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Do gold and the US dollar diversify global sectoral risk? Evidence from connectedness and dynamic conditional correlation measures

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ABSTRACT

The use of Information and Communication Technology (ICT) in fund management coupled with financial liberalization prompts us to explore the global sectoral connectedness and risk management potential of gold and the US dollar. The asymmetric interdependence (and behaviour) of financial markets (and their participants) further motivates us to understand the upside and downside market connections along with their mean-based connections. Variance decomposition-based spillover measures in vector auto-regressive space are used for that purpose. The mean-based total and directional spillover measures show that the global stock markets are highly connected at the sectoral level, reflecting higher odds of global sectoral shock transmission. The directional spillover measures further reveal that the industrial and financial sectors are systematically important sectors for transmitting global sectoral shocks. Their asymmetric and time-varying counterparts suggest that global sectoral connectedness dominates in downside markets and during crisis events. Specifically, the late European Debt Crisis, the Brexit referendum, the US-China trade war, and the COVID-19 pandemic are characterized by asymmetric and higher global sectoral shock transmission. We also show that the inclusion of gold and the US dollar with global sectoral stocks has the potential to diversify the global sectoral risk.

1. Introduction

The use of Information and Communication Technology (ICT) in fund management coupled with financial liberalization across countries provides opportunities for investing and risk management at the global level. However, the downside is that the process has increased global financial connectedness be it across countries or at the global sectoral level (Zhang et al., 2020). Therefore, any form of uncertainty or shock to a specific sector/country has the potential to have an adverse impact on other sectors/countries through spillovers. In fact, with their origin in the financial sector, the spillovers of the global financial crisis were felt across a range of countries and sectors. The evolution of global sectoral indices as reported in Fig. 1 also reflect a pattern of global sectoral connections, which is more pronounced during and after the outbreak of the COVID-19 pandemic. The exploration of global sectoral connectedness, its complexity, and the pattern of risk transmission has implications for global financial market participants, such as institutional

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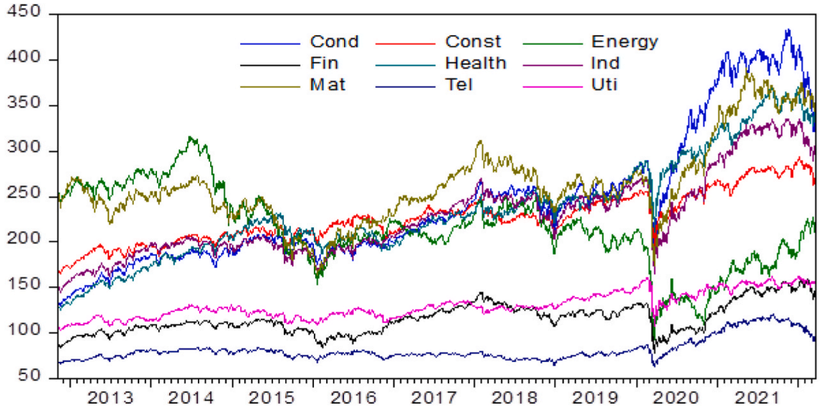


Fig. 1. Evolution of global sectoral indices.

investors and fund managers. For instance, the magnitude and direction of shock transmission provides an idea of the sources of risk transmission and cross-sectoral risk diversification opportunities at the global level (Fabozzi et al., 2002). The investigation would not only help investors reduce the risk of a portfolio being exposed to country-specific shocks but also sector-specific shocks at the global level. It is, therefore, imperative to understand the strength and the direction of global sectoral spillovers for identifying the sources of shocks and systematically important sectors[1] (Wu et al., 2018). Such insights will put financial market participants in a more informed space while managing global sector-specific risks and formulating effective portfolio rebalancing strategies (Bouri et al., 2021).

The connectedness across sectors is sensitive to a host of time-varying events (Diebold & Yilmaz, 2012). For instance, the period of the global financial crisis in 2008, the European debt crisis of 2010–12, and the recent COVID-19 outbreak have strengthened the connectedness among various markets, be it domestically or globally (Bouri et al., 2021; Zhang & Broadstock, 2018). Besides, the financial market participants perceive information asymmetrically, responding differently to negative and positive information.[2] To this end, Hornik et al. (2015) observe that information dissemination amongst the market participants is higher for negative news than for positive news. The volatility in financial markets, therefore, gets intensified in the downside market than in the upside market, which is perceived to be a result of bad news and good news, respectively. Consequently, the studies of Barunik et al. (2015 and 2017, 2019) and Xu et al. (2019) find that negative shocks have more spillover impact than positive shocks. Thus, it can be said that the investigation of global sectoral connectedness necessitates accounting for the structural change and the asymmetric interdependence of these sectors as well. Building upon this, the present study intends to explore the dynamics of global sectoral connectedness in a symmetric (mean-based) and asymmetric (upside and downside) framework over time.

With growing global sectoral congruence and the likeliness of asymmetric interdependence among these sectors, financial market participants can't diversify their portfolios if connectedness across sectors is strong (Mensi et al., 2022). It is, therefore, critical to identify alternative risk-diversifying investments that could serve in managing global sectoral risks. Owed to their acceptability in the global financial system, gold, and the US dollar have been used as safe investments with stocks (Baur & McDermott, 2010; Shah & Dar, 2021). Since the aggregate stock market index is primarily built on its sectoral components, we, therefore, believe that the sector-specific shocks could also be diversified by including gold and the US dollar. In other words, we expect a weak connection, and thereby the diversification potential of gold and the US dollar with sectoral stock indices. In light of this, the study deepens its inquiry by investigating the connectedness and provides the portfolio weights and hedging effectiveness (H.E) of including gold and the US dollar with global sectoral stocks.

By doing so, this study contributes to the existing empirical investigations in at least three ways. *Firstly,* different from the existing studies, we explore the dynamics of global stock market connectedness at the sectoral level, rather than at the aggregate level. Most of the previous studies focus on the stock market connectedness across countries (see for example, e.g. Youssef et al., 2021). The fewer studies that focus on sectoral connections are confined to specific countries, such as China (Mensi, Al Rababa'a, et al., 2021; Mensi, Nekhili, et al., 2021), Turkey (Ekinci & Gençyürek, 2021), Australia (Choi et al., 2021), and the US (Costa et al., 2022). However, given the fact that the global financial system is more connected than ever due to increased financial flows (Mensi et al., 2021; Wu et al., 2019), there is a greater need for risk management for financial market participants that operate globally. The recent episode of the COVID-19 health crisis and the collapse of Silicon Valley Bank exemplifies this risk, which has affected specific sectors (such as energy, health, and finance) globally.[3] The investigation would not only help investors reduce the risk of a portfolio being exposed to sector-specific shocks at the global level but also country-specific shocks. This is because the global sectoral indices are the aggregation of sector-specific industries that operate across different countries. *Secondly,* unlike others, given the asymmetric interdependence (and

[1] Both Spillovers and Connectedness terms will be used interchangeably. [These measures, in particular, provide h-period ahead uncertainty in a variable(s) due to random shock in other variable(s)].

[2] The negative and positive returns are a reflection of negative and positive information respectively in the market.

[3] Though we have not accounted for the Silicon Valley Bank Collapse in our empirical estimations, its fallout is still in its infancy stage as of now.

behaviour) of financial markets (and market participants) and the potential impact of COVID-19 and other events on the connectedness relationship over time, the study also investigates the asymmetric connectedness and spillover interactions over time. The extant empirical literature (as provided in the literature review section), is more focused on symmetric sectoral connectedness. The few studies that investigate sectoral connections are limited to particular countries only (Mensi et al., 2021). While the dynamic spillover interactions would be effective to account for any structural change owed to various events over time, including the European Debt Crisis, Brexit, and COVID-19. *Thirdly,* amid the likeness of increased financial connectedness due to financial liberalization and increased cross-sectoral portfolio rebalancing, including safer assets is important for managing sector-specific risks. The inclusion of alternative safer assets (gold and the US dollar) is also important due to the headwinds that the global equity market is facing due to higher policy rates to tame the global inflationary conditions. The study, therefore, explores the risk management potential of historically proven safe assets. In particular, the safe investment role of gold and the US dollar with global sectoral indices is investigated by measuring their connection, optimal portfolio weights, and the hedging effectiveness (H.E) with various sectors.

The mean-based total and directional spillover measures demonstrate that the global stock markets are highly connected at the sectoral level, indicating higher odds of sectoral shock transmission. This connotes that managing financial risk through sectoral diversification is difficult for global investors and fund managers. The directional spillover measures reveal that the industrial and financial sectors are systematically important sectors and the management of sectoral risk necessitates active monitoring of these sectors. Furthermore, the asymmetric and time-varying connectedness measures show that global sectoral connectedness is asymmetric and higher during uncertain/crisis periods. The European debt crisis, the Brexit referendum of 2016, the US-China trade war of 2018, and the COVID-19 pandemic, for example, are characterized by asymmetric (negative spillovers dominating positive spillovers) and relatively higher connectedness. Finally, the results of the connectedness and portfolio weights selection strategy show that the inclusion of gold and the US dollar in the portfolio reduces the global sectoral risk in general, and during distress periods in particular.

2. Literature review

The spillover analysis is fundamental to the measurement of risk and portfolio diversification as it provides a measure of the severity that a specific sector could face from a random shock emanating from another sector through information transmission (Nazlioglu et al., 2013; Shah et al., 2021). If any specific sector, for example, is immune to a sector-specific shock, then there is a diversification potential for its inclusion into the portfolio (Bai & Green, 2010). Even though the empirical literature on spillovers dates back to Engle (2002), it was only after the global financial crisis of 2008 that the research on spillover transmission and connectedness measurements started gathering momentum (Chevallier & Ielpo, 2013). Therefore, the present discussion on the existing literature mainly concentrates on the studies conducted post-2008. To begin with, the existing literature on spillover transmission in various markets/assets is discussed first, then a review of the studies on asymmetric spillovers that treats negative and positive price information differently is done. The risk management strategies and the uniqueness of our research are finally presented at the end of the review of literature section.

There is a rich body of literature on connectedness and spillover transmission when it comes to the case of stocks, bonds, foreign exchange, and commodity markets. Diebold and Yilmaz (2012) investigate the dynamics of spillovers among US stock, bond, forex, and commodity markets from January 1999 to January 2010 and report that the cross-market linkages increased significantly post-2007 global financial crisis. Wu et al. (2022) make use of the Financial Stress Index (FSI) for an in-depth understanding of the systemic risk (or stress contagion) faced by the financial markets in China and its impact on the equity and bond markets of the UK, Germany, France, and Italy. Their time-varying parameter vector autoregressive results indicate heightened stress transmission among the bond, equity, real estate, and banking sectors of China during crisis events. Besides, the regression results reveal the positive impact of Chinese stress connectedness on the equity volatility of France and Italy and the bond market of Germany. In a similar vein, Youssef et al. (2021) use daily data of equity indices of eight countries over six years from January 2015 through May 2021 and observe a higher equity connectedness during the COVID-19 pandemic peak, with the European market dominating the spillover transmission to other markets. MacDonald et al. (2018) explore the volatility co-movements and spillover effects during banking and sovereign crisis by employing the multivariate GARCH-BEKK models to the 11 Eurozone markets through a variety of financial stress indicators. They conclude that there are multiple channels of spillover transmission and connectedness among these markets with banks and short-term money markets playing a key role. Likewise, the mutual connection between the sovereign and banking risks through their respective credit default swap spreads across various countries of the European Union is analysed by Bratis et al. (2020). They make use of a variety of econometric tools, such as BEKK-GARCH, DCC-GARCH, and VAR-based connectedness measures to explore the dynamic interdependence in both the core and periphery EU countries. They conclude that the core EMU banking sectors are immune to the risks emanating from the banking sector of peripheral countries. Unlike in the pre-crisis, the study also shows that the post-crisis period witnessed risk pass-through from sovereign sectors of periphery countries. To investigate the dynamics of volatility spillover among the equity markets of G20 countries,[4] Zhang et al. (2020) construct dynamic spillover network graphs from the GARCH-BEKK model. Their findings suggest that the size of the economy, general market conditions, and geographical proximity explain half of the spillover dynamics among these economies. Analyzing the spillover transmission of major currencies against the US dollar, Greenwood-Nimmo et al. (2016) find an increased forex connectedness during the global financial crisis period. Kitamura (2010) studies the spillover transmission among a set of key international currencies, e.g. Euro, Swiss-Franc, and Japanese Yen, for the period July 2008 through

[4] The G20 countries approximately constitute 90% of global GDP and 80% of global trade.

July 2009. Their study finds a higher degree of integration, with Euro significantly affecting the Swiss-Franc and Japanese Yen. For commodity markets, Nazlioglu et al. (2013) investigate the volatility spillovers between oil and agricultural commodity markets for the pre and post-food price crisis period of 2006–08. The study concludes that oil shocks are being transmitted to agricultural commodity prices for the post-food price crisis period only.

The exploration of connectedness and spillover transmission is not only restricted to the traditional assets but has been extended to the newer asset classes as well. Elsayed et al. (2022), for instance, examine the connectedness between Bitcoin and traditional assets (oil, gold, stocks, bonds, and the US dollar). Likewise, Ahmad and Rais (2018) investigate the dynamic spillover relationship of clean energy stocks with technology stocks, energy, equity, and the US dollar at the country-specific level. Their empirical results indicate a higher magnitude of spillovers during specific global events. By using the graph theory and variance decomposition tools, Wu et al. (2019) and Chatziantoniou et al. (2021) explore the sectoral connectedness in China and India, respectively. Their findings reflect an increased susceptibility of a portfolio to cross-sectoral shocks and a reduction in portfolio diversification opportunities post-global financial crises, in general, and during crisis events, in particular.

Barunik et al. (2015) provide a framework for treating negative and positive information differently and introduce various measures of asymmetric connectedness. Their empirical investigation offers strong evidence of asymmetric sectoral connectedness for the US stock market. Using a similar framework, Mensi et al. (2021) explores the dynamic asymmetric spillovers among oil, gold, and Chinese sectoral stocks and report asymmetric return spillover transmission, with negative information dominating the positive information during the global financial crisis, European debt crisis, oil price crash, and the COVID-19 outbreak. To conclude, existing studies indicate that connectedness among various assets/markets is crisis-sensitive and that downside information transmission outperforms upside information transmission during distress periods. It is therefore logical to assume that asymmetry and crisis periods reduce risk management opportunities. Also, due to increased global financial integration induced by unrestricted global financial flows across countries, it would be difficult for the financial market participants to minimize the financial risk through sectoral diversification. Therefore, the need for alternative safe investment arises.

Commodities are often considered immune to shocks emanating from financial assets (Chevallier & Ielpo, 2013; Kat & Oomen, 2007a). Studies in recent years, however, challenged this traditional wisdom with increasing evidence of commodity financialization (Tang & Xiong, 2012). Buyukshahin et al. (2010), for instance, find evidence of an increasing correlation between commodities and equities post-global financial crisis attributed to financialization process. The findings are corroborated by Dasklaki and Skiadopoulos (2011) and Delatte and Lopez (2012), suggesting reduced financial risk management and diversification potential of commodities. However, gold, despite its official detachment from the global financial system in the 1970s, is a unique commodity proposition, with its tradition of being used as a store of value during financial panic (Bhanja & Dar, 2015). The limited supply, non-perishability, global acceptability, and lesser government control, amongst others, explain this confidence and weak (or negative) correlation of gold with stocks (Baur & McDermott, 2010, 2016). The US dollar is also considered a safe asset during crisis times for its higher average returns, liquidity, and confidence in the global financial system (Maggiori, 2011). The domination of the US dollar as a dominant international vehicle currency is attributed to the same logic (Galati & Wooldridge, 2009). The empirical revelations of Baur and McDermott (2016) and Liu, Chang, Wu, & Chui, 2016 also reflect the safe haven property of the US dollar along with gold. With this foundation, the present study attempts to investigate the risk management potential of gold and the US dollar against global sectoral risk.

3. Methodology

The symmetric and asymmetric connectedness measures of Barunik et al. (2016) are discussed in this section. We use the logic of Diebold and Yilmaz's (2012) mean-based connectedness measures from Table 1 to describe in detail the asymmetric measures of connectedness in Table 2 through Table 4. This is because Barunik et al. (2016) is an extension of Diebold and Yilmaz's (2012) mean-based connectedness measures in extreme cases. The advantage of using Diebold and Yilmaz's (2012) connectedness measures over its earlier version, Diebold and Yilmaz (2009), is its insensitivity to variable ordering.

For the quantification purpose, the overall realized sectoral returns are used to calculate mean-based connectedness measures. And, to compute their upside and downside counterparts (extremes), we decompose the overall realized sectoral returns into their positive and negative realizes returns. Specifically, the daily natural logarithmic price change (r_t) is decomposed into its positive [$r_t\ (+)$] and negative [$r_t\ (-)$] components to depict the upside and downside market situations. This representation will help us to measure the spillovers attributed to good and bad shocks and quantify the relative degree of connectedness in good and bad market conditions.

Mathematically, the total return (r_t) with its upside and downside components are computed as follows:

Table 1
Overall Spillover table.

	x_1	x_2	…	x_N	From
x_1	d_{11}	d_{12}	…	d_{1N}	$\sum_{j=1}^{N} d_{1j},\ d_{11} = 0$
x_2	d_{21}	d_{22}	…	d_{2N}	$\sum_{j=1}^{N} d_{2j},\ d_{22} = 0$
⋮	⋮	⋮	d_{ij}	⋮	⋮
x_N	d_{N1}	d_{N2}	…	d_{NN}	$\sum_{j=1}^{N} d_{Nj},\ d_{NN} = 0$
To	$\sum_{i=1}^{N} d_{i1},\ d_{11} = 0$	$\sum_{i=1}^{N} d_{i2},\ d_{22} = 0$	…	$\sum_{i=1}^{N} d_{2j},\ d_{22} = 0$	$\sum_{i,j=1}^{N} d_{ij},\ d_{ij} = 0$ if i = j

Source: Diebold et al. (2017).

Table 2
Upside spillover table.

	x_1^+	x_2^+	…	x_N^+	From
x_1^+	d_{11}^+	d_{12}^+	…	d_{1N}^+	$\sum_{j=1}^N d_{1j}^+, d_{11}^+ = 0$
x_2^+	d_{21}^+	d_{22}^+	…	d_{2N}^+	$\sum_{j=1}^N d_{2j}^+, d_{22}^+ = 0$
⋮	⋮	⋮	d_{ij}^+	⋮	⋮
x_N^+	d_{N1}^+	d_{N2}^+	…	d_{NN}^+	$\sum_{j=1}^N d_{Nj}^+, d_{NN}^+ = 0$
To	$\sum_{i=1}^N d_{i1}^+, d_{11}^+ = 0$	$\sum_{i=1}^N d_{i2}^+, d_{22}^+ = 0$	…	$\sum_{i=1}^N d_{2j}^+, d_{22}^+ = 0$	$\sum_{i,j=1}^N d_{ij}^+, d_{ij}^+ = 0$ if i = j

Source: Author's representation with theoretical support drawn from Diebold et al. (2017).

$$r_t = \ln p_t - \ln p_{t-1}$$

$$r_t\,(+) = \begin{cases} r_{t, r_t > 0} \\ 0, otherwise \end{cases}$$

$$r_t\,(-) = \begin{cases} r_{t, r_t < 0} \\ 0, otherwise \end{cases}$$

where, r_t is the mean-based return, $r_t\,(+)$ is the upside return and $r_t\,(-)$ is the downside return representing normal, upside, and downside market sentiment.

The cells in Table 1 depict the magnitude of future H-period ahead percentage uncertainty (d_{ij}) in a variable 'x_i' due to a shock arising from 'x_j' using overall returns. The cells in Tables 2 and 3 show future H-period ahead percentage uncertainty in the upside (d_{ij}^+) and downside (d_{ij}^-) market respectively. Since we are dealing with the vector autoregressive system-based generalized variance decomposition in all three market conditions, we, therefore, provide the generic calculation and description of various connectedness/spillovers in the following sub-section by using Table 1. The explanation holds true for Tables 2 and 3, which reflect the upside and downside market. To assess the diversification potential of gold and the US dollar with global sectoral indices, we also use the DCC-GARCH model of Engle (2002) to quantify the optimal portfolio weights selection strategy and hedging effectiveness. Therefore, we also provide a brief explanation of the DCC-GARCH approach of Engle (2002) at the end of this section.

3.1. *Symmetric and asymmetric connectedness measures*

Following Diebold and Yilmaz (2015), the methodological framework of mean-based connectedness measures of Diebold and Yilmaz (2012) are shown with the help of Table 1. For estimation and interpretation purposes, the generalized variance decomposition method is used. Therefore, unlike Diebold and Yilmaz (2009) that use the Cholesky decomposition method, the connectedness measures of Diebold and Yilmaz (2012) are independent of ordering in the vector autoregressive system (Koop et al., 1996; Pesaran & Shin, 1998).

3.1.1. *Definitions measurement of connectedness/spillover measures*

Own-spillovers quantify future variation/uncertainty in a variable, say x_i as a result of a shock from itself, while *cross-spillovers* quantify future variation/uncertainty in a variable x_i as a result of a shock caused by another variable, say x_j. The diagonal elements in Table 1 represent own-spillovers, whereas, the non-diagonal elements represent cross-spillovers.

Further, the *net-cross spillovers* quantify the strength of shocks between variable x_i and variable x_j. In particular, net-pairwise spillovers with a negative sign indicate that x_i is a net receiver of shock from x_j, while the positive value indicates that x_i is a net transmitter of a shock to x_j.

The *Directional spillovers (To)* measure future variation in all other variables as a result of a shock in a specific asset/variable, say x_1, whereas directional spillovers (From) measures future variation in a specific variable, say x_1 as a result of a shock in all other system variables.

Table 3
Downside spillover table.

	x_1^-	x_2^-	…	x_N^-	From
x_1^-	d_{11}^-	d_{12}^-	…	d_{1N}^-	$\sum_{j=1}^N d_{1j}^-, d_{11}^+ = 0$
x_2^-	d_{21}^-	d_{22}^-	…	d_{2N}^-	$\sum_{j=1}^N d_{2j}^-, d_{22}^+ = 0$
⋮	⋮	⋮	d_{ij}^-	⋮	⋮
x_N^-	d_{N1}^-	d_{N2}^-	…	d_{NN}^-	$\sum_{j=1}^N d_{Nj}^-, d_{NN}^- = 0$
To	$\sum_{i=1}^N d_{i1}^-, d_{11}^- = 0$	$\sum_{i=1}^N d_{i2}^-, d_{22}^- = 0$	…	$\sum_{i=1}^N d_{2j}^-, d_{22}^- = 0$	$\sum_{i,j=1}^N d_{ij}^-, d_{ij}^- = 0$ if i = j

Source: Author's representation with theoretical support drawn from Diebold and Yilmaz (2015)

Symbolically,

$$\text{Directional Spillover Index (TO)} = \sum_{j=1}^{N} d_{ij}, i \neq j$$

$$\text{Directional Spilover Index (From)} = \sum_{j=1}^{N} d_{ij}, i \neq j$$

The total Spillover index is a measure of overall interdependence among all the considered system variables that shows the percentage of future H-period ahead uncertainty in the vector autoregressive system that is due to cross-spillovers. The spillover index is calculated as the sum of non-diagonal elements to the total number of markets.

Symbolically,

$$\text{Total spillover Index} = \frac{1}{N} \sum_{i,j=1}^{N} d_{ij} * 100$$

For calculating the various asymmetric connectedness matrices, the difference between the spillovers in the upside and downside markets is used as a proxy for the degree of connectedness asymmetry. Table 4 displays the results of various asymmetric connectedness metrics, such as the total spillover asymmetry measure (SAM). Therefore, the negative value of the spillover asymmetry measure in Table 4 indicates the domination of downside shocks over upside shocks (asymmetry). While, the symmetric interdependence is reflected by a zero, meaning upside and downside spillover interactions (connectedness measures) are equal.

3.2. DCC-GARCH and optimal portfolio weights

For calculating optimal portfolio weights, the DCC-GARCH method as proposed by Engle (2002) and used by Antonakakis et al. (2018) is employed. The DCC-GARCH model has been a widely used method for estimating time-varying correlations in the literature, and it is preferred over the alternative BEKK-GARCH model because the latter often experiences difficulties with unreasonable parameter estimates. The following specification is used for the conditional mean equation:

$$r_t | \Omega_{t-1} \sim N(0, H_t)$$

$$H_t = D_t R_t D_t$$

$$e_t = D_t^{-1} r_t$$

Where r_t is a vector of returns for global sectoral stocks and alternative safe assets (gold and the US dollar) at time t. Likewise, the vector of residuals is shown by e_t and the information set at t-1 is given by Ω_{t-1}. The conditional-covariance matrix is depicted by H_t and $D_t = diag\{\sqrt{h_t}\}$, representing the diagonal matrix of conditional standard deviations at time t for the return series. The conditional standard of the return series is obtained from the symmetric GARCH (1,1) specification.

$$h_t = c + a\, e_{t-1}^2 + b\, h_{t-1}$$

here, h_t shows the conditional variance, while the ARCH and GARCH effects are captured through coefficients a and b.

Following Kroner and Sultan (1993) and Kroner and Ng. (1998), we use conditional variance and covariance estimates from the DCC-GARCH model to construct the optimal portfolio between the pairs of sectoral indices and alternative safe assets (gold and the US dollar). The fund allocation strategies with their corresponding diversification effectiveness are also computed from these estimates. Specifically, Kroner and Ng's (1998) method is employed as follows:

$$w_{c,t} = \frac{\sigma_{a,t}^2 - \sigma_{c,a,t}}{\sigma_{c,t}^2 - \sigma_{c,a,t}^a + \sigma_{a,t}^2}$$

with

$$w_{c,t} = \begin{cases} 0, if\ w_{c,t} < 0 \\ wca, t, if\ 0 \leq w_{c,t} \leq 1 \\ 1, if\ w_{c,t} > 0 \end{cases}$$

Where $\sigma_{c,t}^2$ and $\sigma_{a,t}^2$ are the conditional variance of sectoral stocks and alternate safe assets respectively. While $\sigma_{c,a,t}^2$ is the conditional covariance of sectoral stocks and alternative safer investments at time t. Further, $w_{c,t}$ gives the weight of a particular sector in a one-unit currency portfolio (say, one-dollar) at period t. And, finally, following Balcılar et al. (2016), the diversification effectiveness (D.E)

Table 4
Spillover asymmetry table.

	x_1^+- x_1^-	x_2^+-x_2^-	…	x_N^+- x_N^-	From
x_1^+- x_1^-	A_{11}	A_{12}	…	A_{1N}	A_{r1}
x_2^+-x_2^-	A_{21}	A_{22}	…	A_{2N}	A_{r2}
⋮	⋮	⋮	A_{ij}	⋮	⋮
x_N^+- x_N^-	A_{N1}	A_{N2}	…	A_{NN}	A_{rN}
To	A_{c1}	A_{c2}	…	A_{cN}	**Total** ***SAM***

Source: Author's representation with theoretical support drawn from Diebold and Yilmaz (2015) and Barunik et al. (2015)

through optimal portfolio weights selection strategy is given as[5]:

$$PE = \frac{Variance_{UD} - Variance_{D}}{Variance_{UD}}$$

Where $\boldsymbol{Variance_{UD}}$ is the variance of undiversified and $\boldsymbol{variance_{D}}$ is the variance of diversified assets.

4. Data description

Daily data of nine MSCI-based global sectoral indices for the period November 2012 through March 2022 are gathered from investing.com. The Consumer Disc (COND), Consumer Staples (CONST), Energy (ENR), Financials (FIN), Health Care (HLT), Industrial (IND), Materials (MAT), Telecom Services (TEL), and Utilities (UTL) are the nine strategic sectors that have been used as representatives of global sectoral stocks for the analysis. Their availability across sectors restricts the data range from their earliest period. Nonetheless, the late European Debt Crisis, the oil bust of 2014–15, the Brexit referendum of 2016, and the COVID-19 outbreak are accounted for. For estimation purposes, the continuously compounded daily returns are calculated by taking the first difference of their natural logarithms.

We begin the descriptive analysis as reported in appendix A by studying the evolution of the global sectoral returns in Fig. 2A. The return plots reveal relatively higher and extreme fluctuations across all the sectors during the early outbreak of the COVID-19 pandemic. The periods corresponding to the European debt crisis, the oil bust and the Brexit referendum also exhibit rapid price change. The descriptive statistics of the returns of sectoral indices are also presented in Table 1A. As is evident from the table, the average return for ENR is negative, whereas the average return is the highest for CONSD and HLT. The standard deviation as a measure of unconditional risk is highest for energy and lowest for CONST. It can, thus, be comprehended that the energy sector performs worst in terms of both the average risk and returns. The findings of Zhang and Hamori (2021) and Mensi et al. (2022) also confirm the poor performance of the energy sector through these attributes. The skewness and Kurtosis measures indicate that the return distribution of all the sectors is negatively skewed and leptokurtic. Subsequently, the Jarque-Bera (J-B) normality test is significant, reflecting the non-normality of return distributions. Finally, to ensure the stationary of all sectors for the VAR-based connectedness measurements, the Augmented Dickey-Fuller (ADF) and the Philips-Perron (PP) tests confirm their stationarity.

The unconditional pairwise correlations of various sectoral returns and scatter plots are presented in Table 2A. The correlation results and their respective scatter plots suggest a strong positive correlation between most of the sectoral returns. We, hence, expect a higher global sectoral connectedness that warrants the search for alternative assets that could be used alongside sectoral stocks to minimize the potential global sectoral risk. With these initial observations, we proceed with a more robust empirical exploration which is based on Diebold and Yilmaz's (2012) connectedness tools.

5. Empirical results and discussion

5.1. Symmetric connectedness measurements and their dynamics

Since the connectedness measurements are based on VAR, it is, therefore, important to use an appropriate lag length. As shown in Table 5, the optimal lag length for the symmetric VAR system using Final Prediction Error (FPE) and Akaike Information Criteria (AIC) is 3.[6] Various spillover and connectedness measurements are provided in Table 6 and Fig. 2. Specifically, the total spillover index, and directional (To and From) and pairwise spillovers are reported. For example, the total sectoral connectedness index is 80.10%. This means that the global stock market is highly connected at the sectoral level as the majority of the future uncertainty is explained by the cross-connectedness (or cross-spillovers). While, the remaining 19.90% of the sectoral variation is explained by the own-shocks, which are represented by the diagonal elements of Table 6. As an implication, this reflects a higher likelihood of the sectoral shock transmission in the global stock market, and thereby a concern for the financial market participants. Specifically, for institutional investors and fund managers, the management of sectoral risk by sectoral diversification is difficult. The directional spillovers (To and From) indicate that industrial, followed by the financials and basic materials are the largest transmitters and receivers of shocks. This means

[5] Diversification effectiveness is a proxy for the measurement of risk minimization capability.
[6] The empirical results remain almost insensitive to different lag lengths. The sensitivity analysis with different lags can be produced on demand.

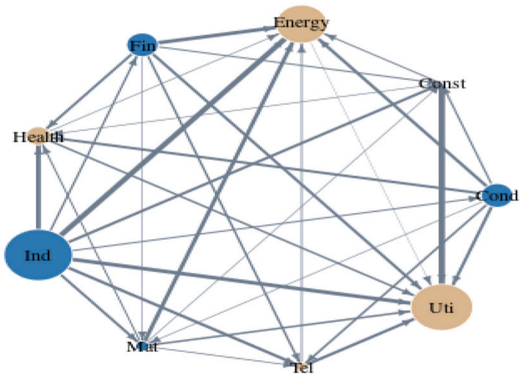


Fig. 2. Net Connectedness
Note: Blue (yellow) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents the weighted average net total directional connectedness. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 5
Lag length for the VAR-system.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	83290.35	NA	1.63e-41	−68.375	−68.35407*	−68.368
1	83570.23	557.4806	1.39e-41	−68.539	−68.325	−68.46091*
2	83676.14	210.1569	1.36e-41	−68.559	−68.152	−68.411
3	83770.89	187.3304	1.34e-41*	−68.57052*	−67.971	−68.352
4	83834.52	125.3278	1.36e-41	−68.556	−67.764	−68.268
5	83898.67	125.8749	1.38e-41	−68.542	−67.557	−68.184
6	83973.55	146.3716	1.39e-41	−68.537	−67.359	−68.109
7	84057.83	164.1366	1.38e-41	−68.54	−67.169	−68.042
8	84137.55	154.6668*	1.39e-41	−68.539	−66.975	−67.971

Table 6
Static symmetric connectedness table.

	COND	CONST	ENR	FIN	HLT	IND	MAT	TEL	UTL	From Others
COND	18.8	9.2	7.1	11.8	10.2	13.5	10.8	12.2	6.3	81.2
CONST	9.7	19.6	6.3	10	11	11.5	9.6	10	12.2	80.4
ENR	8.8	7.1	23.4	13.8	6.6	13.1	13.5	7.5	6.3	76.6
FIN	11.3	8.8	10.6	17.6	8.4	14.6	12.4	9.2	7.1	82.4
HLT	11.5	11.9	6.1	10.2	20.9	12	9.1	9.7	8.5	79.1
IND	12.2	9.6	9.4	13.6	9.3	16.6	12.6	9.2	7.6	83.4
MAT	11	8.9	10.8	12.9	8	14.1	18.5	8.8	7	81.5
TEL	13.3	10.4	6.7	10.8	9.4	11.4	9.7	20.1	8.3	79.9
UTL	7.8	14.4	6.7	9.6	9.2	10.8	8.9	9.3	23.3	76.7
To others	85.4	80.3	63.6	92.6	72.1	101.2	86.6	75.9	63.4	721.2
Total										**80.10%**
Net Directional	4.2	−0.1	−13	10.2	−7	17.8	5.1	−4	−13.3	

that the industrial and financial sectors are systematically important sectors and management of sectoral risk requires active monitoring of these sectors. The net-directional spillovers and net-pairwise spillovers as presented in the network graph of Fig. 2 also support these findings, as these sectors are the largest net transmitters of shocks (to others and to individual assets). Our empirical results authenticate the crude correlation results that indicate a possibility of higher global sectoral connectedness. This corroborates the revelations of Mensi et al. (2022) for the EU which suggests a higher level of sectoral connectedness, with the industrial sector dominating the shock transmission.

Having discussed the sectoral connectedness measurements in a static setting, we now proceed to discuss their time-varying counterparts. The investigation of time-varying spillover measures is potentially more revealing as the study period experienced various significant global events over time that has the potential to alter the connectedness structure. For example, the European debt crisis, the great oil bust of 2014–15, the Brexit referendum of 2016, and the COVID-19 pandemic could have changed the pattern of sectoral connectedness and spillover transmission over time. Therefore, following Diebold and Yilmaz (2012), we set the rolling window size equal to 200 and estimate the time-varying spillover measures for the global stock market at the sectoral level.[7]

The time-varying total spillover index, directional and net-directional spillovers are shown in Figs. 3–6. The total spillover plot indicates that the total global sectoral connectedness witnessed a structural increase during the crisis and distress events. Specifically, it is observed that global sectoral connectedness is stronger during the late European debt crisis (Shah et al., 2021), the Brexit referendum of 2016 (Mensi et al., 2021), the US-China trade war in 2018 (Shah et al., 2021) and the early COVID-19 pandemic in 2020 (Shah & Dar, 2022spillovers (To and From) also reflect a similar pattern, with the industrial sector dominating the spillover transmission to other sectors. The net-directional plots complement the empirical findings and show the industrial sector as the dominant net transmitter of shocks over time. The empirical findings are similar to Shen et al. (2021) and Mensi et al. (2022) whose findings conclude stronger sectoral connectedness during heightened financial uncertainty, probably driven by portfolio rebalancing for ensuring stable portfolio allocation.

5.2. Asymmetric connectedness measurements and their dynamics

We further provide asymmetric spillover measures for the total spillover index and directional spillovers (To and From). The asymmetric connectedness and spillover measurements are shown in Table 7, while their dynamic counterparts are presented in Fig. 7 through Fig. 9. The negative value of spillovers in Table 7 means that downside connectedness is higher than upside connectedness, reflecting asymmetric connectedness. However, if the value of the spillovers in Table 7 is equal to zero, this reflects the symmetric interdependence of financial markets in both the upside and downside markets.

It can be observed from Table 7 that the total spillover asymmetry measure is −4.60%. This implies that global sectoral connectedness is higher for negative information (downside market) than for positive information (upside market). In other words, it can be said that the nature of global sectoral connectedness is asymmetric. Likewise, the directional spillover measures (To others and From others) are also asymmetric. For example, the energy sector (−18.4%) followed by the financials (−6.3%) and health (−4.9%) receives higher spillovers from the system in the downside market than in the upside market. Similarly, they are the largest transmitters of spillover to the system in downside markets. In general, the results suggest asymmetric sectoral interdependence, which is similar to the findings of Mensi et al. (2021) and Maitra, Guhathakurta, and Kang (2021).

Further, the dynamic (or time-varying) asymmetric total spillover index as shown in Fig. 7 indicates that the downside connectedness outperforms upside connectedness during the late European debt crisis, the Brexit referendum of 2016, the US-China trade war in 2018 (Shah et al., 2021), the first and second wave of COVID-19 pandemic. The dynamic asymmetric directional spillovers from Figs. 8 and 9 also reveal that the spillovers from individual sector to other sectors (and vice-versa) is changing and mostly asymmetric during these aforementioned events. Therefore, it can be concluded that the nature of sectoral connectedness and spillover transmission across sectors is mostly asymmetric and changes over time, which is more pronounced during uncertain events. The empirical results support the revelations of Barunik et al. (2015) and Shah and Dar (2022) that demonstrate asymmetric connectedness and its domination in crisis events.

5.3. Sectoral risk reduction strategy with gold and the US dollar

Having provided evidence of higher sectoral connectedness and risk of shock transmission across sectors, it is, therefore, essential for the financial market participants to include safer assets for managing sectoral risks. Thus, in this section, we provide the measurement of connectedness, optimal weights, and the corresponding diversification effectiveness of safe assets (gold and the US dollar) with sector-specific stocks. Fig. 10 provides the total connectedness of different sectors without safe assets and with safe assets. It can be seen that the total sectoral connectedness without safe assets is higher (80.10%) than with safe assets (73.70%). Likewise, the directional spillover measures from Fig. 11 indicate that gold and the US dollar receive (and transmit) a relatively lower amount of spillovers from (to) the system. Therefore, it can be concluded from these results that gold and the US dollar are isolated from the sectoral stocks, and therefore has the potential to diversify the global sectoral risk.

Having provided the diversification and risk reduction potential of gold and the US dollar at the aggregate (or static) level, it is likely that the risk reduction characteristics of gold and the US dollar are changing over time. This is obvious given that various events, such as the European Debt Crisis (2010–2012), Brexit (2016), the US-China trade war (2018–20), and the recent COVID-19 (2020) pandemic were experienced during the said period. Thus, it is more logical and rational to investigate the global sectoral risk management potential of gold and the US dollar to account for the investor's sentiment during distress periods. Therefore, the time-varying overall connectedness of global sectors with and without alternative safe assets (gold and the US dollar) are provided in Fig. 12. And, it can be observed that the overall connection among the global sectoral indices is much lower when gold and the US dollar are also included in the portfolio. The inclusion of gold and the US dollar seems to be more beneficial during distress events in particular. This makes a strong case in favour of gold and the US dollar to be used as a potential diversifier of global sectoral risk when needed most.

Having presented the potential of gold and the US dollar to manage the sectoral risk, we finally assess the sectoral risk management of gold and the US dollar via optimal portfolio weights selection strategy by using the DCC-GARCH model of Engle (2002). We specifically estimate the pairwise optimal portfolio weights of alternative safe assets (gold and the US dollar) with sectoral stocks for the

[7] The results remain almost similar with varying rolling window sizes. The results can be produced on demand.

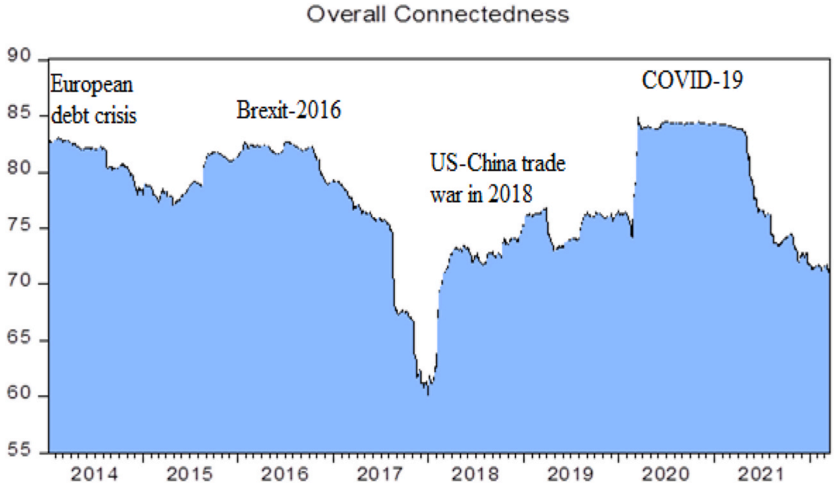


Fig. 3. Time-varying total Spillover Index.

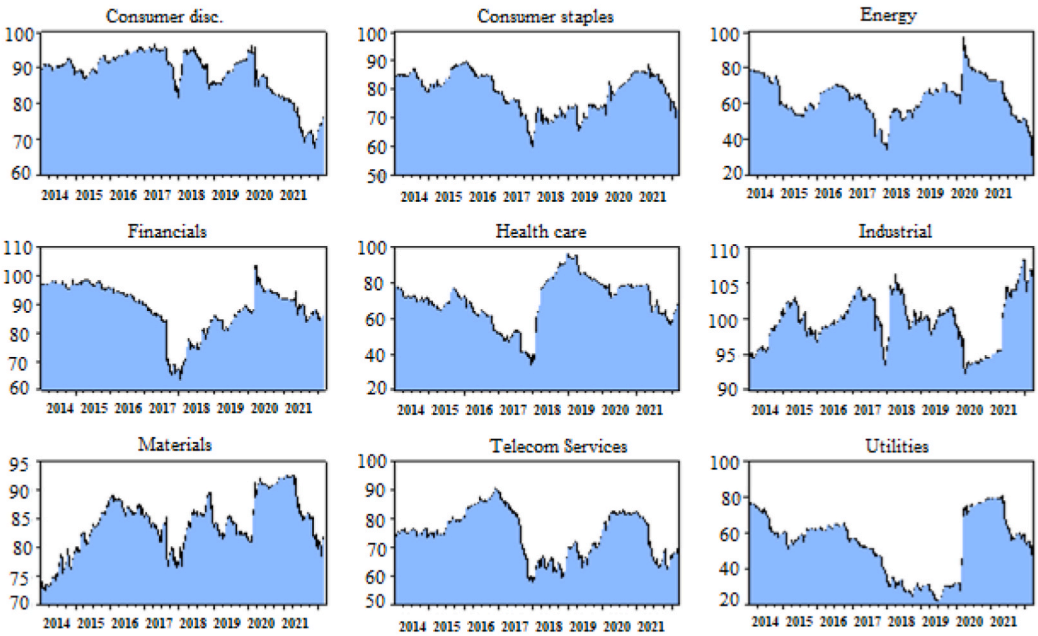


Fig. 4. To others.

full sample and sub-samples (pre-COVID and COVID). We opt for the sub-sample analysis to provide economic implications for the investors during the COVID period[8]. Table 8 reports empirical estimates of overall, pre-COVID-19, and during-COVID- 19 portfolio weights along with their risk management performance measured through H.E measure. The portfolio analysis as presented in Table 8 reveals that the portfolio weights of all pairs are greater than zero and less than one, meaning there is a diversification opportunity. Specifically, it can be seen that the range of the overall optimal portfolio weight is from 0.14 for energy and the US dollar to 0.71 for consumer staples and gold with their corresponding hedging effectiveness of 0.97% and 0.33% respectively. This implies that for a portfolio of 1 dollar of energy and the US dollar, 14 cents should be invested in the energy and the remaining 86 cents in gold which results in a risk reduction of 97%. Whereas, for the portfolio of 1 dollar of consumer staples and gold, 71 cents should be invested in consumer staples and the remaining 29 cents in gold which results in a risk reduction of 33%. Likewise, the US dollar is also outstanding as a diversifier against global sectoral risk. The sub-sample analysis that accounts for the distress period of COVID-19 shows that by increasing the weight of gold and the US dollar with the sectoral stocks in COVID-19, the sectoral risk management

[8] January 1, 2020, is chosen as the start of the COVID-19.

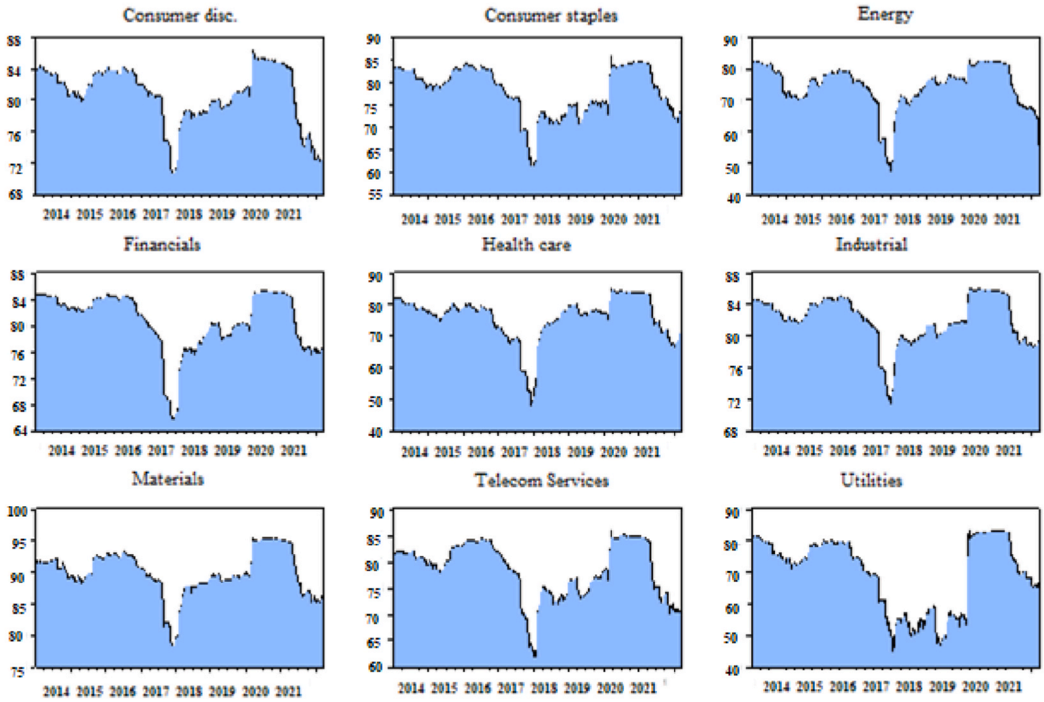


Fig. 5. From others.

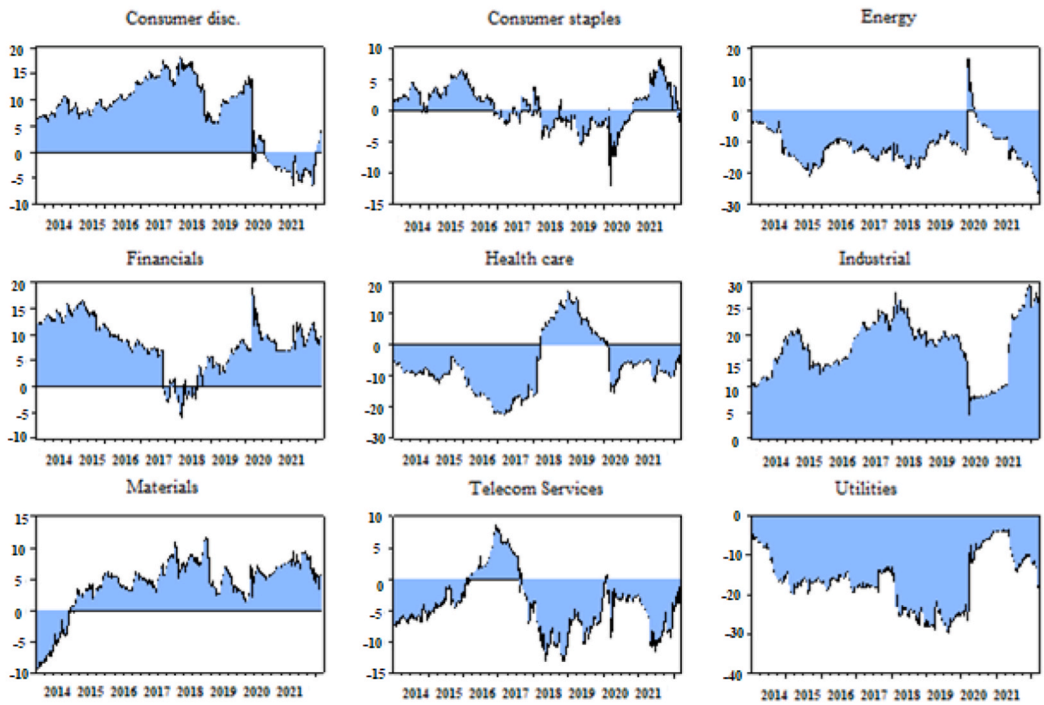


Fig. 6. Net-spillovers.

capability increases to the pre-crisis periods. In particular, the H.E of various pairs of portfolio increased in COVID-19 with an increase in the weight of alternative assets (gold and the US dollar). This is consistent with our time-varying connectedness results that reflect the diversification potential of gold and the US dollar in general and during distress periods, in particular.

Table 7
Spillover asymmetry measures.

	COND	CONST	ENR	FIN	HLT	IND	MAT	TEL	UTL	From Others
COND	3.6	−0.3	−2.6	−0.7	−0.3	0.1	0.4	0.1	−0.4	−3.6
CONST	−0.6	4	−3	−1.9	1.3	−0.8	−1.1	0.5	1.6	−4
ENR	−1.6	−2	9.3	0.6	−2.3	−0.2	−0.6	−1.4	−1.8	−9.3
FIN	−0.1	−1.5	−0.6	4.2	−1.8	1.6	0	−0.6	−1.2	−4.2
HLT	0.1	1.8	−3.1	−2.3	5.3	−1.6	−1.5	0.1	1.2	−5.3
IND	0.2	−0.7	−1.5	1	−1.3	2.8	0.7	−1	−0.3	−2.8
MAT	0.5	−1	−2.1	−0.4	−1.3	0.8	4	−0.5	−0.2	−4
TEL	0.2	0.7	−2.3	−1	−0.2	−1.1	−0.4	4.4	−0.4	−4.4
UTL	−0.6	1.9	−3.3	−1.7	1	−0.6	−0.3	−0.3	3.8	−3.8
To others	−1.8	−1.3	−18.4	−6.3	−4.9	−1.8	−2.7	−3	−1.2	−41.4
Total Spillover Asymmetry										−4.60%

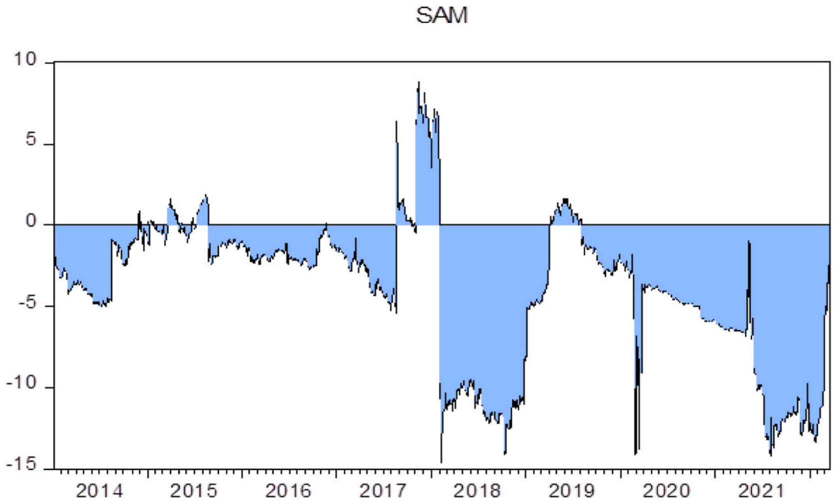


Fig. 7. Time-varying total spillover asymmetry index.

6. Conclusion and policy implications

Financial globalization, global sectoral portfolio rebalancing, and thereby the likelihood of sectoral shock transmission primarily motivates us to investigate global sectoral connectedness. Further, owing to the asymmetric interdependence of the financial markets, the asymmetric behaviour of its participants, and the potential impact of various global events, we explore the connectedness in symmetric and asymmetric settings over time. The connectedness and spillover measures of Diebold and Yilmaz (2012) and their asymmetric extension are used for the purpose. As an implication, the optimal portfolio strategies for the management of sectoral risk are also discussed.

The symmetric total and directional spillover measures indicate that the global stock market was highly connected at the sectoral level, reflecting the higher chance of sectoral shock transmission. For investors and fund managers, this means that the management of sectoral risk by sectoral diversification is difficult. The directional spillover measures reveal that the industrial sector, followed by the financials and basic material is the largest transmitter and receiver of shocks. This means that the industrial and financial sectors are the systematically important sectors and the stabilization of the financial market and management of sectoral risk requires active tracking of these sectors. The net-directional spillovers and net-pairwise spillovers support similar findings. Further, the asymmetric and time-varying spillover counterparts suggest that the global sectoral connectedness is asymmetric and at higher levels during uncertain periods. For example, the European debt crisis, the Brexit referendum of 2016, the US-China trade war of 2018, and the COVID-19 pandemic are characterized by asymmetric and relatively higher connectedness. Finally, we provide the sectoral-risk management strategy by including safe assets (gold and the US dollar). The overall and time-varying connectedness results indicate that the inclusion of gold and the US dollar has the potential to diversify the risk in general, and during the distress period in particular. To confirm this, the portfolio weights selection strategy of gold and the US dollar with sectoral stocks is explored. And, the results confirm the revelations that gold and the US dollar are preferable diversifiers of sectoral risk during distress periods.

Declaration of interest

We confirm that this work is original and has not been published elsewhere nor is currently under consideration for publication

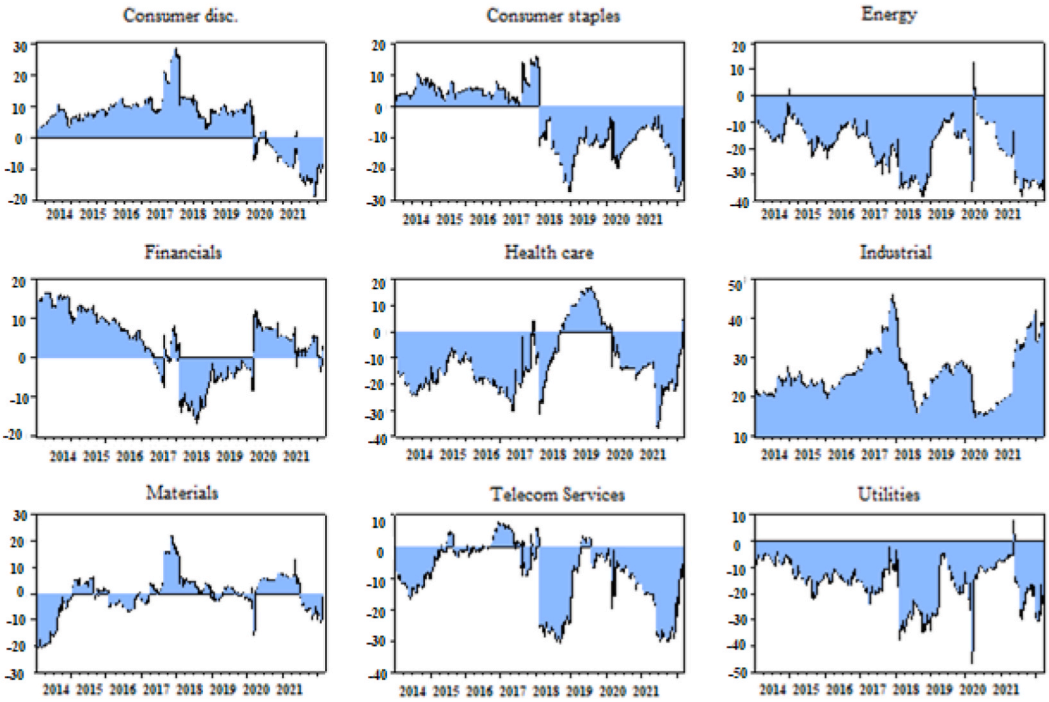


Fig. 8. Time-varying to spillovers asymmetry.

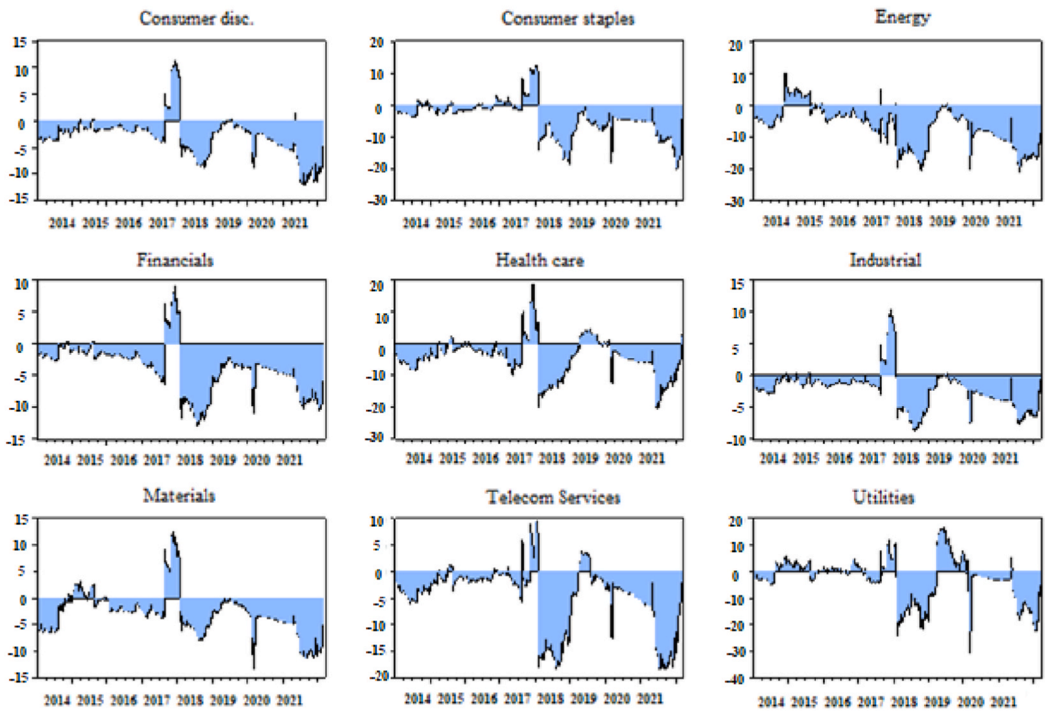


Fig. 9. Time-varying from spillovers asymmetry.

anywhere else. Further, we do adhere that if accepted, the research article will not be published elsewhere in the same form, in English or any other language without the written consent of the copyright holder. We also the research did not received any specific grant from any funding agencies in the public, commercial, or not-for-profit sectors. We declare that there are no conflicts of interest.

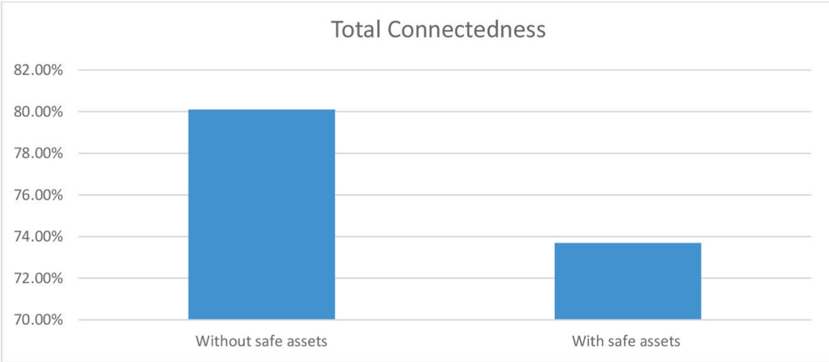


Fig. 10. Total connectedness with and without gold and the US dollar.
Source: Author's Own Calculation
(For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

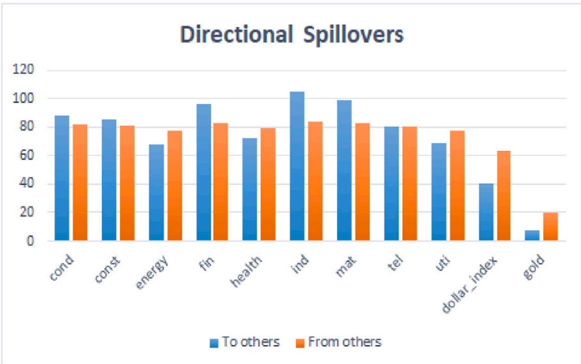


Fig. 11. Directional spillovers with gold and the US dollar.
Source: Author's Own Calculation
(For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

CRediT authorship contribution statement

Adil Ahmad shah: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Niyati Bhanja:** Conceptualization, Writing – review & editing, Supervision. **Arif Billah Dar:** Conceptualization, Writing – review & editing, Supervision.

Data availability

Data will be made available on request.

Appendix A

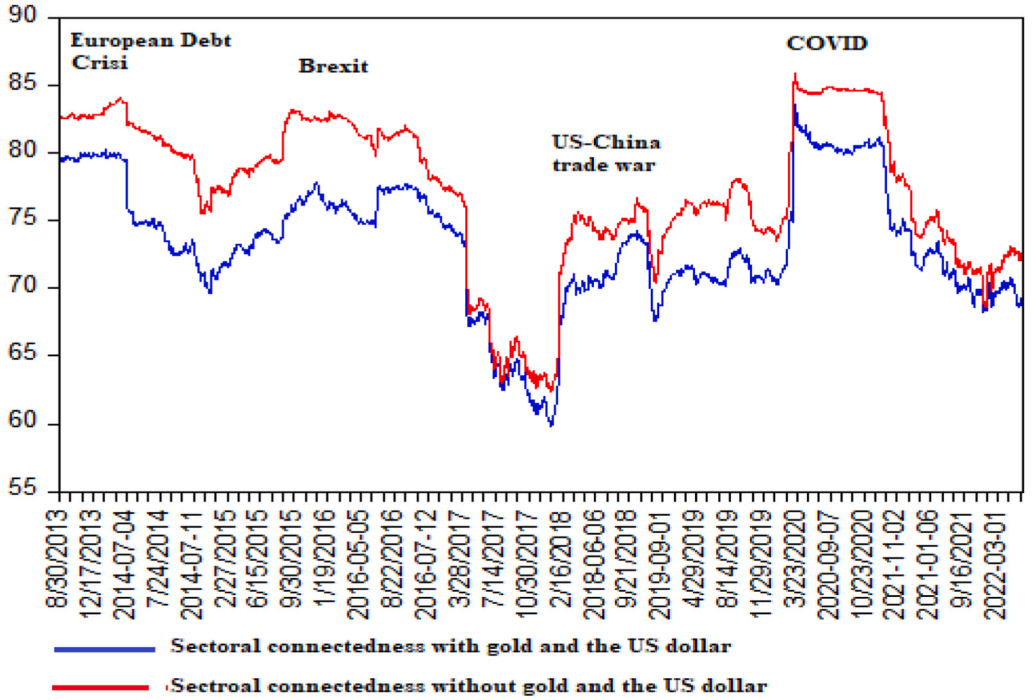


Fig. 12. Time-varying total spillover index with and without safe assets.

Table 8
Sectoral portfolio weights with gold and the US dollar.

	Overall weight (W)	H.E	Pre- COVID (W1)	H.E1	COVID (W2)	H.E2	P-value
Cond/gold	0.58	0.54	0.61	0.49	0.45	0.59	0.00
Cond/Dollar.Index	0.20	0.94	0.22	0.92	0.15	0.97	0.00
Const/gold	0.71	0.33	0.71	0.29	0.72	0.38	0.00
Const/Dollar.Index	0.26	0.91	0.26	0.89	0.25	0.95	0.00
Energy/gold	0.42	0.71	0.46	0.60	0.27	0.79	0.00
Energy/Dollar.Index	0.14	0.97	0.15	0.95	0.09	0.99	0.00
Fin/gold	0.56	0.61	0.58	0.52	0.47	0.70	0.00
Fin/Dollar.Index	0.19	0.95	0.20	0.92	0.61	0.98	0.00
Health/gold	0.60	0.48	0.60	0.48	0.62	0.47	0.00
Health/Dollar.Index	0.19	0.92	0.19	0.90	0.19	0.95	0.00
Ind/gold	0.61	0.52	0.63	0.44	0.54	0.60	0.00
Ind/Dollar.Index	0.22	0.94	0.22	0.91	0.19	0.97	0.00
Mat/gold	0.54	0.45	0.55	0.42	0.48	0.50	0.00
Mat/Dollar.Index	0.19	0.96	0.20	0.95	0.18	0.98	0.00
Tel/gold	0.61	0.47	0.63	0.40	0.50	0.53	0.00
Tel/Dollar.Index	0.21	0.94	0.22	0.91	0.15	0.96	0.00
Uti/gold	0.66	0.45	0.67	0.29	0.60	0.58	0.00
Uti/Dollar.Index	0.22	0.93	0.23	0.90	0.19	0.96	0.00

Note: All the portfolio weights are significant at 1% level of significance.

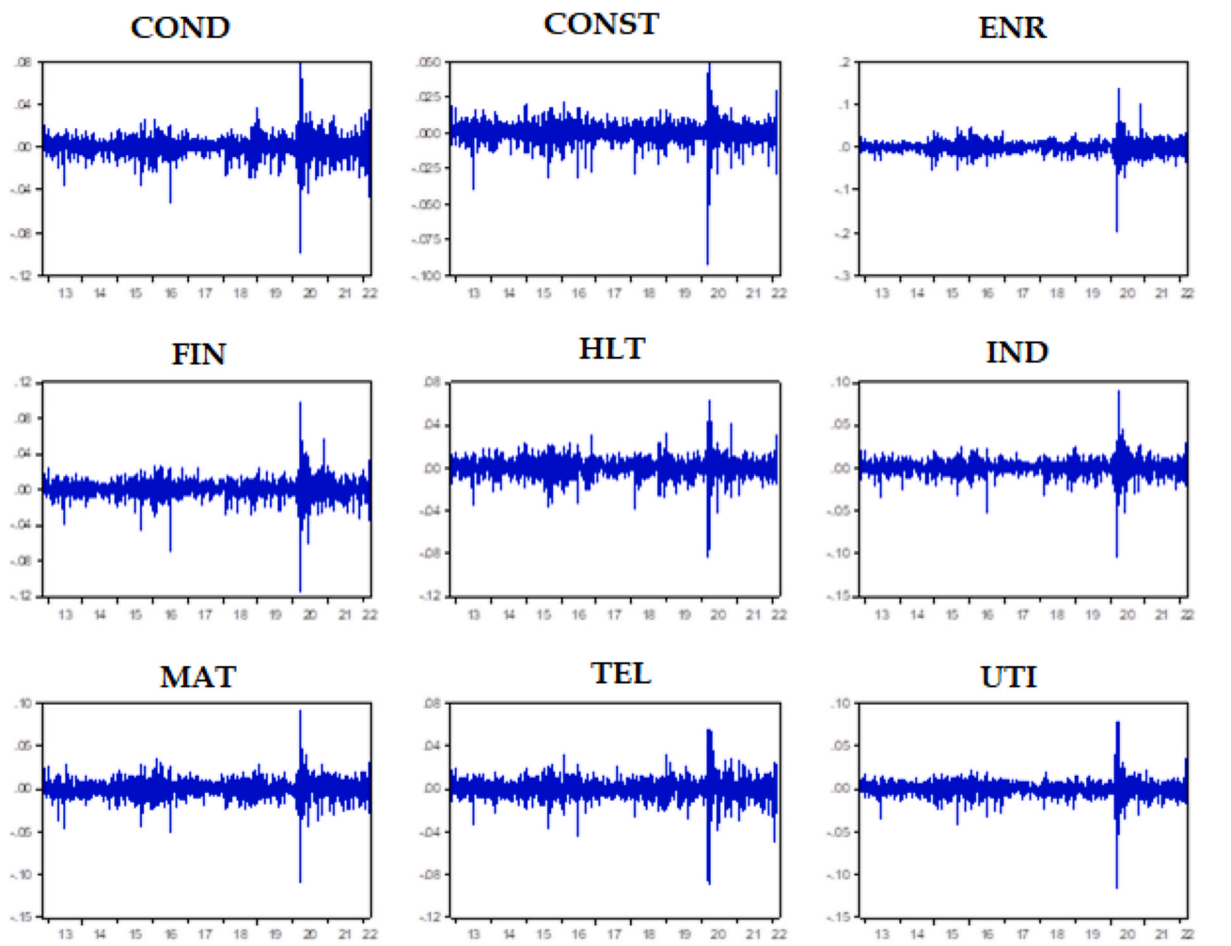
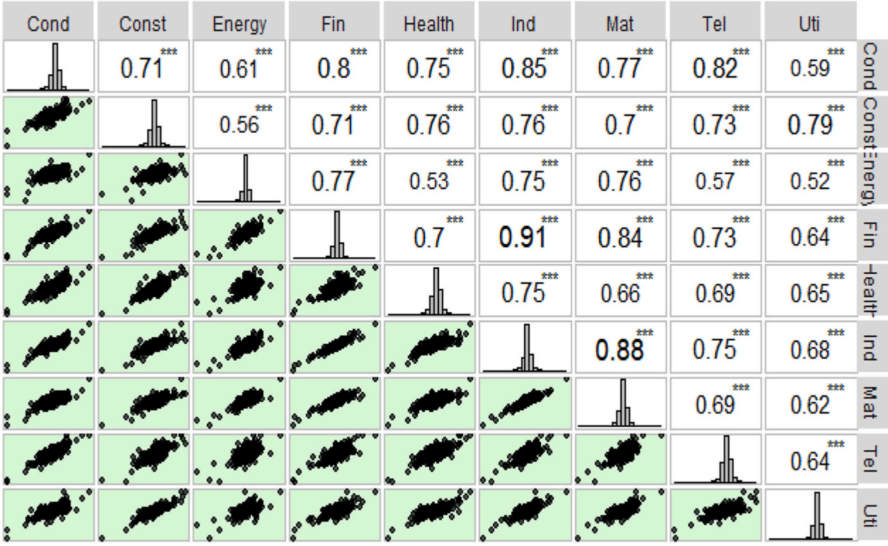


Fig. 1A. Evolution of Global Sectoral Returns.

Table 1A
Descriptive statistics for sectoral returns and unit root tests.

	COND	CONST	ENR	FIN	HLT	IND	MAT	TEL	UTL
Mean	0.0004	0.0002	−0.0001	0.0002	0.0004	0.0003	0.0002	0.0001	0.0002
Median	0.0008	0.0003	0.0001	0.0005	0.0006	0.0005	0.0004	0.0003	0.0005
Max	0.0786	0.0487	0.1395	0.0989	0.0627	0.0910	0.0927	0.0556	0.0793
Min	−0.0989	−0.0924	−0.1995	−0.1144	−0.0834	−0.1042	−0.1094	−0.0901	−0.1158
Std. De	0.0096	0.0071	0.0143	0.0103	0.0086	0.0091	0.0101	0.0088	0.0086
Skew.	−1.0380	−1.1715	−1.4939	−1.3692	−0.6087	−1.0324	−0.8908	−0.8957	−1.1312
Kurt.	17.5468	21.6471	32.3829	25.3882	13.8256	22.8126	16.4307	16.0679	30.7959
Jarque-Bera	21987.8800	35968.0800	88827.5400	51805.6200	12085.1000	40407.5700	18692.1800	17716.8000	79198.6700
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs	2444	2444	2444	2444	2444	2444	2444	2444	2444

Table 2A
Pairwise scatter plots and unconditional correlations of returns.



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