailand, driven by growth in sectors like digital services, remittances, and increased consumer spending. This recovery apparently strengthened its financial markets, allowing it to transmit shocks to Thailand. For THAI-MAL, Thailand becomes transmitter after 2018 mainly attributed to Malaysia's slow growth during this period. It held this position except the years 2019-2020 mainly due to COVID19 and Thailand's higher dependence on tourism compared to Malaysia. For THAI-IND, Thailand emerges as transmitter after 2020 owing to its faster post-pandemic recovery compared to Indonesia. For

PHIL-MAL and PHIL-IND, Philippines remains a receiver of shocks except a brief period in 2020, owing mainly due to better financial position of both Indonesia and Malaysia. For MAL-IND, Malaysia remains a transmitter except at the start of COVID19, visibly due to its better economic fundamentals and more developed financial markets.

As for TMUENG, we find interesting insights: For THAI-TMUENG, Thailand remains transmitter of shocks except years 2021 and 2023. For PHIL-TMUENG, PHIL becomes receiver after 2021. After 2021, global market sentiment, as captured by TMUENG, likely became more volatile due to factors such as inflation, geopolitical tensions, and uneven global economic recovery. The Philippines, with its relatively less resilient financial markets, became more sensitive to these external shocks, making it a receiver. For MAL-TMUENG AND IND-TMUENG, TMUENG remains a transmitter of shocks throughout the sample period except 2021 and 2023. We argue that Malaysia and Indonesia are heavily reliant on commodity exports, which makes them particularly sensitive to global market uncertainties. TMUENG likely transmitted shocks related to commodity price fluctuations, global trade tensions, and supply chain disruptions to both markets. In years 2021 and 2023, local economic and political factors likely played a more significant role in Malaysia and Indonesia, dampening the effects of global sentiment transmitted through TMUENG.

In line with TCI and NTDC results, we find that Islamic (Figure 13) and ESG (Figure 14) indices follow the pattern similar to conventional indices except very few instances.

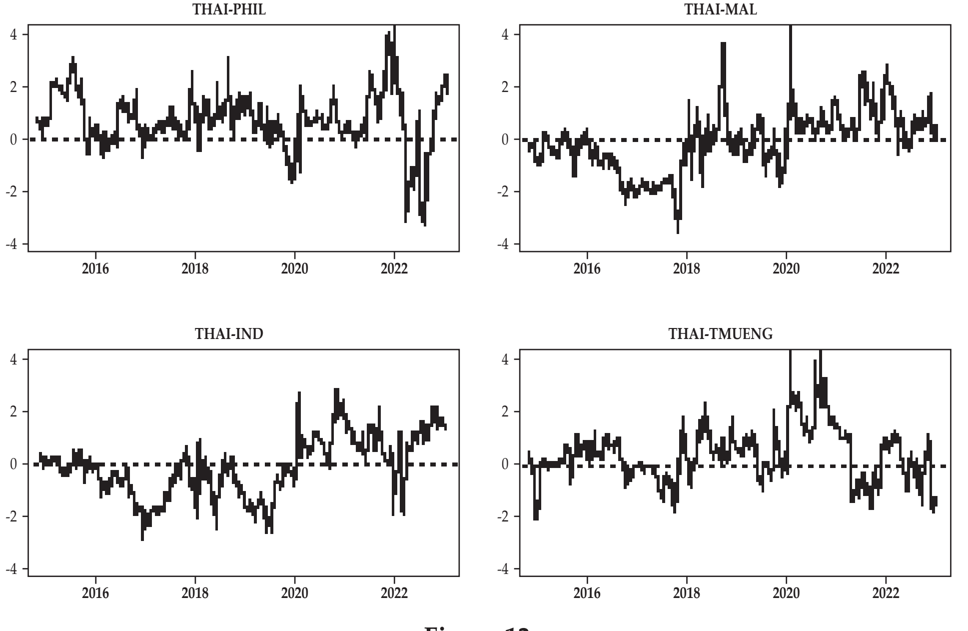


**Figure 12.**
**Net Pairwise Directional Connectedness (ASEAN4 Conventional)**

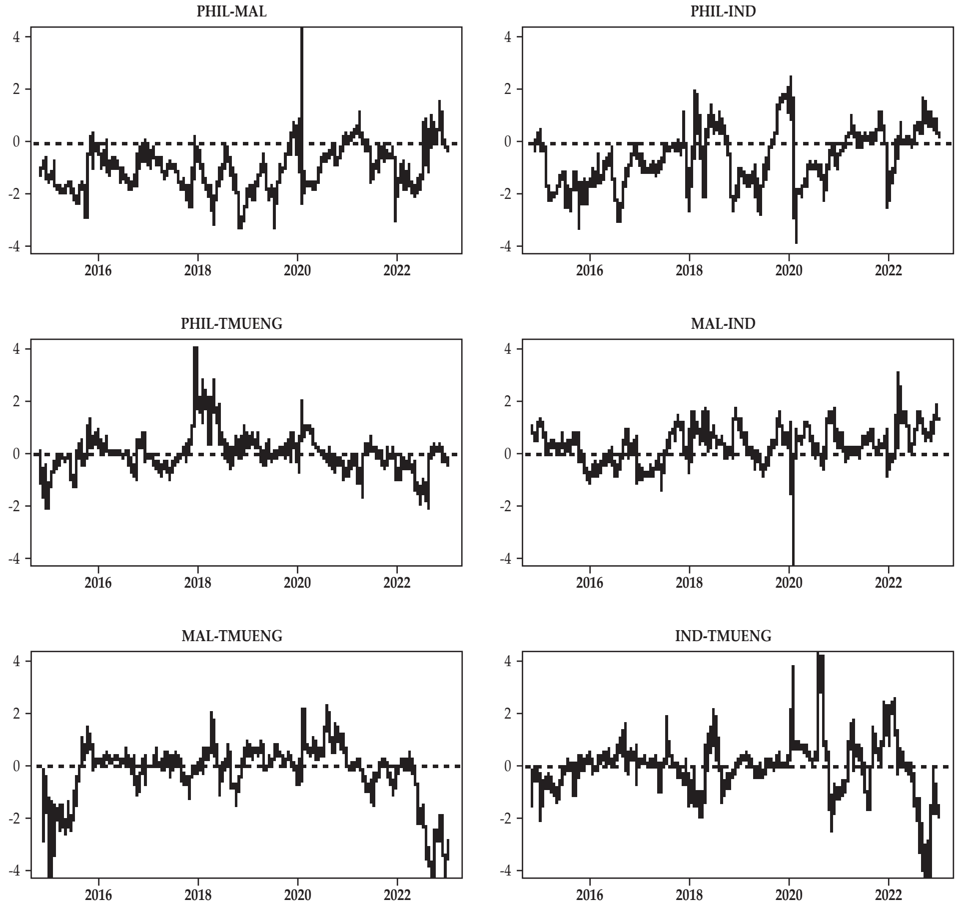


**Figure 12.**
**Net Pairwise Directional Connectedness (ASEAN4 Conventional) (Continued)**

This figure shows Net Pairwise Directional based on a TVP-VAR model for a network of ASEAN4 Conventional Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. Here, positive values in the shaded area indicate periods when an index acts as a net transmitter, while negative values reflect times when the index is a net receiver from others.

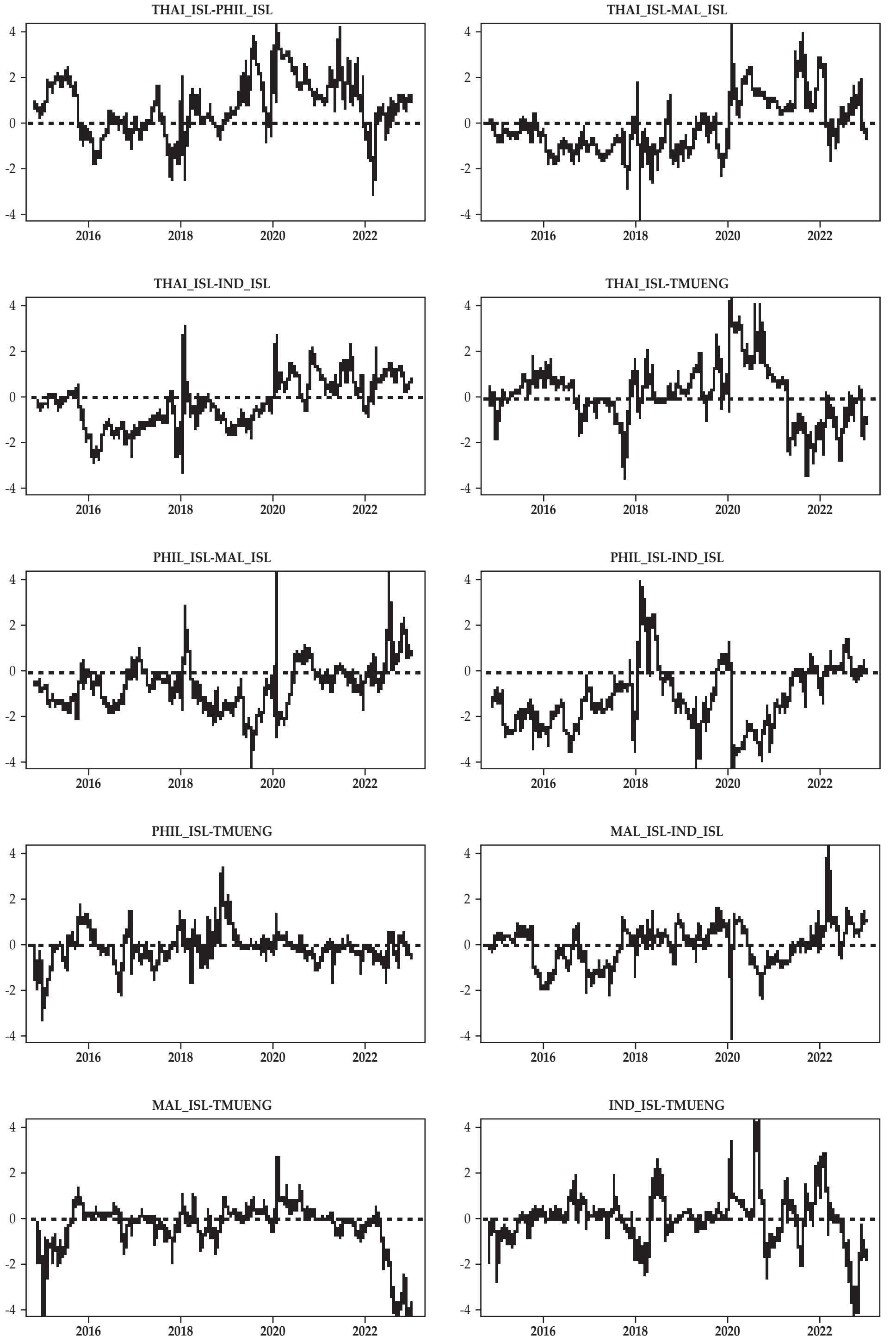


**Figure 13.**
**Net Pairwise Directional Connectedness (ASEAN4 Islamic)**

This figure shows Net Pairwise Directional based on a TVP-VAR model for a network of ASEAN4 Islamic Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. Here, positive values in the shaded area indicate periods when an index acts as a net transmitter, while negative values reflect times when the index is a net receiver from others.

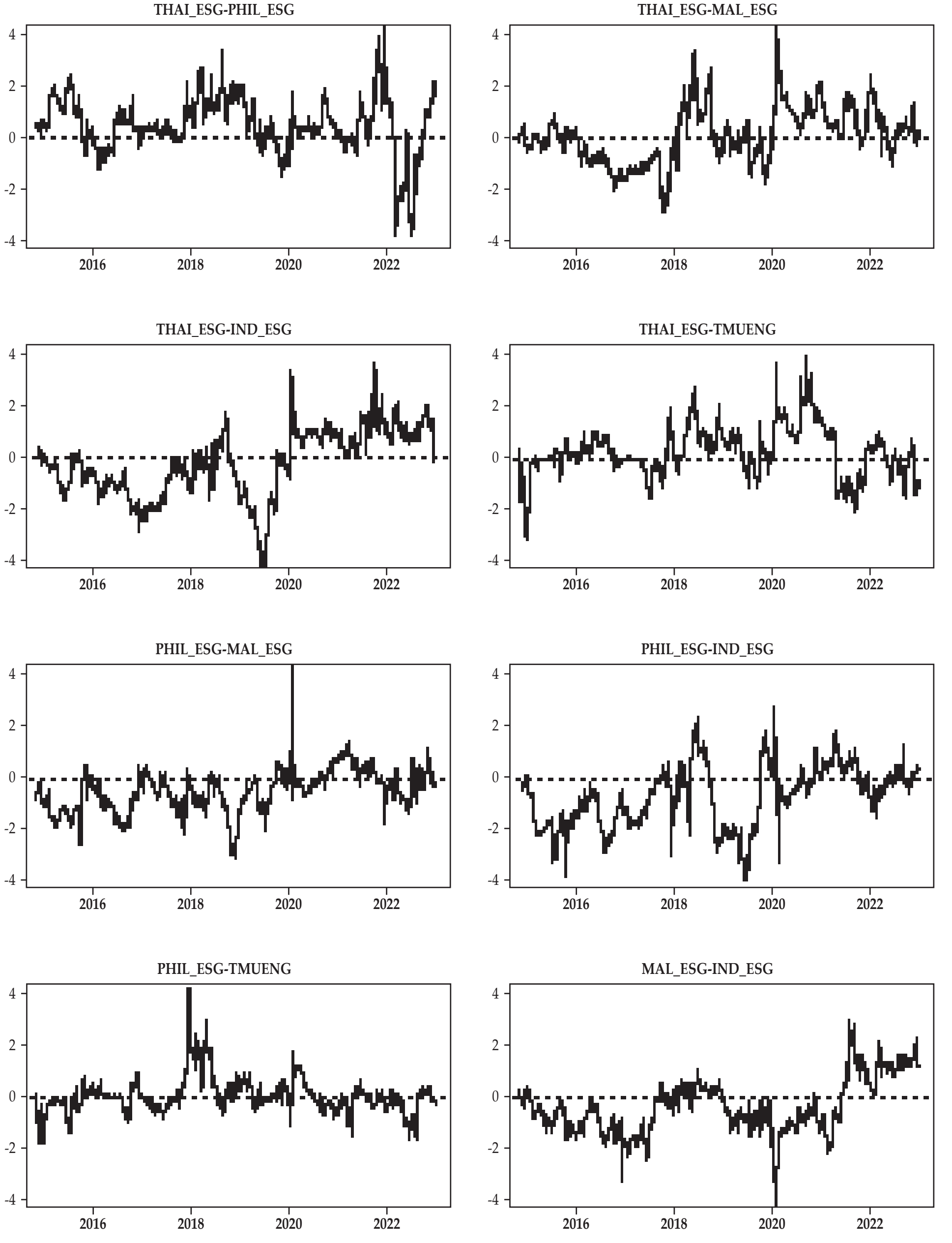


**Figure 14.**
**Net Pairwise Directional Connectedness (ASEAN4 ESG)**

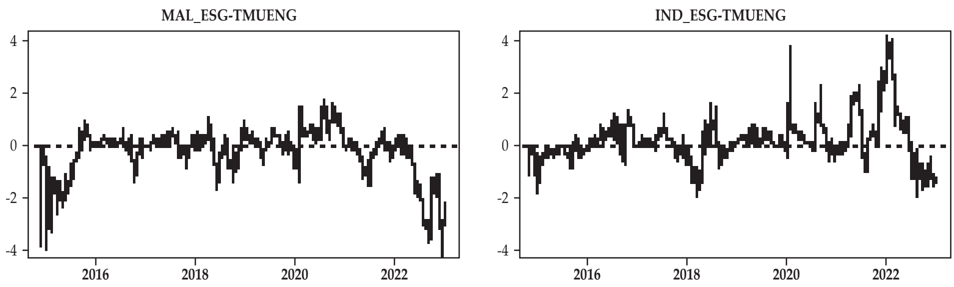


**Figure 14.**
**Net Pairwise Directional Connectedness (ASEAN4 ESG) (Continued)**

This figure shows Net Pairwise Directional based on a TVP-VAR model for a network of ASEAN4 ESG Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. Here, positive values in the shaded area indicate periods when an index acts as a net transmitter, while negative values reflect times when the index is a net receiver from others.

### 4.4. Robustness Tests

We perform a battery of robustness tests. For brevity and the standard practice in TVP-VAR literature, we only report TCI findings. However, the complete findings are available upon request.

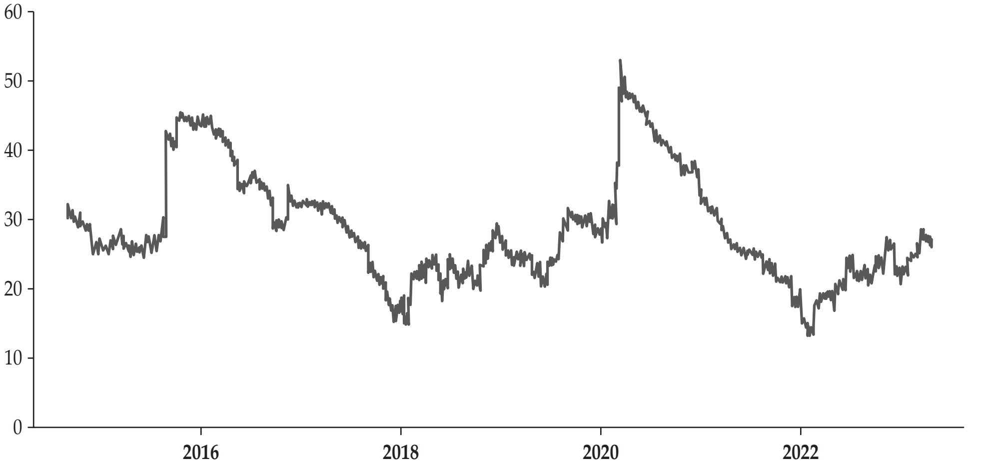


**Figure 15.**
**ASEAN4 Conventional Robustness Check: Total Connectedness Index Estimated Using Twitter Economic Uncertainty**

We first perform estimations using alternate proxy of uncertainty namely Twitter Economic Uncertainty - ENG (TEUENG) developed by S. R. Baker et al., (2021) using variations of keywords ‘uncertain’, and ‘economy’. TEU captures broader economic uncertainty based on Twitter discussions including topics like GDP growth, inflation, unemployment, and fiscal/monetary policies. Hence, by employing TEUENG, we can ensure that our findings are not valid only for market-driven volatility but robust to macroeconomically driven uncertainty that affects markets indirectly through policy changes, labor markets, or consumer sentiment. The results for all asset classes (Figures 15-17) are in line with earlier findings. More precisely, the peaks and troughs are similar to the original findings.

This figure shows the results based on a TVP-VAR model for a network of ASEAN4 Conventional Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Economic Uncertainty – ENG.

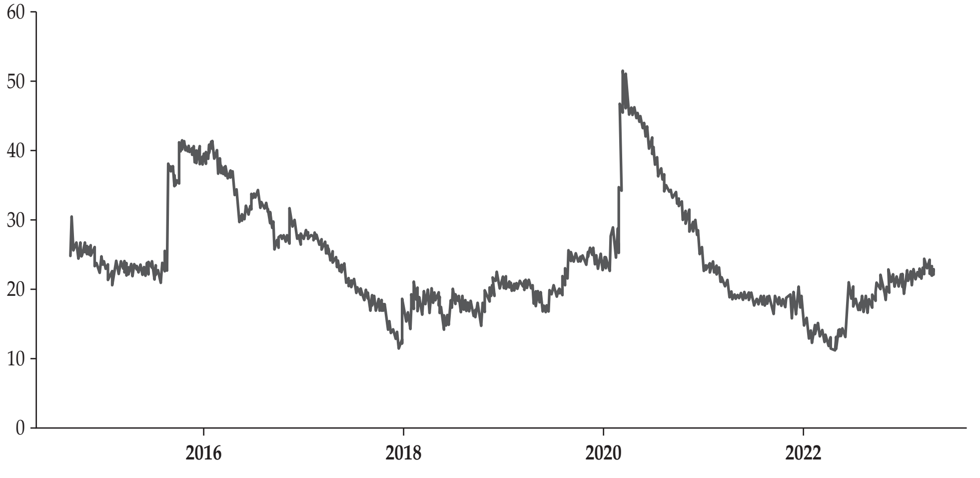


**Figure 16.**
**ASEAN4 Conventional Robustness Check: Total Connectedness Index Estimated Using Twitter Economic Uncertainty**

This figure shows the results based on a TVP-VAR model for a network of ASEAN4 Islamic Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Economic Uncertainty – ENG.

This figure shows the results based on a TVP-VAR model for a network of ASEAN4 ESG Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Economic Uncertainty – ENG.

Next, in line with Antonakakis et al. (2020), we perform estimations using different rolling window sizes for model validation and to test sensitivity of results to the choice of the window size. By using different rolling window sizes, we can capture economic or financial dynamics over different time horizons and ensure that our findings are not just artifacts of a particular time scale. The results (Figures 18-20) remain robust to this specification.

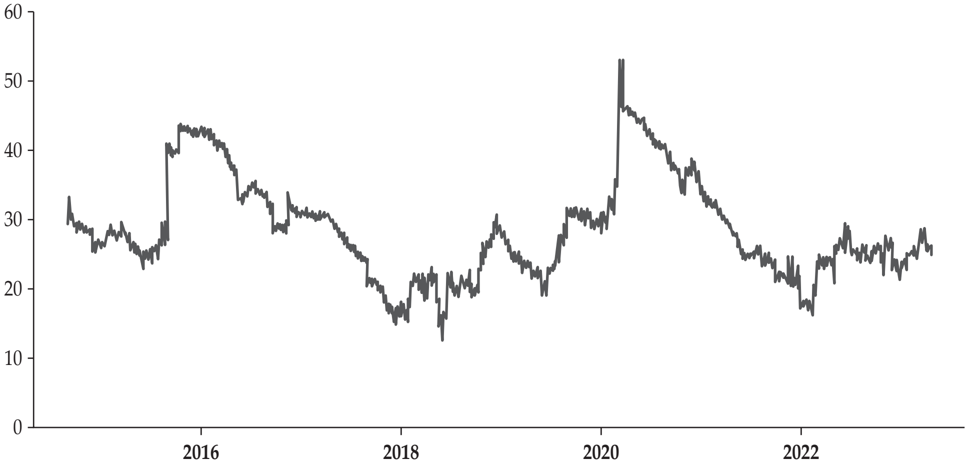


**Figure 17.**
**ASEAN4 Conventional Robustness Check: Total Connectedness Index Estimated Using Twitter Economic Uncertainty**

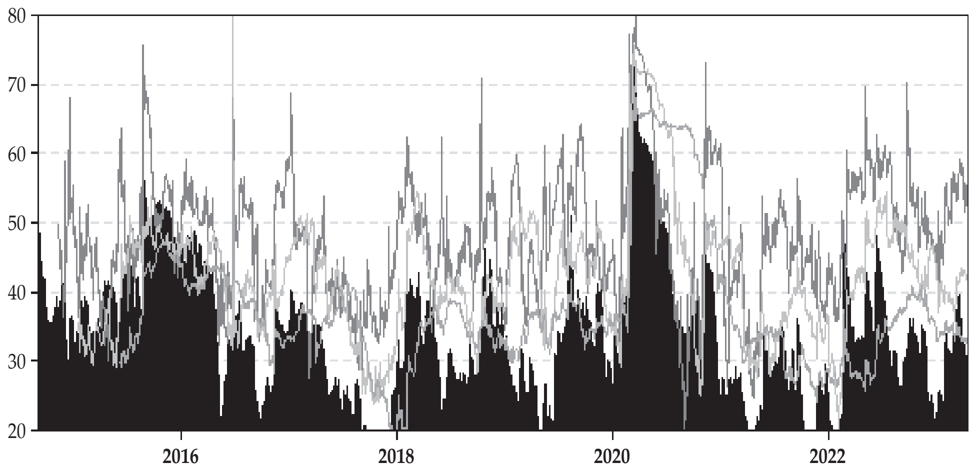


**Figure 18.**
**ASEAN4 Conventional Robustness Check: Total Connectedness Index Estimated for Different Window Sizes**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 Conventional Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. The figure shows results for different window sizes simultaneously including Black → TVP-VAR, Red → 50, Green → 100 and Blue → 200.

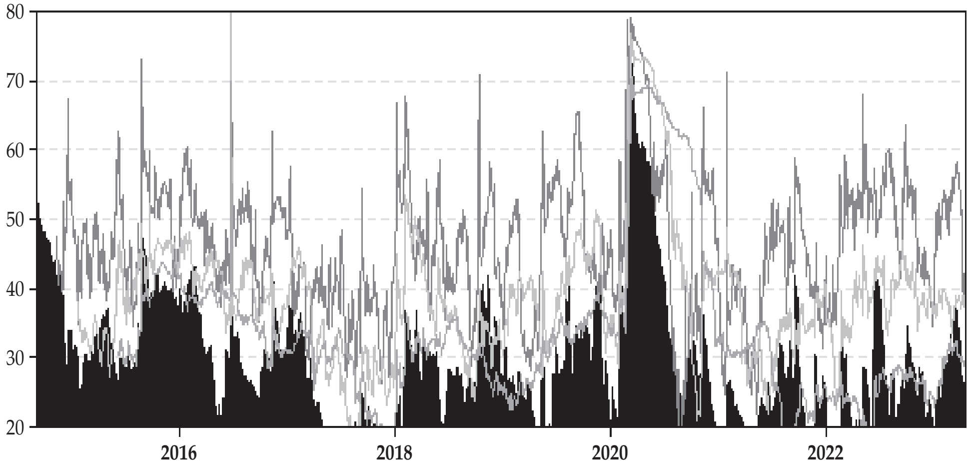


**Figure 19.**
**ASEAN4 Islamic Robustness Check: Total Connectedness Index Estimated for Different Window Sizes**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 Islamic Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. The figure shows results for different window sizes simultaneously including Black → TVP-VAR, Red → 50, Green → 100 and Blue → 200.

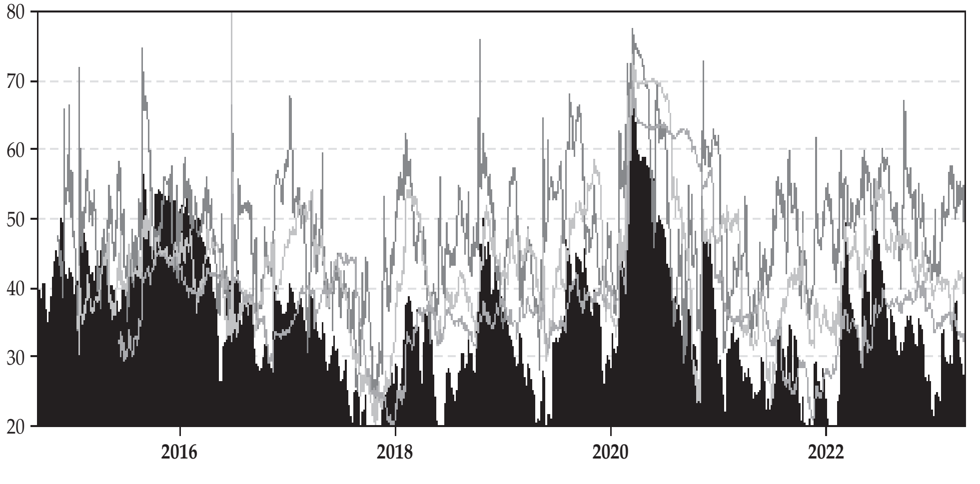


**Figure 20.**
**ASEAN4 ESG Robustness Check: Total Connectedness Index Estimated for Different Window Sizes**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 ESG Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. The figure shows results for different window sizes simultaneously including Black → TVP-VAR, Red → 50, Green → 100 and Blue → 200.

Finally, in addition to originally used "Bayes Prior" we employ two other priors namely "Minnesota Prior", and "Uninformative Prior" to test the robustness of the model under various assumptions about the prior distribution of the parameters. Different priors follow different assumptions about the parameters' distributions and the degree of prior knowledge or beliefs about the relationships among the variables (Sims & Zha, 1998). By employing multiple priors, we can assess the sensitivity of results to these assumptions. The results (Figures 21-23) are qualitatively similar to the original findings and validate robustness of our findings.

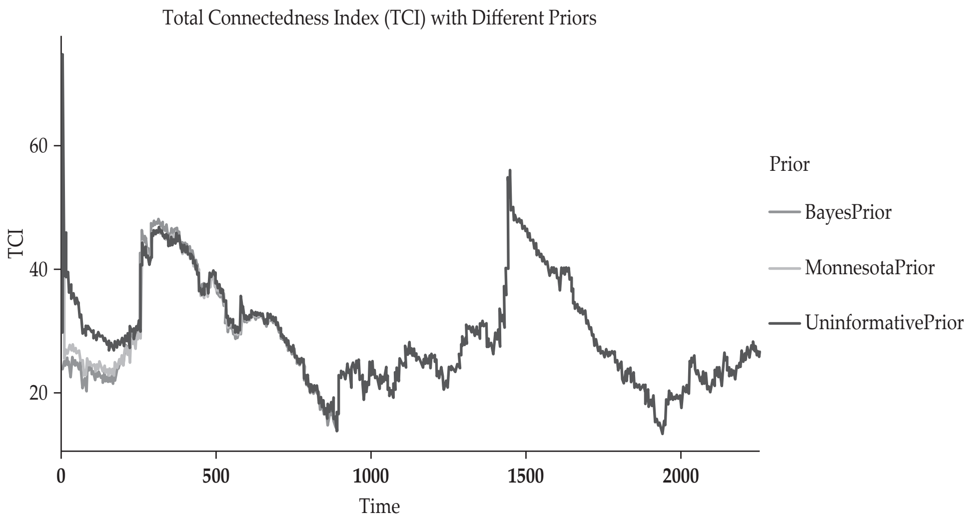


**Figure 21.**
**Robustness Check ASEAN4 Conventional: Total Connectedness Index Estimated Using Three Different Priors**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 Conventional Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. This figure shows the results based on a TVP-VAR model using Bayes Prior, Minnesota Prior and Uninformative Prior. Here 500 implies year 2016, 1000 implies year 2018, 1500 implies year 2020 and 2000 implies year 2022.

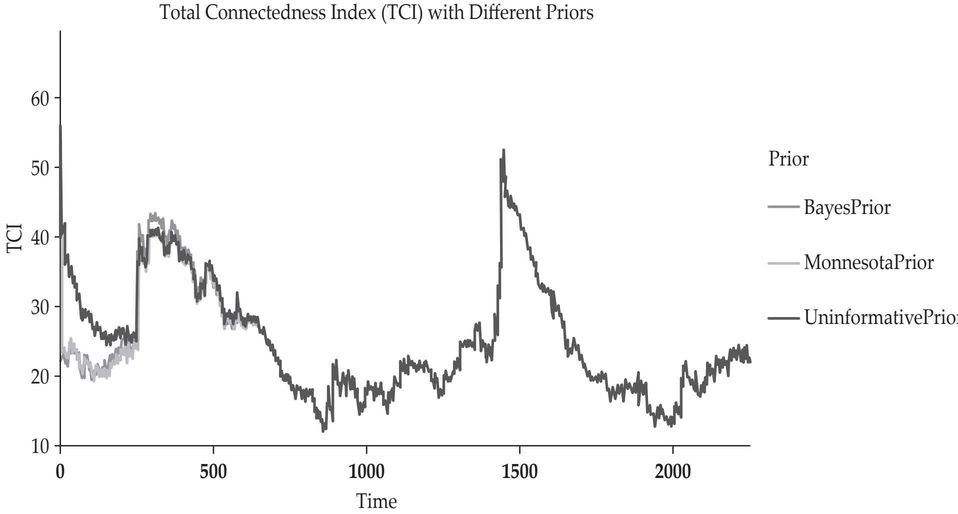


**Figure 22.**
**Robustness Check ASEAN4 Islamic: Total Connectedness Index Estimated Using Three Different Priors**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 Islamic Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. This figure shows the results based on a TVP-VAR model using Bayes Prior, Minnesota Prior and Uninformative Prior. Here 500 implies year 2016, 1000 implies year 2018, 1500 implies year 2020 and 2000 implies year 2022.

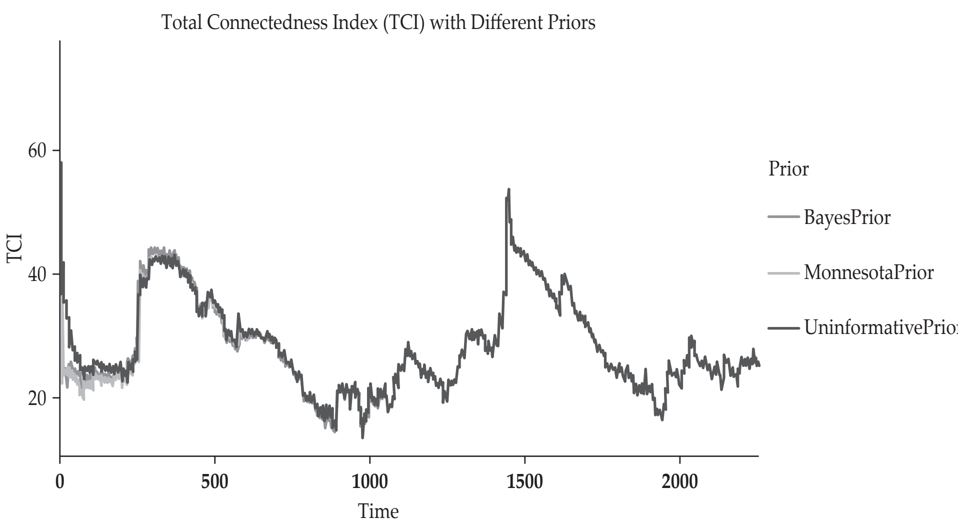


**Figure 23.**
**Robustness Check ASEAN4 ESG: Total Connectedness Index Estimated Using Three Different Priors**

This figure shows Total Connectedness Index based on a TVP-VAR model for a network of ASEAN4 ESG Indices including Thailand, Malaysia, Indonesia, and Philippines and Twitter Market Uncertainty – ENG. This figure shows the results based on a TVP-VAR model using Bayes Prior, Minnesota Prior and Uninformative Prior. Here 500 implies year 2016, 1000 implies year 2018, 1500 implies year 2020 and 2000 implies year 2022.

## V. CONCLUSION AND POLICY IMPLICATIONS

In line with growing debate on how uncertainty may affect different asset classes and increasing role of social media in transmitting uncertainty to financial markets, we test how uncertainty affects ASEAN4 conventional, Islamic and ESG indices. Our results reveal that TMUENG mostly remains a receiver of shocks mainly because ASEAN4 markets are partially information inefficient, and the investor sentiments expressed through Twitter may not transmit shocks to these markets. Moreover, in pre-pandemic period, Indonesia and Malaysia remain net transmitter of shocks whereas in post-COVID period, Thailand become transmitter of shocks to ASEAN4 network.

There are certain policy implications of our results. First, in view of interconnectedness of ASEAN4 indices during bearish periods, regional policymakers should consider strengthening economic cooperation and coordination during times of economic downturns by establishing mechanisms for information sharing and coordinating policy responses. Second, ASEAN4 markets show lower interconnectedness during favorable economic conditions. Therefore, during periods of economic growth, these markets should consider diversifying their industries and sectors to reduce their reliance on a few key sectors. Third, as ASEAN4 Islamic and ESG indices exhibit patterns similar to conventional indices, they do not offer any hedging benefits. And fourth, faith based investors with behavioral preferences may invest in ASEAN4 Islamic and ESG investments as per their preferred habitats without any fear of excess exposure to uncertainty because they have same exposure to uncertainty as conventional investments.

The future research may explore mediation impact of US or global markets behind high average connectedness between countries such as Thailand & Indonesia or Malaysia & Thailand through. For such research, TMUENG may be replaced with USA return index. Finally, future studies may explore asymmetric connectedness of all three categories of indices.

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