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Asymmetric volatility spillover between crude oil and other asset markets

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ABSTRACT

This study uses the Multiplicative Error Model (MEM) to explore asymmetric volatility spillovers between crude oil and other major asset markets. We have extended the MEM of Engle et al. (2012) to include asymmetric volatility spillovers and developed the spillover balance as well as asymmetric spillover indexes. We have then allowed these indexes to vary over time. Our results reveal that the stock market is the dominant contributor to volatility spillover, while the crude oil is mostly the volatility spillover recipient. The asymmetric spillover effects are predominantly negative in the stock and crude oil markets and positive in the bond market. We further show that the spillover indexes are dynamic and influenced by specific events, such as the global financial crisis and the COVID-19 pandemic, as well as varying economic conditions.

1. Introduction

Stocks, bonds, gold, and crude oil represent the main investment vehicles in the world markets. Understanding the interactions and interdependences among these assets is of significant interest to investors and policymakers alike. Comprehending the spillover of risks among these assets can provide investors with useful trading signals and greater hedging opportunities (Asadi et al., 2022). It can also help policymakers decide when and how to intervene in response to adverse shocks to achieve greater economic stability.

The spillover of risks, which is commonly known as the volatility spillover effects, characterize how shocks and risks propagate and spread among different asset markets (Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2015). To analyze these effects, it is important to understand the characteristics of the volatility itself. For instance, several studies document asymmetries in volatility, which imply that past returns are negatively correlated with present volatility (Bekaert and Wu, 2000). Such asymmetries may also be important when investigating the volatility transmission across markets (Segal et al., 2015). Thus, because of their relevance for risk valuation and portfolio diversification strategies (Garcia and Tsafack, 2011), both volatility and its spillover asymmetries need to be properly quantified.

The realm of volatility spillover effects in financial markets has been thoroughly charted, with seminal works, like (Gallo and Otranto, 2008; Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2015; Engle et al., 2012), leading the way. Typically, these studies are anchored in the Vector Auto-regression (VAR) models or the multivariate GARCH model, often integrating the volatility spillover index as highlighted by Diebold and Yilmaz (2009). However, the domain of asymmetries in volatility spillovers remains less traversed. While there are studies that focus on asymmetric spillovers in the U.S. stocks (Baruník et al., 2016), foreign exchange markets (Baruník et al., 2016), Australian electricity markets (Chanatásig-Niza et al., 2022), and between the crude oil and stock markets (Wang and Wu, 2018; Xu et al., 2019), a comprehensive exploration in this direction is sparse.

This study furthers the literature by providing new evidence on the asymmetric volatility spillover dynamics among major global investment vehicles. Our main contribution to the literature stems from the use of a novel approach for analyzing the asymmetric spillover effects. Specifically, we employ a modified version of the Multiplicative Error Model (MEM) of Engle et al. (2012) to incorporate the dynamic nature of the spillover asymmetry. As highlighted by Engle et al. (2012), the MEM is favored for its ability to overcome the shortcomings of the widely used VAR model (i.e, Diebold and Yilmaz (2009), Baruník et al. (2016, 2017)), especially in resolving issues of zero and non-negative predictions of volatility. The MEM is also shown to be better suited for spillover modeling than the multivariate GARCH model (i.e., Bauwens et al. (2006), Wang and Li (2021)), which imposes restrictions on the number of asset markets that can be investigated. Our proposed approach allows the MEM to incorporate the asymmetric volatility spillovers. This development has given rise to a new spillover balance index and asymmetric spillover indexes, which enable us to effectively analyze the spillovers of both negative and positive news. We have also evolved the spillover and asymmetric indexes from their static versions to time-varying forms, marking a significant stride in examining the

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dynamic links and spillover effects over time. This contribution is significant, especially considering the scarce literature on the intricate subject of time-varying analysis, a fact supported by Apergis et al. (2017).

The closest work to ours is that of Wang and Wu (2018) and Xu et al. (2019), who investigated asymmetric spillovers between oil and stock markets, focusing primarily on the Chinese and U.S markets. These studies have used VAR and Multivariate GARCH models and found that the negative spillovers are stronger than their positive counterparts. In a similar vein, Wang and Li (2021) examined asymmetric volatility spillovers between the crude oil and other financial markets in China. Other pertinent works in this context include those by Arouri et al. (2012), Li et al. (2016), Siddiqui et al. (2020), Reboredo et al. (2014), Turhan et al. (2013) and Zhang and Wang (2014). Departing from these studies, our research explores the global interplay between crude oil, stock, bond, and gold markets, broadening the scope beyond the common context of the Chinese financial markets. More importantly, we advance the literature by introducing a novel approach, which incorporates the time-varying nature of asymmetric spillovers in the modeling of both the dynamic links and spillover effects of positive and negative news in the global asset markets.

Our dataset comprises S&P 500 futures (ES: CME GROUP), Treasury bond futures (US: CCBOT/CME GROUP), gold futures (GC: COMEX/CME GROUP), and crude oil futures (CL: NYMEX/CME GROUP), spanning from July 1, 2003 to August 5, 2022. We use futures rather than spot prices for two reasons. Firstly, futures contracts are traded for 23 h during the sample periods, offering a near whole-day variance, thereby enhancing the precision of the realized variances and semi-variances. Secondly, the fact that all four futures are traded on the same exchange negates the necessity for time zone adjustments. In accordance with (Barndorff-Nielsen et al., 2010; Baruník et al., 2016, 2017; Chanatásig-Niza et al., 2022), we compute the realized variance and semi-variance from five-minute intraday returns, capturing the closing times from day $t-1$ to day t. These realized semi-variances are then used to estimate the asymmetric volatility spillover indexes.

Our empirical analysis yields several interesting results. First, we document strong evidence that the bad volatility in the stock market spillover into other markets. We also show that the stock market is the main provider, whereas the oil market is the primary recipient of the volatility spillover. This finding is, economically, reasonable due to the considerable size of the stock market, which leads to the propagation of its crashes and the potential dissemination of information to other asset markets. Second, we uncover evidence that the total asymmetric volatility spillover effects across different asset markets tend to be negative and significant. Specifically, we find negative spillover asymmetries in the stock, gold, and oil markets, but their magnitudes are larger in the stock market. This finding is consistent with prior studies, which show that negative spillovers are more prevalent than their positive counterparts (Baruník et al., 2016, 2017; Xu et al., 2019). It also lends support to loss aversion and the disposition effect, which predicts that investors tend to hold on to losers and sell winners (Frazzini, 2006). Third, unlike other markets, bonds exhibit significantly positive asymmetric spillover effects, implying that positive news from the bond market engenders more substantial spillover to other markets than negative news. This highlights the bond market's quintessential role as a safe-haven during bad times. Such behavior underscores the efficacy of bonds in dampening spillover effects and their utility as valuable hedging vehicles during turbulent market conditions. Finally, we uncover evidence that volatility spillover effects across different asset markets vary considerably over time, implying that the degree and direction of spillovers are influenced by major events and economic conditions that vary across time. Finally, we show that the 2009 Global Financial Crisis has had a more significant and enduring influence on the volatility spillovers than the COVID-19 pandemic, presumably because the Covid-19 is a health pandemic that did not originate from the financial markets.

The remainder of the study proceeds as follows. Section 2 introduces the concept of realized semi-variance and the multiplicative error model for their dynamics. Section 3 proposes the volatility spillover balance and asymmetric volatility spillovers index. Section 4 presents the dataset. Section 5 discusses the empirical results and Section 6 concludes.

2. The methodology framework

Andersen et al. (2001) introduced a natural estimator for the quadratic variation of a process, known as the realized variance (RV), defined as the sum of frequently sampled squared returns. To simplify, let us assume that prices $p_0, \ldots, p_n$ are observed at $n+1$ intervals, evenly distributed over the interval $[0, t]$. Using these returns, the n-sample realized variance, RV, can be defined as follows:

$$RV = \sum_{j=1}^{n} r_j^2 \tag{1}$$

where $r_j = p_j - p_{j-1}$ is the realized variance (RV), which converges in probability to the quadratic variation of log prices as the number of intraday observations increases, i.e., as $n \to \infty$. Barndorff-Nielsen et al. (2010) and Patton and Sheppard (2015) further introduce a measure that decomposes RV into components that are due to positive and those that are attributable to negative returns, terming this measure “realized semi-variance” (RS). These estimators are defined as follows:

$$\begin{aligned} RS^+ &= \sum_{j=1}^{n} r_j^2 I\left\{r_j > 0\right\}, \\ RS^- &= \sum_{j=1}^{n} r_j^2 I\left\{r_j < 0\right\}. \end{aligned} \tag{2}$$

where $I\{\}$ is the indicator function that returns a value of 1 if the condition in $\{\}$ is met. These estimators provide a complete decomposition of RV, in that $RV = RS^+ + RS^-$. This decomposition holds exactly for any n, as well as in the limit.

2.1. Multiplicative error models

Since the RV is non-negatively valued and highly persistent over time, we follow the work of Engle and Gallo (2006), Shephard and Sheppard (2010), Engle et al. (2012), and Xu et al. (2018) and use the MEM to model the dynamics of RV. The MEM was initially proposed by Engle (2002) and has been widely used for modeling the dynamics of non-negative, highly persistent financial time series, such as absolute return, daily range, realized volatility, trading duration, trading volume, and bid–ask spread. Instead of modeling the RV directly, we extend the MEM to incorporate RS^+ and RS^- in its modeling process.

Given the information set I_{t-1}, the realized semi-variance in market i, denoted as $RS_{i,t}^+$ and $RS_{i,t}^-$, is modeled as follows:

$$\begin{aligned} RS_{i,t}^+ | I_{t-1} &= \mu_{i,t}^+ \epsilon_{i,t}^+, \\ RS_{i,t}^- | I_{t-1} &= \mu_{i,t}^- \epsilon_{i,t}^-. \end{aligned} \tag{3}$$

where $i = 1, 2, \ldots, k$, the innovation term $\epsilon_{i,t}^+$ and $\epsilon_{i,t}^-$ is a unit mean random variables, such that $\epsilon_{i,t}^+ | I_{t-1} \sim \text{i.i.d}(1, \sigma_i^+)$ and $\epsilon_{i,t}^- | I_{t-1} \sim \text{i.i.d}(1, \sigma_i^-)$. The conditional expectation $\mu_{i,t}^+$ and $\mu_{i,t}^-$, can be specified as a base MEM(1,1):

$$\mu_{i,t}^+ = \omega_i^+ + \alpha_{ii}^+ RS_{i,t-1}^+ + \beta_i^+ \mu_{i,t-1}^+, \tag{4}$$

$$\mu_{i,t}^- = \omega_i^- + \alpha_{ii}^- RS_{i,t-1}^- + \beta_i^- \mu_{i,t-1}^-. \tag{5}$$

Furthermore, the heterogeneous autoregressive (HAR) model of Corsi (2009) has emerged as a simple and powerful way to include the long-memory feature of realized volatilities. Adding HAR terms to the realized semi-variance equations, results in richer dynamic equations:

$$\mu_{i,t}^+ = \omega_i^+ + \alpha_{ii}^+ RS_{i,t-1}^+ + \beta_i^+ \mu_{i,t-1}^+ + \alpha_{ii}^{w+} RS_{i,t-1}^{w+} + \alpha_{ii}^{m+} RS_{i,t-1}^{m+}, \tag{6}$$

$$\mu_{i,t}^{-} = \omega_i^{-} + \alpha_{ii}^{-} RS_{i,t-1}^{-} + \beta_i^{-}\mu_{i,t-1}^{-} + \alpha_{ii}^{w-} RS_{i,t-1}^{w-} + \alpha_{ii}^{m-} RS_{i,t-1}^{m-} \tag{7}$$

where $RS_{i,t}^{w+} = \frac{1}{5}\sum_{l=1}^{5} RS_{i,t-l}^{+}$, $RS_{i,t}^{m+} = \frac{1}{22}\sum_{l=1}^{22} RS_{i,t-l}^{+}$, $RS_{i,t}^{w-} = \frac{1}{5}\sum_{l=1}^{5} RS_{i,t-l}^{-}$, $RS_{i,t}^{m-} = \frac{1}{22}\sum_{l=1}^{22} RS_{i,t-l}^{-}$. In the HAR model, $RS_{i,t}^{w+}$ and $RS_{i,t}^{w-}$ represents the medium-term weekly realized semi-variance, whereas $RS_{i,t}^{m+}$ and $RS_{i,t}^{m-}$ denote the long-term monthly realized semi-variance.

To study the semi-variance spillover effects, we incorporate the lagged daily semi-variance observed in other markets into the specification and allow for the interactions between positive/negative semi-variance spillover effects among different markets. This yields the following general semi-variance volatility spillover model:

$$\mu_{i,t}^{+} = \omega_i^{+} + \alpha_{ii}^{+} RS_{i,t-1}^{+} + \beta_i^{+}\mu_{i,t-1}^{+} + \sum_{j\neq i}\alpha_{ij}^{+} RS_{j,t-1}^{+} + \sum_{i,j}\alpha_{ij}^{-} RS_{j,t-1}^{-} + \alpha_{ii}^{w+} RS_{i,t-1}^{w+} + \alpha_{ii}^{m+} RS_{i,t-1}^{m+}, \tag{8}$$

$$\mu_{i,t}^{-} = \omega_i^{-} + \alpha_{ii}^{-} RS_{i,t-1}^{-} + \beta_i^{-}\mu_{i,t-1}^{-} + \sum_{j\neq i}\alpha_{ij}^{-} RS_{j,t-1}^{-} + \sum_{i,j}\alpha_{ij}^{+} RS_{j,t-1}^{+} + \alpha_{ii}^{w-} RS_{i,t-1}^{w-} + \alpha_{ii}^{m-} RS_{i,t-1}^{m-}. \tag{9}$$

Following Engle et al. (2012) and Xu et al. (2018), the semi-variance models in (8) and (9) can be estimated using quasi-maximum likelihood estimation. This is under the assumption that the innovation terms $\epsilon_{i,t}^{+}|I_{t-1}$ and $\epsilon_{i,t}^{-}|I_{t-1}$ follow exponential distributions.

3. Spillover analysis

Engle et al. (2012) and Xu et al. (2018) propose a quantitative measure for the volatility spillover effects across multiple markets, premised on the measure of spillovers as responses to shocks. Following their methodology, we derive analogous measures for our semi-variance models.

Let $RS_t^{+} = (RS_{1,t}^{+}, RS_{2,t}^{+}, \cdots, RS_{k,t}^{+})'$, $\mu_t^{+} = (\mu_{1,t}^{+}, \mu_{2,t}^{+}, \cdots, \mu_{k,t}^{+})'$, $RS_t^{w+} = (RS_{1,t}^{w+}, RS_{2,t}^{w+}, \cdots, RS_{k,t}^{w+})'$, $RS_t^{m+} = (RS_{1,t}^{m+}, RS_{2,t}^{m+}, \cdots, RS_{k,t}^{m+})'$ and $\epsilon_t^{+} = (\epsilon_{1,t}^{+}, \epsilon_{2,t}^{+}, \cdots, \epsilon_{k,t}^{+})'$. Let $RS_t^{-} = (RS_{1,t}^{-}, RS_{2,t}^{-}, \cdots, RS_{k,t}^{-})'$, $\mu_t^{-} = (\mu_{1,t}^{-}, \mu_{2,t}^{-}, \cdots, \mu_{k,t}^{-})'$, $RS_t^{w-} = (RS_{1,t}^{w-}, RS_{2,t}^{w-}, \cdots, RS_{k,t}^{w-})'$, $RS_t^{m-} = (RS_{1,t}^{m-}, RS_{2,t}^{m-}, \cdots, RS_{k,t}^{m-})'$ and $\epsilon_t^{-} = (\epsilon_{1,t}^{-}, \epsilon_{2,t}^{-}, \cdots, \epsilon_{k,t}^{-})'$. Conditional on the information available at time t, (8) and (9) can be stacked in a compact matrix form as

$$\begin{pmatrix}\mu_t^{+}\\ \mu_t^{-}\end{pmatrix} = \begin{pmatrix}\omega^{+}\\ \omega^{-}\end{pmatrix} + \begin{pmatrix}A^{+} & A^{+-}\\ A^{-+} & A^{-}\end{pmatrix}\begin{pmatrix}RS_{t-1}^{+}\\ RS_{t-1}^{-}\end{pmatrix} + \begin{pmatrix}B^{+} & \\ & B^{-}\end{pmatrix}\begin{pmatrix}\mu_{t-1}^{+}\\ \mu_{t-1}^{-}\end{pmatrix} + \begin{pmatrix}A^{w+} & \\ & A^{w-}\end{pmatrix}\begin{pmatrix}RS_{t-1}^{w+}\\ RS_{t-1}^{w-}\end{pmatrix} + \begin{pmatrix}A^{m+} & \\ & A^{m-}\end{pmatrix}\begin{pmatrix}RS_{t-1}^{m+}\\ RS_{t-1}^{m-}\end{pmatrix} \tag{10}$$

If further assuming $\mathbf{x}_t = (RS_t^{+\prime}, RS_t^{-\prime})'$, $\boldsymbol{\mu}_t = (\mu_t^{+\prime}, \mu_t^{-\prime})'$, $\mathbf{x}_t^{w} = (RS_t^{w+\prime}, RS_t^{w-\prime})'$, $\mathbf{x}_t^{m} = (RS_t^{m+\prime}, RS_t^{m-\prime})'$ and $\boldsymbol{\epsilon}_t = (\epsilon_t^{+\prime}, \epsilon_t^{-\prime})'$, (3) and (10) can be expressed as:

$$\mathbf{x}_t = \boldsymbol{\mu}_t \odot \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathrm{D}(\mathbf{1}, \boldsymbol{\Sigma}),$$
$$\boldsymbol{\mu}_t = \boldsymbol{\omega} + \mathbf{A}\mathbf{x}_{t-1} + \mathbf{B}\boldsymbol{\mu}_{t-1} + \mathbf{A}^{w}\mathbf{x}_{t-1}^{w} + \mathbf{A}^{m}\mathbf{x}_{t-1}^{m}. \tag{11}$$

where $\odot$ denotes the Hadmard (element by element) product. The innovation vector $\boldsymbol{\epsilon}_t$ has support over $[0, +\infty)$, with a unit mean vector $\mathbf{1}$ and general variance–covariance matrix $\boldsymbol{\Sigma}$. The first two moment conditions of the vector MEM are given by $\mathrm{E}(\mathbf{x}_t|\Omega_t) = \boldsymbol{\mu}_t$ and $\mathrm{var}(\mathbf{x}_t|\Omega_t) = \boldsymbol{\mu}_t\boldsymbol{\mu}_t'\odot\boldsymbol{\Sigma}$, with the latter being a positive definite matrix by construction.

By defining appropriate error term, the above process (i.e., Eq. (11)) can be written as VARMA(1,1). Given this representation, the covariance stationarity condition requires that the largest eigenvalue of $\mathbf{A} + \mathbf{B} + \mathbf{A}^{w} + \mathbf{A}^{m}$ to be less than unity. Consequently, the unconditional first moment can be obtained as $E(\mathbf{x_t}) = (I_{2k} - \mathbf{A} + \mathbf{B} + \mathbf{A}^{w} + \mathbf{A}^{m})^{-1}\,\boldsymbol{\omega}$.

Next, we derive a multiple-step ahead forecasting $\mathbf{x}_{t+\tau}$ (where $\tau > 0$). The forecast is computed at date t, but since it is not known, it needs to be substituted with its corresponding conditional expectation $\boldsymbol{\mu}_{t+\tau|t}$. Hence:

$$\boldsymbol{\mu}_{t+1|t} = \boldsymbol{\omega} + \mathbf{A}\mathbf{x}_t + \mathbf{B}\boldsymbol{\mu}_t + \mathbf{A}^{w}\mathbf{x}_t^{w} + \mathbf{A}^{m}\mathbf{x}_t^{m}, \tag{12}$$

and for $2 \le \tau < 22$,

$$\boldsymbol{\mu}_{t+\tau|t} = \boldsymbol{\omega} + (\mathbf{A} + \mathbf{B})\boldsymbol{\mu}_{t+\tau-1} + \mathbf{A}^{w}\mathbf{x}_{t+\tau-1}^{w} + \mathbf{A}^{m}\mathbf{x}_{t+\tau-1}^{m}, \tag{13}$$

where $x_{t+\tau-1|t}^{w} = \frac{1}{5}\sum_{l=1}^{5} x_{t+\tau-l|t}$, $x_{t+\tau-1|t}^{m} = \frac{1}{22}\sum_{l=1}^{22} x_{t+\tau-l|t}$ and $x_{t+\tau-l|t} = \mu_{t+\tau-l|t}$ if $\tau > l$. And then, for any $\tau \ge 22$,

$$\boldsymbol{\mu}_{t+\tau|t} = \boldsymbol{\omega} + (\mathbf{A} + \mathbf{B} + \mathbf{A}^{w} + \mathbf{A}^{m})\boldsymbol{\mu}_{t+\tau-1}, \tag{14}$$

which can be solved recursively for any horizon τ.

The terms $\mu_{t+\tau}^{+}$ and $\mu_{t+\tau}^{-}$ can then be extracted from $\boldsymbol{\mu}_{t+\tau|t}$. Once $\mu_{t+\tau}^{+}$ and $\mu_{t+\tau}^{-}$ are obtained, the multiple-step ahead forecasts of $RV_{t+\tau|t}$ can be directly derived as follows:

$$E(RV_{t+\tau|t}) = \mu_{t+\tau|t}^{+} + \mu_{t+\tau|t}^{-}, \tag{15}$$

where $RV_t = (RV_{1,t}, RV_{2,t}, \cdots, RV_{k,t})'$.

Next, we derive a spillover balance index and spillover asymmetry measure. Let us recall that the MEM in a system,

$$\mathbf{x}_t = \boldsymbol{\mu}_t \odot \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathrm{D}(\mathbf{1}, \boldsymbol{\Sigma}). \tag{16}$$

The innovation vector $\boldsymbol{\epsilon}_t$ has a mean vector $\mathbf{1}$ with all components unity and general variance–covariance matrix $\boldsymbol{\Sigma}$. We can interpret $\boldsymbol{\mu}_{t+\tau} = E(\mathbf{x}_{t+\tau}|I_t, \boldsymbol{\epsilon}_t) = \mathbf{1}$, that is, the expectation of $\mathbf{x}_{t+\tau}$ conditional on $\boldsymbol{\epsilon}_t$ being equal to the unit vector $\mathbf{1}$: this is the basis for the dynamic forecast obtained before. Let us now derive a different dynamic solution, $\boldsymbol{\mu}_{t+\tau}^{(i)} = E(\mathbf{x}_{t+\tau}|I_t, \boldsymbol{\epsilon}_t = \mathbf{1}+\mathbf{s}^{(i)})$, for a generic ith element $\mathbf{s}^{(i)}$, where $i = 1, 2, \ldots, 2k$. The ith element equal to the unconditional standard deviation of $\epsilon_{i,t}$ and the other terms $j \neq i$ equal to the linear projection $E(\epsilon_{j,t}|\epsilon_{i,t} = 1 + \sigma_i) = 1 + \sigma_i\frac{\sigma_{i,j}}{\sigma_i^2}$. The element-by-element division ($\oslash$) of the two vectors,

$$\rho_{t,\tau}^{(i)} = \boldsymbol{\mu}_{t+\tau}^{(i)} \oslash \boldsymbol{\mu}_{t+\tau} - 1. \tag{17}$$

Given the multiplicative nature of the model, $\rho_{t,\tau}^{(i)}$ gives us the set of responses (relative changes) in the forecast profile starting at time t for a horizon τ brought about a 1 standard deviation shock in the ith market. The cumulated impact of the shock from market i to market j is:

$$\Phi_t^{j,i} = \sum_{\tau=1}^{K}\rho_{t,\tau}^{(i)}. \tag{18}$$

The total spillover effect (TSI) as:

$$TSI = \sum_{i\neq j}\sum_{t=1}^{T}\Phi_t^{j,i} \tag{19}$$

which measures the overall contribution of volatility spillover shocks across markets.

This is also a way to assess the total change induced by the shock of different markets. Following Engle et al. (2012), we express the spillover balance as the ratio of the average responses "to" to the average response "from" (excluding one's own):

$$Balance_i = \frac{\sum_{j\neq i}\sum_{t=1}^{T}\Phi_t^{j,i}}{\sum_{j\neq i}\sum_{t=1}^{T}\Phi_t^{i,j}}. \tag{20}$$

A value bigger than unity signals that the market is a net creator of volatility spillover.

The use of semi-variances in the model estimation allows us to distinguish between the spillovers from positive and those from negative returns. This, in turn, enables us to quantify the asymmetries in the volatility spillovers over time. Following Baruník et al. (2015), we define directional spillover from an asset i to (ST) all other assets (excluding one's own) as:

$$ST_i^{-} = \sum_{j\neq i}\sum_{t=1}^{T}\Phi_t^{j,i} \tag{21}$$

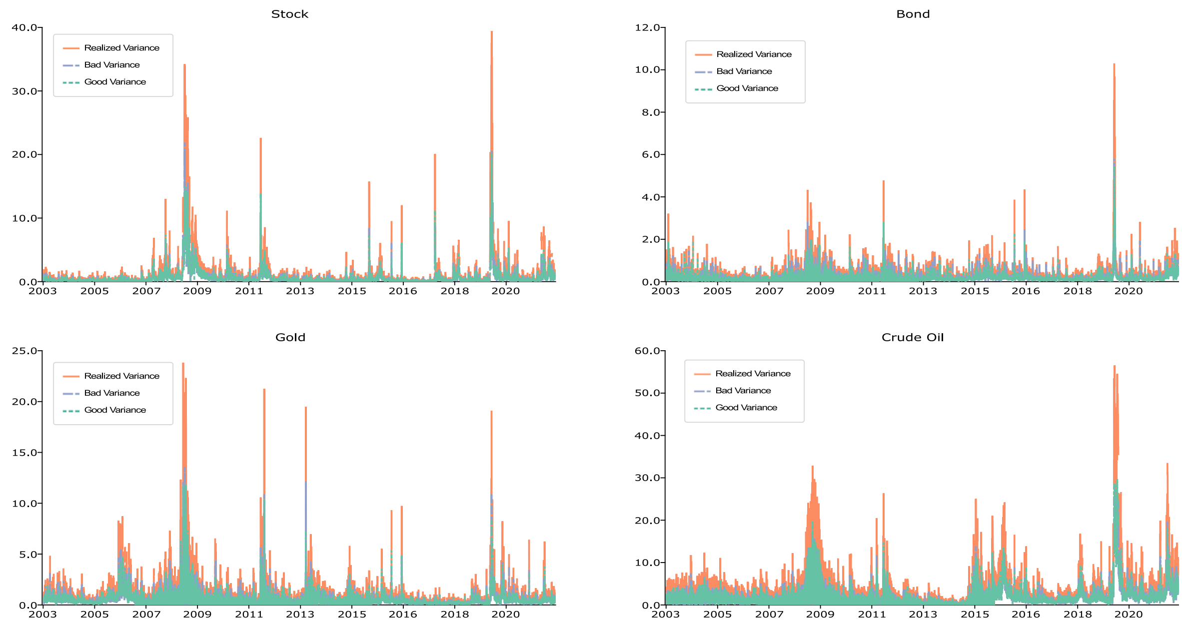

Fig. 1. Realized volatility, bad volatility and good volatility for all markets.

for $i = 1, 2, \ldots, k$ and for $j = 1, 2, \ldots, 2k$, and

$$ST_i^+ = \sum_{j \neq i} \sum_{t=1}^{T} \Phi_t^{j,i} \tag{22}$$

for $i = k+1, k+2, \ldots, 2k$ and for $j = 1, 2, \ldots, 2k$.

We compute the spillover asymmetry measure (ASM) index as

$$ASM_i = ST_i^+ - ST_i^-, i = 1, 2, \ldots, k \tag{23}$$

A positive ASM indicates that spillovers from positive realized semi-variances are larger than those from negative realized semi-variances, and the opposite is true for a negative ASM. By contrast, if ASM takes a value of zero, the volatility spillover measures are symmetric. The total asymmetric spillover effect (TASM) is computed as:

$$TASM = \sum_i ASM_i \tag{24}$$

To test the significance of ASM_i and $TASM$, we use the bootstrapped standard error (see Appendix A)

4. Dataset

Our data comprises four futures contracts: S&P 500 futures (ES: CME GROUP), Treasury bond futures (US: CCBOT/CME GROUP), gold futures (GC: COMEX/CME GROUP), and crude oil futures (CL: NYMEX/CME GROUP). The first three contracts were studied by Fleming et al. (2001, 2003). Our sample period spans from July 1, 2003 to August 5, 2022, over a total of 4,864 trading days. The data are obtained from TickData, Inc. We selected July 1, 2003, as our starting date because it encompasses both daytime and evening, ensuring that our estimated realized variance represents a reasonable proxy for the whole-day variance.

There are two benefits to using futures rather than spot prices in our analysis. First, the futures contracts are traded for 23 h during the sample periods, which closely approximates the whole-day variance, enhancing the accuracy of the realized variance estimates. Second, the four futures contracts used in our analysis are traded on the same exchange, eliminating the need for time zone adjustments. Thus, the use of futures contracts does not only simplifies the analysis, but also allows us to make more accurate comparisons across the different markets.

Our portfolios are rebalanced at specific times each day during different periods, i.e., at 13:30 each day between 07/01/2003 and 01/31/2007, at 15:15 each day between 02/01/2007 and 11/17/2012, and at 16:00 each day between 11/18/2012 and 08/05/2022. We calculate the realized variance and semi-variance using all intraday returns between day t and $t-1$ and use the last transaction prices before the chosen close times as the close prices. This procedure is consistent with Fleming et al. (2001, 2003). Table 1 presents the trading close times and date ranges for the four assets.

Table 1
Data description for different assets.

Futures contracts	Close time	Date range
Gold futures	13:30	07/01/2003 – 12/03/2006
	17:00	12/04/2006 – 08/05/2022
Bond futures	16:00	07/01/2003 – 08/05/2022
Stock futures	15:15	07/01/2003 – 11/17/2012
	16:00	11/18/2012 – 08/05/2022
Crude oil futures	15:15	07/01/2003 – 01/31/2007
	13:30	02/01/2007 – 08/05/2022

Notes: This table reports the close time and date range for the four different types of futures contract.

Table 2 summarizes the descriptive statistics for the realized variance and semi-variances. Crude oil displays the highest volatility, while bonds exhibit the lowest mean of realized variance and semi-variance. This implies that crude oil is riskier than the other markets, possibly due to its lower liquidity, susceptibility to natural disasters, and sensitivity to geopolitical risks. This finding is consistent with Xu et al. (2019), who reported a risk ratio of oil to stock that is notably similar to ours. The negative semi-variance contributes slightly more than its positive counterpart to the total realized variances of the asset markets. The Ljung Box statistic shows strong serial autocorrelations in both the realized variance and semi-variance. The overdispersion, which is the ratio of standard deviation to mean, ranges from 1.1 to 2.1. This large overdispersion requires a high value of α (ARCH coefficient) in GARCH/MEM models. Additionally, the positive skewedness and high leptokurtic together with overdispersion, indicates that a more flexible distribution is required for modeling the realized variance.

Fig. 1 shows that asset volatility increases considerably during global financial crisis. Subsequently, the realized variance declines significantly and jumps occasionally. At the start of the COVID-19 pandemic, there was a sharp increase in volatility, but this was not as persistent as in the case of global financial crisis. The graph also

Table 2
Summary statistics.

	Mean	Std	Min	Max	Skewness	Kurtosis	LB(12)
			Panel A: Realized volatilities				
Stock	1.298	2.623	0.031	39.409	7.016	69.668	34 164
Bond	0.450	0.487	0.002	10.262	8.191	123.104	14 195
Gold	1.285	1.575	0.054	23.827	5.536	52.738	17 833
Oil	4.743	5.230	0.100	56.532	3.940	25.414	38 341
			Panel B: Realized Negative semi-variance RS^{-}				
Stock	0.657	1.362	0.009	21.746	7.367	78.635	32 211
Bond	0.231	0.266	0.002	5.749	0.215	109.360	11 097
Gold	0.651	0.850	0.023	13.561	5.654	55.834	15 097
Oil	2.398	2.697	0.057	27.729	3.837	24.197	35 996
			Panel C: Realized Positive semi-variance RS^{+}				
Stock	0.641	1.299	0.013	20.219	6.963	68.269	32 197
Bond	0.219	0.245	0.001	5.478	8.018	117.477	12 572
Gold	0.634	0.772	0.031	11.846	5.453	51.249	17 448
Oil	2.345	2.636	0.043	29.651	4.068	27.433	35 112

Notes: This table reports summary statistics of realized volatilities and semi-variances. LB(12) is the Ljung–Box statistics for the serial correlation of order 12.

Table 3
Estimated results.

		Negative semi-variance				Positive semi-variance			
		Stock	Bond	Gold	Oil	Stock	Bond	Gold	Oil
	w	0.040	0.030	0.021	0.053	0.029	0.011	0.028	0.027
	α	0.546	0.114	0.224	0.258	0.016	0.105	0.087	0.059
	β	0.164	0.041	0.440	0.257	0.196	0.587	0.328	0.403
	α^{w}	0.189	0.257	0.000	0.171	0.156	0.000	0.100	0.083
	α^{w}	0.080	0.272	0.139	0.178	0.052	0.072	0.180	0.102
$RS^{-}_{j,t-1}$	Stock		0.024	0.060	0.340	0.572	0.020	0.072	0.210
	Bond	−0.021					0.157		
	Gold				0.071			0.239	
	Oil								0.323
$RS^{+}_{j,t-1}$	Stock			−0.53	−0.267		−0.014	−0.060	−0.168
	Bond	−0.092	0.122			−0.120			
	Gold			0.165	−0.092				
	Oil			−0.002	0.105				
	LL	−167.36	2962	−1537	−7769	37.95	3210	−1475	−7623
	BIC	394.12	−5864	3151	15 624	−16.50	−6361	3019	15 314
	LB(12)	10.93	9.37	15.91	7.41	23.84	19.58	14.13	23.12

LL denotes the values of the log-likelihood. BIC is Bayesian Information Criteria. LB(12) denotes the Ljung Box statistics up to order 12.

shows that the realized variance and semi-variance are highly persistent over time, suggesting that the effects of the information transmitted by positive and negative returns cannot be eradicated completely over a short period of time. These features, along with the Ljung Box statistics in Table 2, suggest that MEM-type models are well-suited for modeling the dynamics of the realized semi-variances. Additionally, the semi-variances associated with two of the four assets in our sample tend to move in tandem with their corresponding realized variances. Notably, the common volatility spikes across the various markets occurred during the 2008 Global Financial Crisis and the 2019 Coronavirus outbreak.

5. Empirical results

Based on the equation-by-equation estimation results, we proceed to select a more parsimonious specification, based on the significance of the zero restrictions. The large number of coefficients in the general specification of Eqs. (8) and (9) yields inefficient parameter estimates and, therefore, less precise spillover forecasts analysis (Engle et al., 2012). We report only the coefficients estimates that are significant at 5 percent level or better in Table 3. The model diagnostics are summarized in the lower panel of Table 3. where the values of the log-likelihood functions, Bayesian Information Criteria (BIC) and Ljung box (LB) statistics for residuals are reported.

We find significant interactions between good and bad volatility within each of the four markets included in the analysis. For example, bad volatility of bonds has significantly positive effect on the good volatility of bonds, and vice versa. Similar patterns are observed in the cases of gold and crude oil. However, the stock market appears to be an exception, with only bad volatility exerting a significantly positive influence on the good volatility. Across the four markets, we also show that the magnitude of the effect of bad volatility on good volatility is larger than that of good volatility on bad volatility[1], indicating that the bad volatility dominates the semi-variance dynamics. We also notice that the bad volatility of the stock market exerts significant influences on both the good and bad volatility of the other three markets (see the row of $RS^{-1}_{j,t-1}$). Finally, the two HAR parameters, α_{w} and α_{m}, are significant in all cases, implying a high level of persistence in the semi-variances. The LB statistics are small and insignificant, suggesting that our model successfully captures the dynamics of the semi-variance processes.

[1] Similar patterns have been shown by earlier studies (see, e.g., Patton and Sheppard (2015).

Table 4
Bad and good volatility spillovers.

	From bad volatility				From good volatility				
	Stock	Bond	Gold	Oil	Stock	Bond	Gold	Oil	Total from
To bad volatility									
Stock	15.96	2.66	4.30	2.95	9.07	3.93	4.24	1.84	19.91
Bond	7.87	3.62	2.87	1.63	5.10	3.58	2.76	1.20	21.43
Gold	9.71	4.96	12.48	2.35	6.67	5.10	9.79	1.82	30.62
Oil	16.06	3.95	7.23	13.02	9.67	6.01	5.89	7.61	48.81
To good volatility									
Stock	16.36	2.75	4.43	3.03	9.47	4.04	4.37	1.90	20.52
Bond	8.71	4.13	3.27	1.88	5.78	5.09	3.34	1.41	24.40
Gold	9.67	4.70	11.60	2.42	6.61	5.06	9.66	1.90	30.36
Oil	16.31	4.13	7.41	13.14	9.90	6.20	6.16	8.07	50.11
Total To	68.34	23.16	29.50	14.27	43.72	30.34	26.75	10.07	
Balance	3.43	1.08	0.96	0.29	2.13	1.24	0.88	0.20	
ASM	−24.62**	7.18**	−2.75	−4.20				**TASM**	−24.39**

The table presents spillovers for the full sample with a forecast horizon of τ = 200 days. We use bootstrapped standard errors with 1,000 resamplings to test the significance of ASM and TASM.

** The symbol denotes significance at the 5% level.

5.1. Volatility spillover effects

In this section, we quantify the volatility spillover effect with the aim to answer the following questions: (1) Which markets, if any, serve as the primary net provider or receiver of spillovers? (2) How is good and bad volatility transmitted within each market? And (3) are volatility spillovers symmetric or asymmetric? To explore these questions, we employ the spillover balance index and asymmetric spillover measure derived in Section 3. A value of a spillover balance index that is greater (smaller) than unity indicates that the asset is a net provider (receiver) of spillover. A significantly negative asymmetric measure implies that the spillovers from negative news cause more shocks to other markets than their counterparts from positive news, and vice versa. The results are presented in Table 4.

For the ease of exposition, hereafter we refer to spillovers from bad and good volatility as negative and positive spillovers, respectively. Firstly, the spillover balance indexes in the second-to-last of Table 4 indicate that stock volatility is the primary provider of spillovers, with spillover balances of 3.43 and 2.13 from bad and good volatility, respectively. Gold and oil, on the other hand, are spillover recipients, as their spillover balance indexes are less than unity. The observed imbalance is largely attributed to the significant transmission of negative shocks from the stock market, impacting both the good and bad volatility in the oil market. This observation aligns with the findings presented in Table 3, suggesting that the stock market is the primary conduit of volatility spillovers. The bond market seems to be more balanced, with spillover balances from the bad and good volatility being 1.08 and 1.24, respectively. The prevalent influence of the stock market is presumably rooted in its extensive size and renown for dispersing risks (Yang and Zhou, 2017), coupled with the oil market's illiquidity, which is often susceptible to natural disasters and geopolitical uncertainties, making it a "recipient" of risks. Intriguingly, this conclusion contrasts with the results of Wang and Li (2021), who found that crude oil instigates volatility in the Shanghai stock index. A plausible explanation for this divergence lies in the contextual differences. Specifically, unlike our study, which focuses on the global context, Wang and Li (2021) examined the inter-play between WTI crude oil and the Chinese stock market. Since the Chinese stock market is relatively local and less accessible to international investors, its ability to induce volatility in the crude oil market is potentially limited.

The last row of Table 4 reports the asymmetric measures of the volatility spillover. The TASM of the four assets is negative and significant (−24.39), indicating the presence of asymmetric volatility spillover among these assets. The stock market has the largest significantly negative asymmetry index (ASM = −24.62), suggesting that the stock market creates more negative than positive shocks for other markets. For the gold and oil markets, the asymmetry index is negative and insignificant, suggesting no asymmetric volatility spillover effects between these two assets. Interestingly, the bond market has the significantly positive asymmetry index (ASM = 7.18), implying that the bond market creates more positive than negative shocks to other market. The unfavorable news in the stock and crude oil markets can have a beneficial impact on the bond market, as investors tend to seek refuge in safe-haven assets during stock market crashes to mitigate risk. Further support for the negative relationship between stocks and bonds can be found in Chiang et al. (2015), while evidence of the negative relationship between oil and bond markets is provided by Ciner et al. (2013). This elucidated the crucial role bonds as safe haven instruments during bad times. In other words, this evidence indicates that bonds can effectively mitigate spillover effects and offer valuable hedging opportunities for investors.

Overall, we document a complex interconnectedness among the four asset markets, with the stock market playing a central role in transmitting volatility spillovers. The oil market appears to be the primary recipient of these spillovers, while contributing minimally to the volatility in other markets. Furthermore, we find evidence of asymmetric spillover effects, particularly in the stock and bond markets. In the bond market, the spillover balance of good volatility is larger than of bad volatility, and the ASM index is significantly greater than zero. This suggests that spillover of shocks from good news are more prevalent than that from bad news. This direction of asymmetry differs significantly from those in other markets.

5.2. Dynamics analysis

To better understand the time series evolution of volatility spillovers, we estimate Eqs. (8) and (9) using a rolling window of 500 days to allow for the spillovers to change over time. This approach enables us to derive time-varying spillover balance indexes and asymmetric spillovers. This dynamic analysis also enables us to investigate the impact other events, such as the global financial crisis, Eurozone debt crisis, and the recent COVID-19 pandemic, on spillovers across markets.

5.2.1. Dynamics of total spillovers

The plot in Fig. 2 indicates that the volatility spillover effects increase sharply during the global financial crisis (i.e., between 2008 and 2009). The timing of the spikes identified in the total volatility spillovers during the year 2009 and at the end of 2010 in the stock market are remarkably similar those reported in Fengler and Gisler (2015). After the financial crisis, the total volatility spillover remained stable and low until 2014, followed by several jumps between 2015 and 2016. These timings correspond to the stock market selloff, in which the Dow Jones Industrial Average fell by 530.94 (3.1%) on August 21, 2015. The total spillover effects in 2015/16 may have possibly

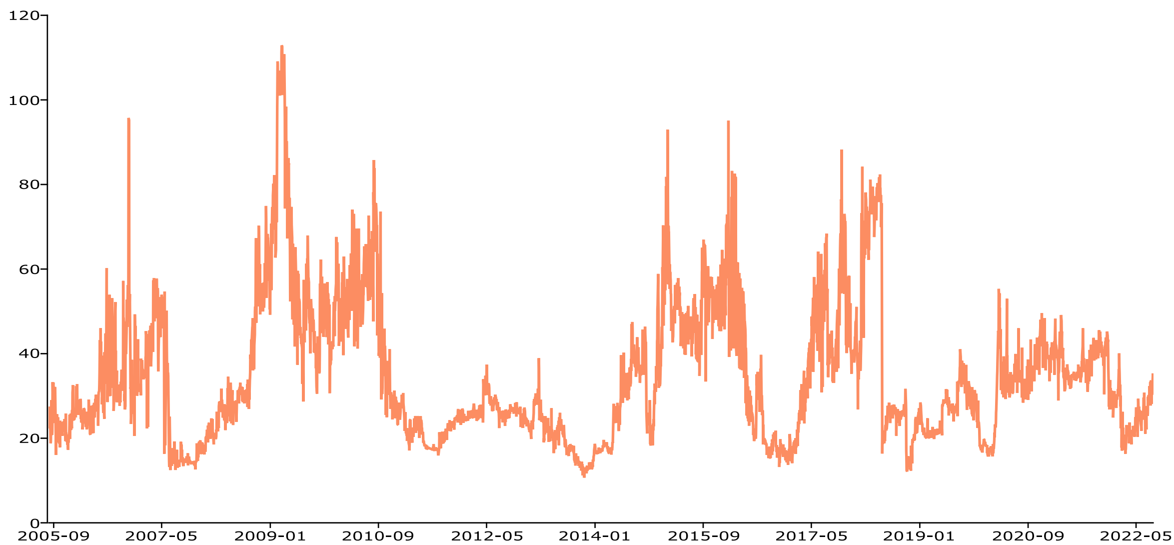

Fig. 2. Total volatility spillovers.

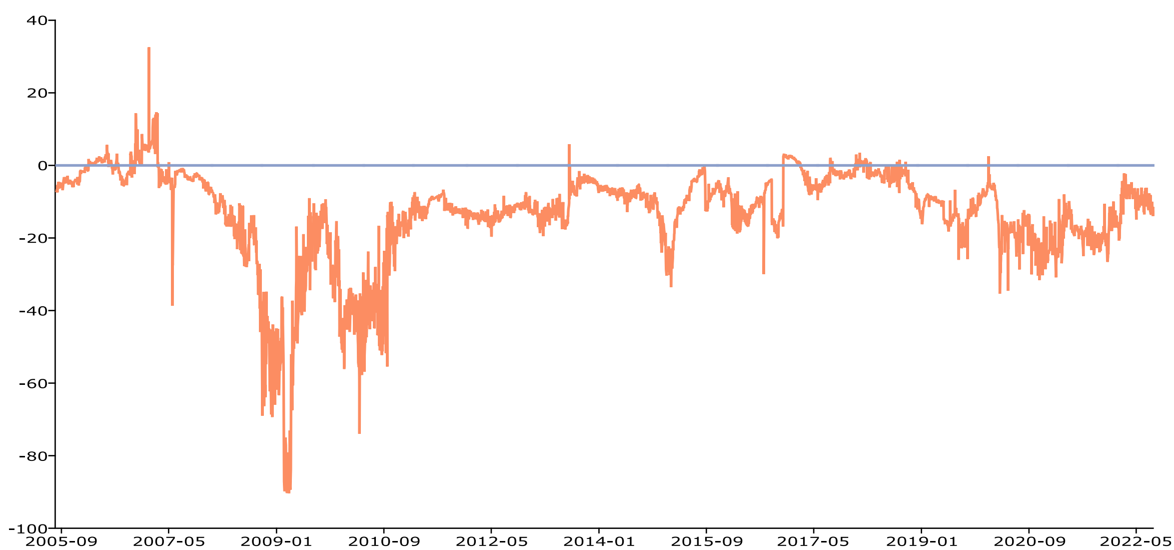

Fig. 3. Total asymmetric spillovers ($TASM$).

originated from the big selloffs and two flash crashes in the stock market. There were also some increments of volatility spillover effects during the recent COVID-19 pandemic, i.e., between 2020 and 2022. However, the fluctuations of total volatility spillover effects were not as significant as those observed during the global financial crisis, plausibly because the Covid-19 is a health pandemic that did not originate from the financial market. Overall, the cyclical behavior observed in our Fig. 2 aligns closely with findings in Wang and Li (2021) and Xu et al. (2019).[2]

Fig. 3 presents the time-varying TASM index. The total asymmetric index is negative for most of the sample periods, indicating that volatility spillovers caused by negative news are greater than those resulted from the positive news. However, during a few periods, such as the period preceding the subprime mortgage (i.e.,2006–2007), the asymmetry approaches zero or even becomes positive. These periods suggest that the negative and positive return shocks led to similar sizes of volatility spillovers across asset markets. The period between 2007 and 2009 had the largest asymmetry, with the spillover index bottoming out around February 2009. This is expected, as the spillovers were widespread during the global financial crisis. The COVID-19 pandemic period also displays a clear negative asymmetry in volatility spillovers, although the magnitude of the asymmetry is not quite as substantial as that of the global financial crisis. The volatility spillovers were more significant during the financial crisis and exacerbated by the European Sovereign Debt crisis. These negative spillovers lasted over seven years and then began to diminish gradually. This indicates the effect of global financial crisis is long lasting. Xu et al. (2019) reported similar results for the total asymmetric spillover of volatility between the oil and stock markets. They also observed dips around the years 2009, 2010, and 2015 and corroborate the prevalence of negative volatility.

5.2.2. Dynamics of spillover balance index

Figs. 4 and 5 present the dynamics of the spillover balance index for each asset market. Fig. 4 shows that the spillover balance of the stock market's bad volatility of stocks is greater than unity for most of the sample period, indicating that this market is a net provider of bad volatility spillover. Similarly, in Fig. 5, the spillover balance indexes of the good volatility associated with each of the four asset

[2] See Figures 3 and 9 in Wang and Li (2021) and Figure 1 in Xu et al. (2019)

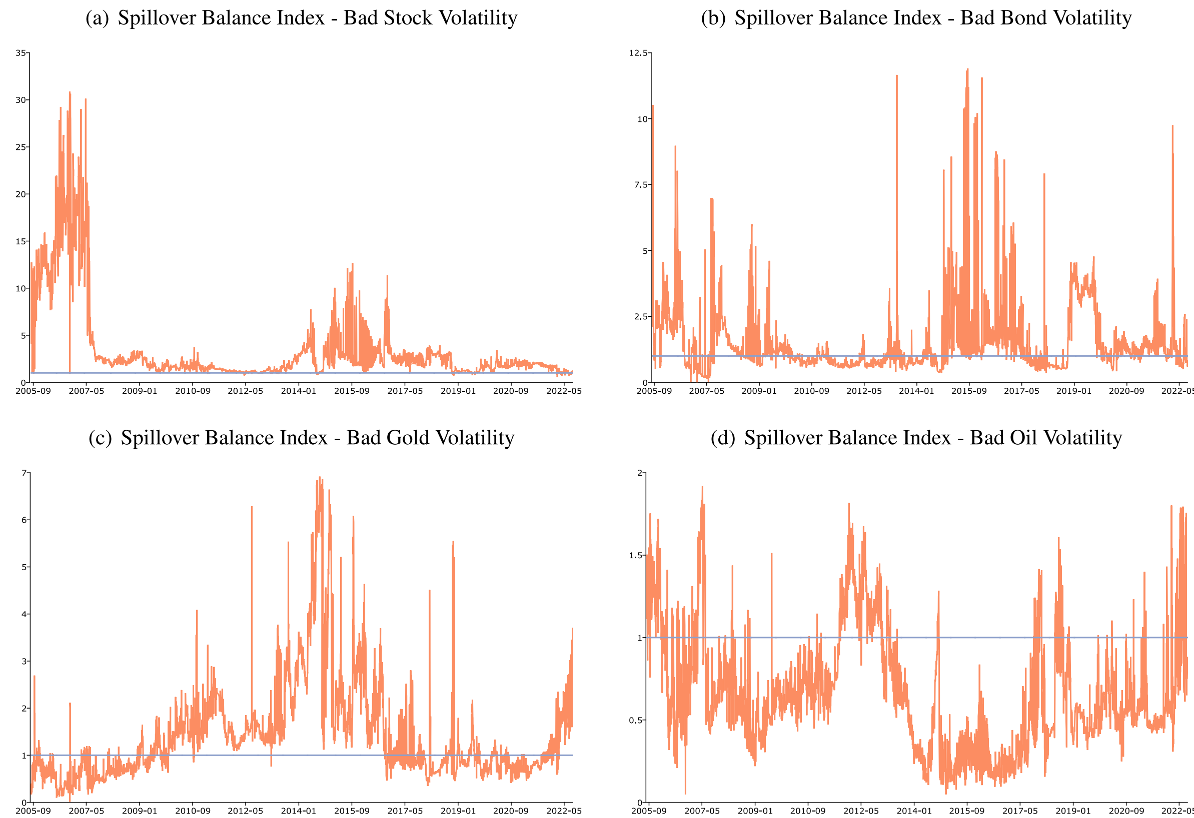

Fig. 4. Spillover balance index - bad volatility.

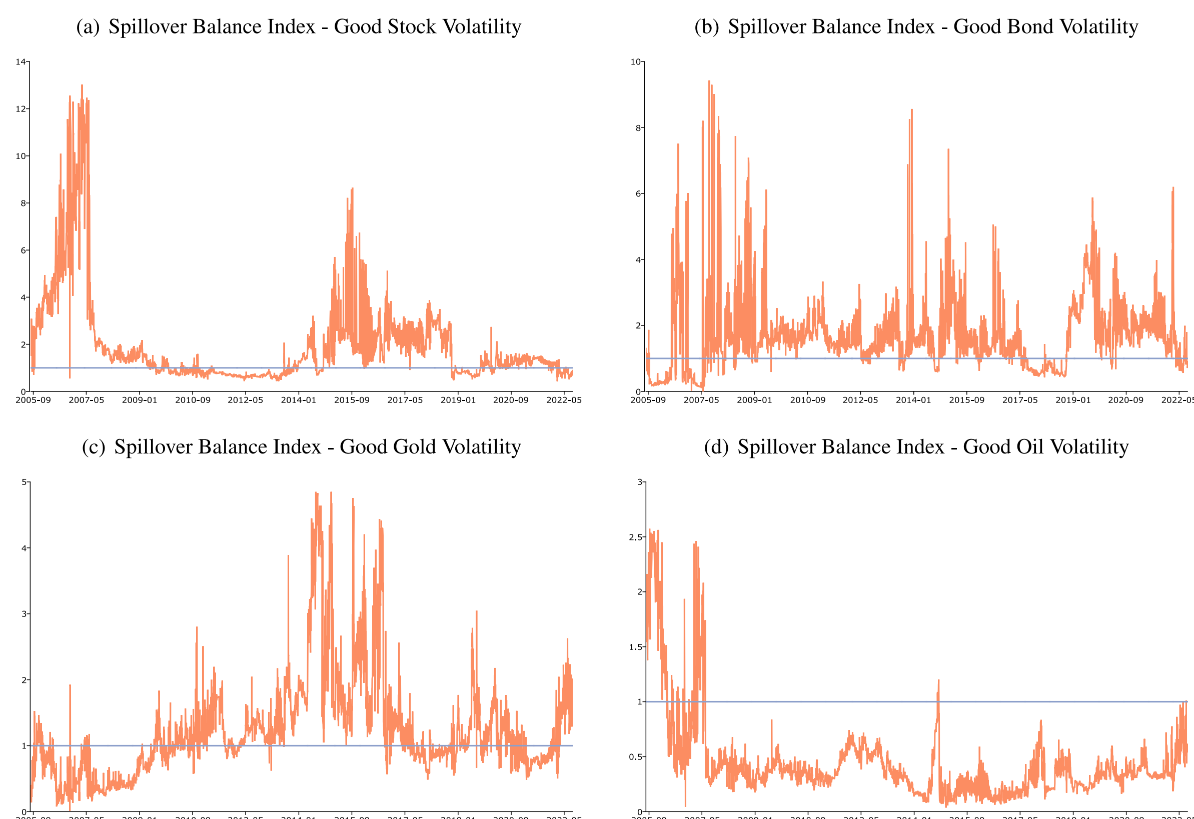

Fig. 5. Spillover balance index - good volatility.

markets are mostly greater than unity, albeit their magnitudes are much smaller than spillover indexes of the bad volatility. These findings are consistent with Fig. 4, which indicates the dominance of negative asymmetric spillovers. Interestingly, during the period 2009–2013, the bad volatility spillover index of the stock market is close to unity, suggesting that the volatility spillover has been dissipated to other markets. Overall, we find that the stock market is a net provider of spillover, especially during significant events, such as the 2008 Global Financial Crisis, massive stock market selloffs, and the two major flash crashes in 2015.

Our results also show that the bond market is generally a provider of bad volatility spillover, especially during the period 2015–2017 as well as during and after the Covid-19 pandemic. However, the good news from the bond market has also provided large spillover effects during the period from 2006 to 2008, i.e., before the global financial crisis. This may be due to investors flocking to safety and buying bonds during the financial crisis, signaling the spillover of good news. It is difficult to conclude whether the bond market is a net spillover provider or a net spillover receiver, as its spillover balance index remains above and below unity for almost equal proportions of time. The bond market was relatively a spillover provider for good volatility during the 2008 global financial crisis and the massive stock market selloff of 2015, while it was relatively a spillover provider of bad volatility during the period from 2014 to 2015, when a massive stock market selloff and flash crash took place.

The gold market behaved rather differently, as it is neither a net spillover provider nor a net spillover receiver of news. Both its good and bad spillover balance indexes are above unity during the period 2009–2017, reaching their peaks between 2014 and 2015. This timing coincides with the massive stock market selloffs and flash crashes. The results also indicate that the gold market was dissipating positive and negative risks between 2009 and 2017. At the end of the sample window, i.e., around 2022, there have been steep increases in good and bad volatility spillovers transmitted from the bond to the other markets.

Since around mid-2007, the crude oil market mostly served as a spillover receiver, with spillover balance indexes fluctuating evenly between zero and two. Combined with the results in Table 3, the bad volatility spillover to the oil market is transmitted from both the stock market and within the crude oil market itself. Interestingly, the bad volatility of the oil market exhibited mild cyclical behavior around the cutoff point, with a spillover balance index of one, peaks during the years 2007, 2012, 2018, and 2022, and troughs in 2006 as well as over the period 2014–2017. However, the good volatility of the oil market was transmitted to other markets only in 2005–2007, which could be the calm prelude before the crash in the stock market. Subsequently, the crude oil began to receive spillovers from the other markets, except for the years 2014 and 2022, where there was a brief temporary balance between the spillover balance indexes.

5.2.3. Dynamics of asymmetric spillover index

Fig. 6 displays the dynamics of the ASM spillover index of each asset market. For the stock market, the ASM index is mostly negative, with a large negative asymmetric effect reported during and after the global financial crisis (i.e., the period 2008–2011). The negative spillovers intensified following the collapse of Lehman Brothers in September 2008 and were further exacerbated during the Eurozone crisis. However, the net spillover effect of the stock market was dampened during subsequent events, such as the debt ceiling debate in 2011, fiscal cliff in 2012, government shutdown in 2013, and the stock market selloff in 2015. The net spillover effect dipped more during the Global Financial Crisis than other periods. Asadi et al. (2022) suggest that stock market crashes significantly impact profitability, overhead cost, and competitiveness in raw material markets, which may explain how shocks of bad volatility of the stock market contributed to spreading the spillover effects to other markets. Ghosh et al. (2021) also argue that technological inefficiency and a weak outlook may affect other markets, supporting the argument that the negative spillover effect caused by the flash crash in 2015 was transmitted to other markets. Overall, this implies that the stock market is the main driver of bad volatility, which spreads negative shocks to other markets.

Interestingly, the ASM index in the bond market is positive most of the time, suggesting that the positive news from the bond market exerts more influence on other markets than negative news. As bonds provide investors with relatively stable incomes during crises, they are regarded as useful hedging instruments during periods of market turmoil. This, in turn, explains why economic downturns may bring good news to the bond market, which is then transmitted to other markets. However, the period near 2015–2016 experienced a negative spillover shock for a few months, indicating a shift in negative shocks from the stock to the bond market. But shortly after, investors fled to safety and, consequently, causing the bond market to spillover the good volatility. Near the end of 2018, a drop in the ASM to zero corresponded to rising tariffs and trade policy tensions, particularly between the US and China, and the impact of the Covid-19 health pandemic on the global economy.

As for gold, the first half of the sample was positively asymmetric, while the second half exhibited a negative asymmetry. Interestingly, we observe several similarities in the movement of the net volatility spillover between the bond and gold markets. This may be due to the hedging benefits of these two instruments, as gold and bond markets are typically considered safe haven assets (see, e.g., Agyei-Ampomah et al. (2014)). However, the range of the gold market's ASM fluctuations are not as wide as those of the bond market, indicating a relatively more stable volatility spillover effect of the gold market.

The negative returns in the crude oil caused spillover shocks in all markets, with the ASM index being negative most of the time. The dominance of negative asymmetries is also reported by Xu et al. (2019), who investigated the asymmetric volatility transmission between the crude oil and stock market, and by Pham et al. (2022) in the context of cryptocurrency and thermal coal futures. The volatility spillover effect of the crude oil market displays similar behavior patterns to that of the stock market, but with a narrower range of fluctuations, possibly due to relative size difference between the two markets. The asymmetric measure in the oil market moves in the same direction as its counterpart in the stock market, except for the period around 2015, when a spike in the positive volatility was observed in the crude oil, but not in the stock market.

5.3. Robustness check

We have also conducted several checks to verify the sensitivity of our results to the choice of forecasting horizons and rolling windows. The results from these tests are largely consistent with our primary analysis and our conclusions remain largely unchanged. Details of these additional tests and their associated results are provided in Appendix B.

5.4. Discussion and policy implications

Overall, our TASM results indicate that the negative volatility spillovers are more prevalent than positive volatility spillovers at the aggregate level. This is consistent with the theory of loss aversion in behavioral finance, where investors are emotionally attached to negative news than positive news. Our finding that the TASM is mostly negative and takes a long time to become positive is also in line with the disposition effect of Frazzini (2006), which suggests that investors tend to hold on to losers and sell winners. Furthermore, our evidence that the spillover from bad to good volatility is stronger than that from good to bad volatility is supported by Bollen and Whaley (2004)'s view that the buying pressure from investors tends to increase during episodes of high volatility.

Another interesting finding is that the stock market is the main provider, whereas the oil market is the main receiver, of volatility spillover and that the oil market has a limited spillover effect on other

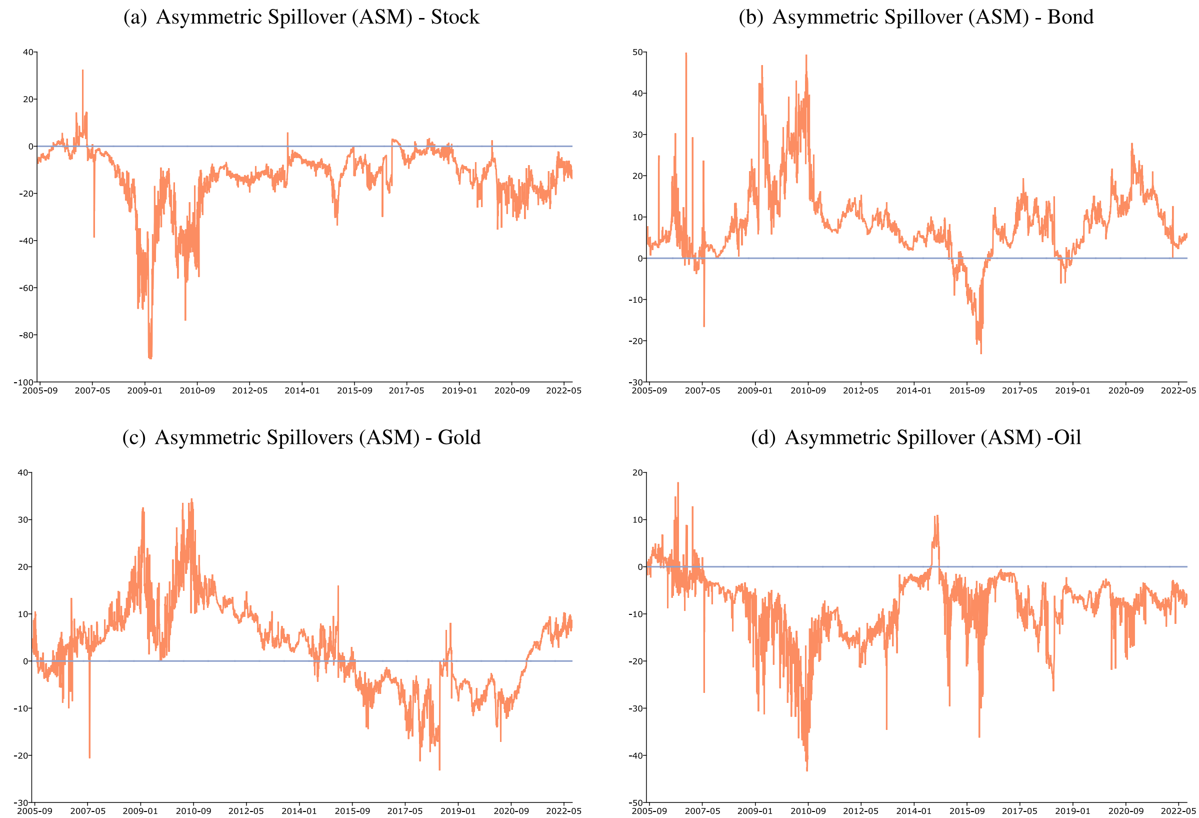

Fig. 6. Asymmetric spillovers (ASM).

markets. This may be attributed to the stock market's considerable size, causing its crashes to spread to other markets. In addition, due to potential information transmission across asset markets (related to market efficiency), negative shocks in the stock market may be immediately transmitted to the oil market. The bond and gold markets behave differently, as they are generally viewed as safe haven (Bredin et al., 2015), where investors seek safety during times of market stress.

Finally, we find that for the bond market, the overall spillover balance of good volatility is greater than that of bad volatility. This may be because investors, who seek safety from bonds, interpret stock market crashes as buying signals in the bond market.

In terms of policy implications, researchers have been consistently calling for more efforts on the part of regulator authorities to better measure and monitor the risks and uncertainties in different asset markets (Fengler and Gisler, 2015; Chiang et al., 2015). Our methodological innovation should serve as a useful tool for policymakers, who are interested in understanding and monitoring volatility transmission among different markets. The finding that stock market is the main transmitter of negative shocks also supports the need for the stock market to be more heavily regulated (Ghosh et al., 2021). Regulatory policies, such as the circuit breaker, can prevent asset bubbles (Turhan et al., 2013), restrict the volatility spillovers within the stock market, and minimize the spread of negative volatility from the stock market to the other markets (Li et al., 2016). Furthermore, this study shows that the bond market spills over good volatility during the financial crisis. Policies need to be implemented to keep a moderate amount of good volatility in the bond market. In addition, as there is significant awareness of the speculative fluctuations in the cryptocurrency market (Pham et al., 2022), policies can be made to minimize the impact of cryptocurrency on other markets. When policies are announced, policymakers need to assess their full impact (Ciner et al., 2013) and ability to mitigate financial distresses (Jiang et al., 2019). Furthermore, considering the potential amplification of the volatility caused by the releases of negative news, regulators should work with media to ensure responsible reporting. A more accurate and balanced information dissemination can mitigate panic and overreaction in the markets. Moreover, as suggested by Baruník et al. (2015) in the context of petroleum markets, introduction of regulations for institutions can similarly be made across the four markets to reduce spillover effects. As a preventive measure, macroeconomic policies can also be designed to control the impact of global crude oil industry and encourage the development of alternative sustainable energy resources (Jiang et al., 2019), Finally, given the susceptibility of oil markets to geopolitical and other global events, diversifying the energy portfolio and increasing investments in sustainable energy can mitigate the risks associated with oil market volatility.

6. Conclusion

This study uses a Multiplicative Error Model (MEM) to investigate the asymmetric volatility spillovers across four major global asset markets, namely stocks, bonds, gold, and crude oil. This approach overcomes some important shortcomings of other popular models, including VAR and multivariate GARCH models. The asymmetric volatility spillover index derived from the MEM enables us to capture more accurately the impact of positive and negative news on different markets as well as the interdependence of the volatility transmission across these markets. We have also expanded the scope of the volatility spillover balance and asymmetric spillover indexes to reflect their time-varying features.

Our novel empirical model offers new insights into volatility spillovers between different asset markets. Firstly, we find that the volatility spillovers are time varying, and both the degree and the direction of the spillovers are influenced by changes in economic conditions. Secondly, we identify the net providers and the net receivers of volatility spillovers. Specifically, we find that the stock market is the provider, the bond and gold markets are largely balanced, while the crude oil market mostly serves as a receiver of volatility spillovers.

Table 5
Bad and good volatility spillovers.

	From bad volatility				From good volatility				
	Stock	Bond	Gold	Oil	Stock	Bond	Gold	Oil	Total from
To bad volatility									
Stock	11.00	1.84	3.02	2.05	6.31	2.77	2.98	1.29	13.95
Bond	5.33	3.44	2.20	1.16	3.66	3.11	2.10	0.91	15.36
Gold	6.64	3.74	9.20	2.08	4.65	3.79	7.11	1.54	22.45
Crude Oil	7.64	2.43	4.17	7.81	4.73	3.42	3.25	4.53	25.64
To good volatility									
Stock	11.27	1.92	3.12	2.11	6.64	2.84	3.08	1.34	14.42
Bond	6.00	3.91	2.55	1.38	4.24	4.56	2.63	1.11	17.91
Gold	6.57	3.52	8.44	2.09	4.58	3.76	7.08	1.58	22.10
Crude Oil	7.70	2.56	4.26	7.78	4.85	3.54	3.44	4.91	26.35
Total To	39.89	16.01	19.33	10.87	26.71	20.12	17.47	7.78	
Balance	2.86	1.04	0.86	0.42	1.85	1.12	0.79	0.30	
Asym	−13.18**	4.11**	−1.86	−3.09			TASM		−14.02**

The table presents spillovers for the full sample with a forecast horizon of $\tau = 10$ days. We use bootstrapped standard errors with 1000 resamplings to test the significance of ASM and TASM.

** The symbol denotes significance at the 5% level.

Thirdly, we show that the asymmetric spillover effects are mostly negative in the cases of the stock and crude oil markets and positive in the bond market. Fourthly, we investigate the impact of the variation in economic conditions, such as the global financial crisis, the Eurozone crisis, and the COVID-19 pandemic, on volatility spillovers among asset markets. We provide evidence that such events exert a significant influence on both the magnitude and direction of spillovers and that the spillover effects are amplified during times of economic stress. Finally, we shed light on the role of safe-haven assets, namely gold and bonds, in times of market volatility. We find that these assets help mitigate spillover effects and provide hedging opportunities for investors.

CRediT authorship contribution statement

Bo Guan: Drafting the literature review and introduction. **Khelifa Mazouz:** Supervising, Reviewing, Editing and polishing the paper. **Yongdeng Xu:** Drafting the methodology, Working on data and estimation.

Appendix A. Bootstrap standard error

The definitions of $TASM$ and ASM_i aid in testing our initial hypotheses concerning the symmetry of spillovers. When utilizing these spillover asymmetry measures, the two hypotheses are redefined as follows:

$$\mathcal{H}_0^1: \quad TASM = 0 \quad \text{against } \mathcal{H}_A^1: \quad TASM \neq 0$$
$$\mathcal{H}_0^2: \quad ASM_i = 0 \quad \text{against } \mathcal{H}_A^2: \quad ASM_i \neq 0, \quad \text{for } i = 1, 2, \dots, k. \tag{25}$$

To test the hypotheses about the symmetry of volatility spillovers, we opt to bootstrap the measures. It is crucial to ensure that the empirical results are not attributable to estimation errors from the MEM or discretization errors from realized semi-variances. The latter, in particular, could be significant due to the limited number of observations during the day in the real data used for the computation of realized semi-variance.

We bootstrap the two realized semicovariance data directly from (11). The LB statistics, as shown in the last column of Table 3, suggest that the estimated residuals do not exhibit autocorrelation, thus we can bootstrap the data from these residuals. The bootstrap procedure is as follows:

- After estimation, acquire the fitted residual $\hat{\epsilon}_t$.
- Bootstrap new residuals from $\hat{\epsilon}_t$, denoted as ϵ_t^b, where $b = 1, 2, \dots, 1000$. The residuals are bootstrapped 1000 times.
- Then, the realized semi-variance data X_i can be simulated from the vector MEM model as follows:

$$\mathbf{x}_t^b = \boldsymbol{\mu}_t^b \odot \boldsymbol{\epsilon}_t^b,$$
$$\boldsymbol{\mu}_t^b = \hat{\boldsymbol{\omega}} + \hat{\mathbf{A}}\mathbf{x}_{t-1}^b + \hat{\mathbf{b}}\boldsymbol{\mu}_{t-1}^b + \hat{\mathbf{A}}^w \mathbf{x}_{t-1}^{w,b} + \hat{\mathbf{A}}^m \mathbf{x}_{t-1}^{m,b}. \tag{26}$$

where $\mathbf{x}_{t-1}^{w,b} = \frac{1}{5}\sum_{l=1}^{5} \mathbf{x}_{t-l}^b$, $\mathbf{x}_{t-1}^{m,b} = \frac{1}{22}\sum_{l=1}^{22} \mathbf{x}_{t-l}^b$,

- For each set of simulated data, we estimate the model and calculate $TASM$ and ASM_i.

Using 1,000 bootstrapped processes, we obtain the bootstrapped standard errors of $TASM$ and ASM_i. We then test the significance of the two null hypotheses.

Appendix B. Robustness checks

To assess robustness, we first re-evaluate the volatility spillover effects in Table 4 using different forecast horizons of $\tau = 100$, $\tau = 30$, and $\tau = 10$. Secondly, we present both the spillover index and the asymmetric spillover index using a shorter 200-day rolling window.

Table 5 displays the bad and good volatility spillover effects when a forecasting horizon of $\tau = 10$ is employed[3]. From Table 5, the spillover effects, including the spillover balance and TASM results, are qualitatively consistent with Table 4. Stocks exhibit the largest negative volatility spillover, while the TASM spillover is both negative and significant. The only difference is that the values in Table 4 are larger than those in Table 5. This is expected, as our volatility spillover is calculated as the sum of shock effects across all future forecasting horizons.

Figs. 7 and 8 present the dynamics of total volatility and asymmetric spillovers using a 200-day rolling window[4]. Our core findings remain consistent. The global financial crisis greatly affected market interconnectedness. While the COVID-19 pandemic increased volatility spillovers, its impact was less pronounced than the financial crisis. The asymmetric spillover index was mostly negative. The most significant asymmetry occurred during 2007–2009, with the COVID-19 period showing lesser negative asymmetry. The difference observed from Figs. 7 and 8 is that 2015/16 exhibited pronounced high total volatility spillover effects and larger negative asymmetric effects. This might be attributed to our use of a shorter rolling window. The 2015/16 stock market sell-off had a significant but relatively short-lived impact on volatility. When a shorter rolling window is employed, this effect appears more pronounced.

[3] The forecast horizons of $\tau = 100$ and $\tau = 200$ days yield results very similar to the $\tau = 10$ case. These are not shown to save space but are available upon request.

[4] Details on individual asset market asymmetries are available upon request

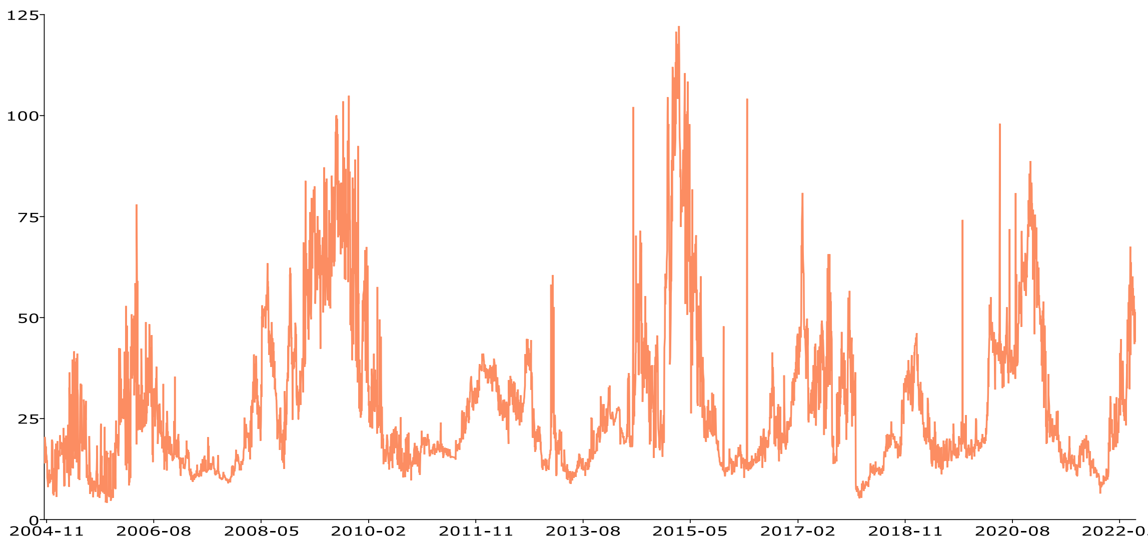

Fig. 7. Total volatility spillovers.

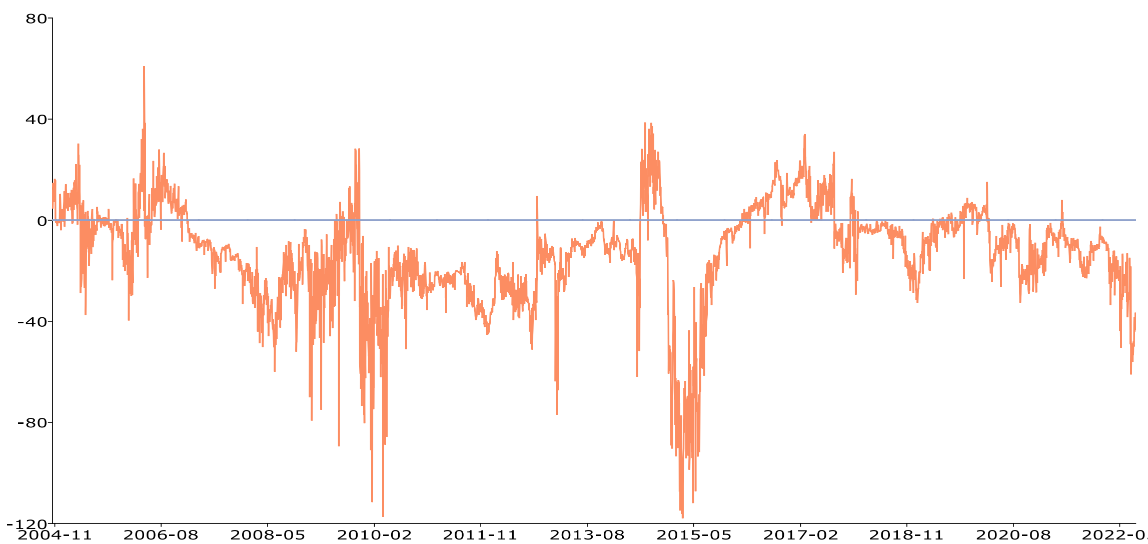

Fig. 8. Total asymmetric spillovers ($TASM$).

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