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Deciphering asymmetric spillovers in US industries: Insights from higher-order moments

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ABSTRACT

Incorporating higher-order moments, like realized volatility, skewness, and kurtosis, is crucial for understanding asymmetric asset pricing trends. Our research rigorously calculates static and dynamic higher-order moment spillovers across nine distinct US industries, using ultra-high-frequency data. We dive into the complex factors driving these spillovers, examining micro and macro-level factors. Our findings illuminate how higher-order moments are transmitted among these industries, particularly during disruptive global events with time-varying patterns. Notably, we discover that crash risk's persistence surpasses that of volatility risk, highlighting a significant divergence in market agents' asset pricing mechanisms. Importantly, firm-level risk factors significantly influence crash risk, showing an inverse relationship with industry-specific uncertainty. On the other hand, external macro-level risk factors directly impact the realized volatility of these industries. Our study's insights have substantial implications for various stakeholders, including investors, fund managers, policymakers, and financial regulators.

1. Introduction

Higher order moments are more informative in inferring asymmetries in asset pricing under extreme conditions of favour or adversity (Amaya et al., 2015; Jiang, 2013). The extant literature in finance focuses on the relationship between returns and volatility (second moment), ignoring the valuable information that is present in the higher moments like Skewness (third moment) that captures asymmetry; Kurtosis (fourth moment) that reflects tail and peak characteristics of the return distribution. Higher order moments contain vital information that can explain returns of risky assets/markets (See (Arditti and Levy, 1975; Ingersoll, 1975; Simkowitz and Beedles, 1978)), thus helps in pricing of risky assets (Christie-David and Chaudhry, 2001; Conrad et al., 2013; Dittmar, 2002; Doan

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et al., 2010). As actors and agents in the financial markets prefer to hold assets with low volatility, high and positive skewness, and low kurtosis (Ahmed and Al Mafrachi, 2021; Chang et al., 2013), we posit that connectedness in their higher order moments across asset markets will facilitate actors and agents holding portfolios that seeks higher premiums.

Studies examining the realized higher moments document strong linkages in their third and fourth moments among asset markets (Bonato et al., 2020; Do et al., 2016; Hasan et al., 2021); between cross-border markets (Bonato et al., 2022; Finta and Aboura, 2020). Studies at aggregate stock market level examining the realised higher order moments of realized volatility, realized skewness, and realized kurtosis asserts that actors and agents need to heed to adverse effects on asymmetric risk of investments (see for instance, (He et al., 2020; Liu and Zhang, 2015; Wang et al., 2020)).

This phenomenon can be extended to the industries since the tail risks of different industries are not equal and asymmetrical (Baruník et al., 2016) needs a careful examination of their higher order moments at skewness and kurtosis level. On a related note, (Hanif et al., 2021) documented zero tail dependence for financials, health care, and industrials sectors between United States of America (US) and China, whereas (Mensi, Hanif, Bouri, et al., 2023) reported symmetric tail dependence among US sectors with oil. However, studies on higher moments at the industry level are sparse and fragmented. They do not explain the factors causing its connectedness, thus motivating our study as it adds to the price formation and information transmission literature. Through this research, we intend to answer the following research questions: Are the U.S. industries stock returns interconnected in their realized higher order moments? If so, what are the plausible factors that causes the connectedness?

We attribute our research questions to the theoretical lens of Cumulative Prospect Theory, the Expected Utility Theory, and the Rank Dependent Utility Theory as evidenced from the literature (See e.g., Apergis, 2023; Barberis and Huang, 2008; Ebert and Karehnke, 2022). The linkages and spillovers in the higher order moments across US industries needs optimal attention as it leads to optimal risk management and asset pricing for actors and agents alike. The portfolio holdings of actors and agents will be calibrated to match their expectations about assets stemming from their preference (aversion) towards skewness and kurtosis.

1.1. Summary of the existing literature

During periods of stress, actors and agents will keenly observe the risk transmission across assets (industries) pronounced through their within-moment and cross-moment spillovers (Finta and Aboura, 2020), thus substantiating us to examine the connectedness in their higher-order moments. The novelty of our study is that we have estimated the higher-order moments viz., Realized Volatility, Realized Skewness, and Realized Kurtosis of nine United States of America (US) industries using 1-minute ultra-high frequency data. We computed the connectedness (static and time-varying total spillovers) of nine US industries in each of their higher-order moments. Furthermore, we explain the factors determining the higher moment connectedness (spillovers) by individually regressing the connectedness of the Realized Volatility, Realized Skewness, and Realized Kurtosis separately over the micro-firm level regressors (six Fama-French and Carhart factors); macroeconomic-level regressors (nine uncertainty indices); and including both micro & macro regressors. The whole analysis is conducted in the periods pre-Covid-19 and post-Covid-19. This effectively portrays the differential impact of micro and macro-level factors explaining the connectedness (spillovers) among the nine US industries granulated at their higher order moments before the Covid-19 and after the Covid-19 pandemic.

Ross (1989) argues that asset price variation equals variation in information under the direct influence of the rate of information flow. This is because new information rapidly gets adjusted in the asset markets. Thereby, asset prices vary with the uncertainty that affects cash flows. Transmission of uncertainty across markets occurs when common information and hedging strategies are shared, simultaneously shaping agent beliefs and expectations (Fleming et al., 1998). Such common information in the hands of agents and actors about short-term and long-term prospects of assets is plausible to cause underreaction or overreaction in prices (Jegadeesh and Titman, 1993).

The flow of information in extreme situations (i.e., shocks or “innovations” to the market, such as the global financial crisis, Covid-19, Russia-Ukraine war) can be observed as ’financial contagion.’ Contagion spreads from players’ responses and actions in the local interaction systems to the whole population (Morris, 2000). Financial contagions often manifest in the price of one asset fluctuating abnormally due to a shock in another asset, and this phenomenon passes from asset/market to asset/market (Allen and Gale, 2000). There is an interesting body of literature that examines spillovers and tail dependence during extreme events like Covid-19 (Mensi, Hanif, Bouri, et al., 2023; Mensi, Hanif, Vo, et al., 2023; Zhang et al., 2024); El Nino climate change (Wei et al., 2022, 2023). From a theoretical standpoint, the globalization of financial markets and their spillovers have providence on their economic growth (Chen, N., 1991) and macroeconomic risks (Sander et al., 2020). Thus, the expected market risk premium is conditional on the exposure to variations in higher moments and macroeconomic state variables (Chen, N., 1991). According to (Kodres and Pritsker, 2002), such phenomena are due to agents holding ’rational expectations’ and reducing their exposure to macroeconomic risks by revising their portfolios (containing multiple assets). Thereby, agents and actors look for macro signals at an aggregate level and micro information at the stock level (Chen. N., 1991; Glasserman and Mamaysky, 2022); expect variations arising out of macroeconomic uncertainty and industry characteristics get priced in the assets floated in the financial markets (Chiu et al., 2015; Segal et al., 2015). This concept is easily extendable to sectors and regions within one specific country, as well as those across borders facing similar macroeconomic risks or not (Allen and Gale, 2000; Kodres and Pritsker, 2002).

We posit that variations in higher-order moments arising out of macroeconomic risks will spillover to its sectors (industries) and stocks (Baruník et al., 2016; Bekaert et al., 2014); and the connectedness of the higher-order moments in their sectors is high economic value at macro and firm-level asset pricing (Acemoglu, 2012; Acemoglu et al., 2017; Nguyen et al., 2020). Eiling and Gerard (2015) has shown that industry convergence plays a prominent role in the local co-movements in developed equity markets, which is extended by (Hanif et al., 2023) to cryptocurrency, stock, and commodity markets. Firm-level systemic relevance is key to the stability of the

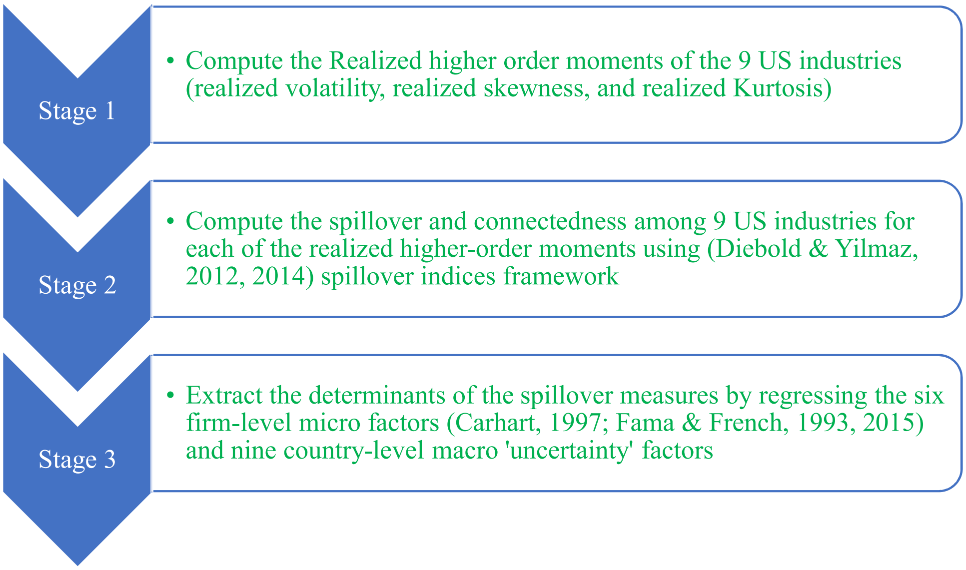


Exhibit 1. Schematic flow of our estimation methodology.

financial system. The connectedness among firms and industries can potentially churn micro-economic shocks into collective variations in asset markets (Branger et al., 2021). We argue that connectedness among the industries can help explain the sectoral spillover of higher-order moments.

Besides the extant literature on volatility connectedness between assets and markets[1] fresh evidence is required to develop parsimonious factor models for the covariance structure of equity returns (Andersen et al., 2001b). We posit a notable gap exists in empirically unearthing the nature and determining factors of the highly efficient proxy, viz., realized higher-order moments (Alizadeh et al., 2002) in a state-space framework, which we attempt to fulfil in this study through higher-order moments with ultra-high-frequency data. Hence, we are motivated to empirically analyze the sectoral (industrial) higher moment connectedness as it promises to provide valuable insights into the rate and magnitude of information flow, volatility and shock transmission, tail risk, peakiness, and propagation of financial contagion across the industries in the United States of America (US). With better data quality (Feng et al., 2020), the US stock market has a significant influence on the transmission of volatility to the local and global financial markets (Aggarwal et al., 1999; Bartram et al., 2012; Jansen, 2021), making it a center stage for research in volatility connectedness literature.

The extant literature is proliferated with studies on realized moments connectedness aggregated on markets[2] and between countries. Strikingly, studies unearthing underlying factors in the industry and firm-level settings are scarce (Christiansen et al., 2012), which brings novelty to our work. We differ from the works of (Barunik et al., 2016; Baruník and Čech, 2021) by extracting the macro aggregate-level and micro firm-level explanatory factors of the sectoral connectedness in each of the higher-order moments, viz., realized volatility, realized skewness, and realized kurtosis in US industries, which in our humble opinion is a notable novelty of our work and adds to the higher-order moments connectedness literature. Exh. 1

1.2. Our methodological framework in brief

Methodologically, we proceed in three stages.

First, we compute higher order moments with the 1-minute-high-frequency returns data for each of nine prominent US industries from 02 January 2014–30 September 2021. This stage is to estimate higher moment measures such as Realized Volatility (RV), Realized Skewness (RS), and Realized Kurtosis (RK).[3] More recently, (Apergis, 2023; Hanif et al., 2021; Nekhili et al., 2024) have applied the realized higher order moments measures in other asset markets and thus substantiating it to be contemporary and relevant.

Second, we compute the spillover and connectedness for each of the realized higher-order moments of the nine sample industries with the (Diebold and Yilmaz, 2012, 2014) spillover indices framework. This stage is to assess the varying connectedness between the realized higher-order moments. The (Diebold and Yilmaz, 2012, 2014) spillover indices we have applied is being widely used in the

[1] See (Andersen et al., 2001b; Andersen et al., 2003; Bates, 1991; BenSaïda and Litimi, 2021; Billio et al., 2012; Corradi et al., 2012; Fleming et al., 1998; Fry-McKibbin et al., 2014; Heston, 1993; Naeem et al., 2022) among others.

[2] For instance, (Hanif et al., 2023) reported that cryptocurrency, stock, and commodity markets are strongly connected through realized volatility, but a weaker connection is found in their realized skewness and realized kurtosis.

[3] These acclaimed model-free higher moment volatility measures were developed concurrently by (Amaya et al., 2015; Andersen et al., 2001a; Andersen et al., 2001b; Barndorff-Nielsen & Shephard, 2001, 2002).

asset markets connectedness literature, such as BenSaïda (2019), Naeem et al. (2022); and more recently by Hanif et al. (2021) and Nekhili et al. (2024)[4] thus demonstrating the relevance and effectiveness in addressing our research question.

Third, as a novel addition,[5] we regress each of the realized higher-order moment spillover measures on the factor variates of six firm-level micro factors (Carhart, 1997; Fama and French, 1993, 2015) and nine country-level macro 'uncertainty' factors to identify the influential factors explaining the sectoral higher-moment realized volatility connectedness. All three stages are performed on sample data before Covid-19 and post-Covid-19 to examine the effect of extreme events.

1.3. Contributions of our research

We discuss the contributions of our research here.

First, the higher-order moments contribute to the transmission of shocks across asset markets, channelled through their co-movements and amplified during periods like subprime and European debt crises (Fry-McKibbin et al., 2014). The association between volatility and spot prices of assets generates skewness, whereas, in the absence of association, it generates kurtosis (Heston, 1993). Investors tend to reassess these shocks occurring in one market with risks of other asset markets during an imminent financial crisis (Finta, 2022). Higher moments of return distributions (Volatility, Skewness, and Kurtosis) are relatively more prominent in developed markets. The stability in the financial system, policymaking, and portfolio choice is served better by examining the level of asymmetry through linkages in skewness and the spread of fat tail risk across sectors through linkages in their kurtosis (Do et al., 2016). For instance, the risk premium for skewness is attributed directly to the skewness in the asset price volatility (Bates, 1991). (Amaya et al., 2015) shows that high positive skewness attracts investors, albeit with low returns and high volatility, while negative skewness is compensated with higher returns. Realized Semi-variance provides better forecasts of future volatility. High-frequency data is rich with information about future volatility (Barunik et al., 2016) and apt for examining higher-order moments. Notably, studies on higher-order moments with high-frequency data are scant in the literature, and we contribute to this aspect.

The second contribution of our research is through the deployment of realized higher moments to the connectedness literature. The discontinuities or sudden variations in asset prices during extreme events are termed "jump risk." It is systematic and has significant economic implications for the actors and agents in the financial markets (Bates, 1991); associated with macroeconomic variates, the cross-section of returns, non-diversifiable risk premium, and portfolio choice (Johnson et al., 2022). Thereby, models that capture jump risk (jump-in-volatility) generate better realistic volatility dynamics and robust returns predictability (Jin, 2015). Standard latent volatility is more suitable for low-frequency data resulting in loss of information; it fails to capture information in the high-frequency data (Andersen et al., 2003). The seminal contributions of (Andersen et al., 2001b; Andersen and Bollerslev, 1998) paved the way for the empirical measure of variability termed Realized Volatility (RV) which is the sum of all squared returns in high-frequency intra-day data. RV and its components are more suitable for post-assessment of volatility and price jumps (Busch et al., 2011); improving forecasts of realized variance, determining risk premium and explaining the cross-section of returns (Feunou and Okou, 2019). These features make realized volatility more suitable for forecasting the connectedness among the asset markets since RV extracts more economic value (Ma et al., 2018) and is more efficient with high-frequency data (Han and Park, 2013). The realized volatility estimates have the merits of being asymptotically free from model specification and measurement errors (Andersen et al., 2001a, b). The RV can measure, model, and forecast stochastic volatilities of high-frequency returns (Andersen et al., 2003; Barndorff-Nielsen and Shephard, 2002). Asset market linkages in the developed markets are more pronounced through the spillover of realized volatility via their second and third-order moments (Do et al., 2016). Our second contribution to the literature is our volatility estimates based on the realized higher moment measures.

As a third contribution of our research, we note that there are very few studies examining the higher-order moments of sectors (industries). Notable exceptions are (Bonato et al., 2020; Ma et al., 2018; Zhang et al., 2022). Industry-specific shocks affect co-movements in sectoral stock market indices (Dutt and Mihov, 2013). The heterogeneity in the higher-order moments can be better captured by examining their spillovers. In our study, the connectedness among the realized daily higher moments is analyzed using the (Diebold and Yilmaz, 2012, 2014) spillover indices framework. Their spillover framework is based on a generalized Vector Auto Regression (VAR) approach of (Koop et al., 1996; Pesaran and Shin, 1998). It measures total connectedness caused by the shocks to the moments of random variables in the dynamic VAR system. This measure is widely preferred for examining connectedness as it is dynamic, directional, and delivers the content in a single spillover measure that is highly informative (BenSaïda, 2019). It is dynamic as it can measure the extent of higher-order moments connectedness in the time domain. It is directional since it traces the origin of the spillover transmission, thus indicating the contributors to the higher-order moments connectedness using the normalized elements of the generalized variance decomposition matrix (Baruník et al., 2016). Also, its forecast error variance decomposition is immune to variable ordering bias (Antonakakis et al., 2016). As a third contribution, we take a different look by identifying the directional spillover in the higher-order moments of US industries using the (Diebold and Yilmaz, 2012, 2014) spillover indices framework.

The fourth contribution of our research stems from the pandemic context. Extreme events create jump risks and increase idiosyncratic tail risks in financial markets (Bégin et al., 2019). Covid-19, as an extreme black swan event, had devastating disruption on

[4] See for bank networks (Demirer et al., 2018); foreign exchange markets (Bubák et al., 2011); sovereign credit default swap markets (Bostanci and Yilmaz, 2020); cross-sector spillovers in US credit markets (Collet and Ielpo, 2018); interconnectedness between financial and real economy sectors in the US (Uluceviz and Yilmaz, 2021); volatility from EPU and US housing sector spillover to US stock market (Antonakakis et al., 2016) among others.

[5] More information is provided in the fifth contribution of our research.

the sovereign states and financial markets (Haddad et al., 2021). (Augustin et al., 2022) show that the financial markets penalized countries with low fiscal capabilities owing to shocks in economic growth and sovereign default risk. According to Falato et al., (2021) and Jiang et al., (2022), financial assets and markets that experienced high fragility before COVID-19 experienced higher return volatility during the crisis. At the firm level, for instance, Elenev et al., (2022) show that firms with fragile leverages in their balance sheets warranted government bailouts in the financial and banking sector. Further, Ding et al., (2021) found evidence that firm characteristics like cash holdings, debt ratio, profit margins, global supply chain networks, and managerial ownership have significantly altered stock returns and volatility during the covid-19 pandemic. Our sample period extends to the period of the Covid-19 crisis. Thereby, as our fourth contribution, the sectoral higher-order moment's connectedness in the US during the Covid-19 crisis is a valuable addition to the literature.

The fifth contribution of our research arises from the dissection of the factors that causes connectedness in the sectoral higher-order moments of US industries. Uncertainty is the conditional volatility of a disturbance unforecastable by the agents (Jurado et al., 2015) and implicates agents' behavior in asset pricing (Brogaard and Detzel, 2015). Thereby, extreme shocks (like Covid-19, and the Russia-Ukraine war, to name a few) to the system shoot up uncertainty in the asset markets (Bloom, 2009) and increase the volatility in the connected markets. Financial shocks induced by uncertainty thus transmit significantly to the observed dynamics of real and financial variables at the micro (firm) level (Gulen and Ion, 2016; Jermann and Quadrini, 2012). Thus, observable macroeconomic variances play a role in determining asset prices with behavior and rational expectations (Cox et al., 1985). To empirically explain the connectedness among the higher-order moments in US industries, we regress each of the higher-order moments' connectedness on the factors from acclaimed asset pricing models suited for global markets and the US market in particular. To explain the variations in average returns from a micro-level firm perspective, we use the five factors (Fama and French, 1993, 2015) proxying for Risk Premium, Size, Book to Market, Profitability, and Investment. Globally and in the US market, the five-factor model has provided robust empirical results in asset pricing (Fama and French, 2017).

The extant literature shows the relevance of factor models in volatility spillover and asset pricing.[6] Additionally, to capture the short-term persistence in stock returns, we include a sixth factor, the One-Year Return Momentum Portfolio as proposed by (Carhart, 1997). The Momentum factor manifests 'abnormal returns' as it involves a sluggish response of prices to firm-specific information (Jegadeesh and Titman, 1993). We posit that higher-order moments arising out of macroeconomic uncertainty will spillover to its sectors (industries) and stocks (Baruník et al., 2016; Bekaert et al., 2014); and the connectedness (each of higher order moments) in their sectors is of high economic value at macro and firm-level asset pricing (Acemoglu, 2012; Acemoglu et al., 2017; Nguyen et al., 2020). Therefore, we extend our regression model to incorporate nine country-level 'uncertainty' factors that reflect the information on the macro-economy and are publicly available. These Uncertainty factors at the macroeconomic level include CBOE implied volatility indices proxying oil, gold, Eurocurrency, Options, interest rate spread; at the public information level, we include uncertainty indices like Economic Policy, Disease tracker, and Geopolitical risk. Our motivation to include these nine uncertainty factors is to resemble a state-space framework (in our case, realized higher order moments) in which asset prices are dependent on macroeconomic factors and publicly available information (Andersen et al., 2005; Fleming et al., 2006). The literature finds that state-space variables, including priced factors (as above), are better capable of predicting (forecasting) the variations in stock market returns (Chen, N., 1991; Flannery and Protopapadakis, 2002).[7] Our fifth contribution lies in the macro and micro-level explainable factors contributing to the connectedness in the higher-order moments among the US industries.

1.4. Key findings

We summarize the results of our research here. Our results show that related industries in the US show the presence of higher-order moment connectedness in their volatilities.

First, financial and related industries are large transmitters of risk to the real industries in the US economy.

Second, we document time-varying total connectedness among US industries, thus interpreted as increased volatility risk and contagion during the episodes of extreme events like Covid-19 and the BREXIT referendum. Although, the jump/crash risk transmission extends further than volatility risk, which allows us to imply the dichotomy in risk pricing among agents in the US market.

Third, similar to total connectedness, the time-varying net connectedness reinforces the financial industry as the net propagator of risk spillover to other industry sectors in the US. Interestingly during the first wave of Covid-19, the financial sector subsided, whereas Technology, Telecommunications, Health Care, and Utilities sectors rose to prominence as net transmitters of volatility. This finding is plausible as the Covid-19 stimulus packages averted panic in the US financial sector but not in the other sectors. Consistency and business continuity amidst the pandemic lockdown benefitted the jump/crash risk profiles. The static connectedness results remain identical to the net connectedness. In the post-covid period, the connectedness in jump risk got aggravated. Notably, the Telecommunications industry sustained the risk profile.

[6] (Fama and French, 1993, 2015, 2017) show that five common risk factors explain the shared volatility in the asset markets at the local and global level; (Bali and Zhou, 2016) show that market and uncertainty factors, along with size, book-to-market, momentum, and industry factors, contribute significantly to asset pricing; (Guo and Savickas, 2008) show that Value premium and Book-to-market factor explains stock price volatility; (Chen and Petkova, 2012; Durand et al., 2011) show the relevance of fear and volatility factor and Fama-French factors in asset pricing; (Brogaard and Detzel, 2015) show that EPU is a significant risk factor and significantly affects the risk premiums of market factors; (Jansen, 2021) shows the global interdependence factor in US financial market, among other studies.

[7] Through this paragraph, we justify the rationale for using the independent variables in our regression equation (Eq.10).

Table 1
Descriptive statistics for Realized Volatility (RV), Realized Skewness (RS), and Realized Kurtosis (RK).

RV	Enrgy	Finan	Hlth	Indus	Matr	REIT	Tech	Tele	Util
Mean	0.000039	0.000014	0.000011	0.000011	0.000016	0.000011	0.000025	0.000016	0.000010
Std.Dev.	0.000107	0.000049	0.000028	0.000035	0.000043	0.000045	0.000067	0.000042	0.000031
Skewness	8.443	9.609	9.471	9.828	9.886	9.568	11.258	10.618	9.780
Kurtosis	88.447	114.933	108.980	126.693	122.551	111.253	174.569	139.161	125.931
JB	660497[a]	1106165[a]	996719[a]	1339020[a]	1255286[a]	1038093[a]	2523757[a]	1614302[a]	1323040[a]
ARCH	818.083[a]	597.116[a]	999.469[a]	710.461[a]	699.921[a]	750.284[a]	1141.084[a]	1102.308[a]	640.576[a]
Q(20)	11521.594[a]	7649.730[a]	9522.599[a]	6342.058[a]	6085.705[a]	7720.119[a]	8006.022[a]	11225.575[a]	11020.817[a]
RS	**Enrgy**	**Finan**	**Hlth**	**Indus**	**Matr**	**REIT**	**Tech**	**Tele**	**Util**
Mean	0.988	2.919	4.558	4.433	3.916	1.960	6.908	0.399	0.464
Std.Dev.	23.633	28.118	30.774	35.938	31.455	29.505	49.528	22.233	22.410
Skewness	0.213	0.289	0.205	0.203	0.224	0.034	0.040	-0.073	0.099
Kurtosis	4.457	2.471	2.606	1.214	1.721	3.216	0.766	4.663	5.418
JB	1635.350[a]	525.653[a]	568.052[a]	134.102[a]	258.478[a]	844.309[a]	48.729[a]	1775.338[a]	2397.372[a]
ARCH	287.423[a]	273.868[a]	170.321[a]	253.248[a]	161.316[a]	172.238[a]	164.665[a]	39.091[a]	159.972[a]
Q(20)	20.530[a]	18.599[a]	20.236[a]	10.851[a]	23.382[a]	27.463[a]	16.289[a]	18.555[a]	47.140[a]
RK	**Enrgy**	**Finan**	**Hlth**	**Indus**	**Matr**	**REIT**	**Tech**	**Tele**	**Util**
Mean	1181.734	1555.995	1901.358	2342.449	1916.467	1700.883	3859.914	1140.360	1159.393
Std.Dev.	2126.719	2411.332	2911.090	3151.694	2717.358	2723.082	5032.746	1944.241	2046.953
Skewness	3.198	2.642	2.481	2.175	2.399	2.881	1.509	3.354	3.330
Kurtosis	11.786	8.270	6.792	5.281	6.714	9.398	1.413	14.554	13.720
JB	14652.782[a]	7848.670[a]	5764.926[a]	3814.931[a]	5549.214[a]	9901.290[a]	904.783[a]	20925.927[a]	18951.400[a]
ARCH	209.661[a]	253.149[a]	131.867[a]	243.836[a]	120.267[a]	156.326[a]	101.374[a]	34.178[a]	112.539[a]
Q(20)	1418.611[a]	1043.175[a]	539.372[a]	1044.647[a]	476.059[a]	690.089[a]	606.847[a]	53.454[a]	518.792[a]

Note: The table indicates the descriptive statistics for RV, RS, and RK for 9 US Industries. Energy (Enrgy), Financials (Finan), Health Care (Hlth), Industrials (Indus), Materials (Matr), Real Estate Investment Trust (REIT), Technology (Tech), Telecommunication (Tele), and Utilities (Util) for full sample period (2/01/2014–30/09/2021).
JB is the Jarque–Bera normality test. Q(20) refers to the Ljung-Box test for autocorrelation of the return series. The ARCH test checks the existence of the ARCH effect.
[a] indicates significance at 1%.

Fourth, our regression analyses show a better predictive capability of the priced macroeconomic risk factors. They inarguably determine the realized volatility risk of US industries than the firm-level six factors inter alia. In contrast, the jump/crash risk is best determined by firm-level and uncertain factors. Interestingly, we find that the internal factors of uncertainty have an inverse effect implying cross-market rebalancing in the interconnected US industrial networks. In comparison, we find that external risk factors have a direct and relatively limited impact on the realized volatility connectedness among US industries. Relatively, commodities like gold and oil transmit a higher jump/crash risk to the US industries than the other financial variables. We found a dual impact of Covid-19 stimulus packages among the US industries, reasoned through the worsening jump/crash risk in Gold and Oil commodities.

Our study will be relevant to regulators, policymakers, economic agents, portfolio managers, and investors. It helps investors to diversify their portfolios and reduce their exposure to extreme events or market shocks. For instance, investors averse of tail risk may invest in assets with comparatively higher realized skewness or realized kurtosis thus resulting in higher value and implying a lower expected return to suffice. Risk managers can utilize the higher order moments connectedness measures to track the asset market contagion and identify of assets vulnerable to risk. Furthermore, policymakers can use higher-order moments to design and implement effective macroprudential policies and regulations, thereby disentangle plausible sources of systemic instability in financial markets and proactively control fragile markets.

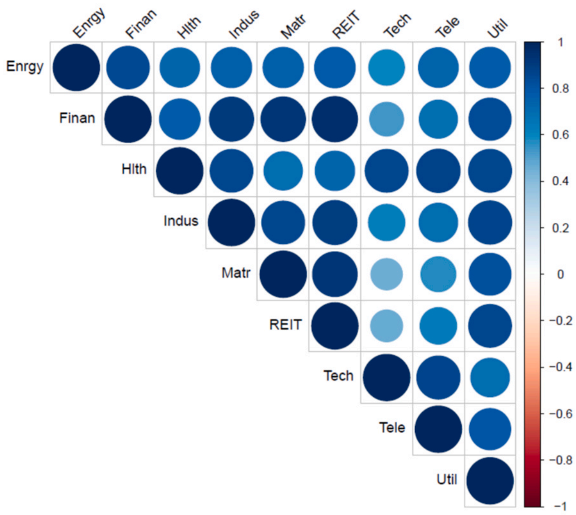
The remainder of this paper is structured as follows: methodology is detailed in Section 2, data and descriptive statistics are presented in Section 3, empirical findings and discussion are depicted in Section 4, and our conclusion is in Section 5.

2. Methodology

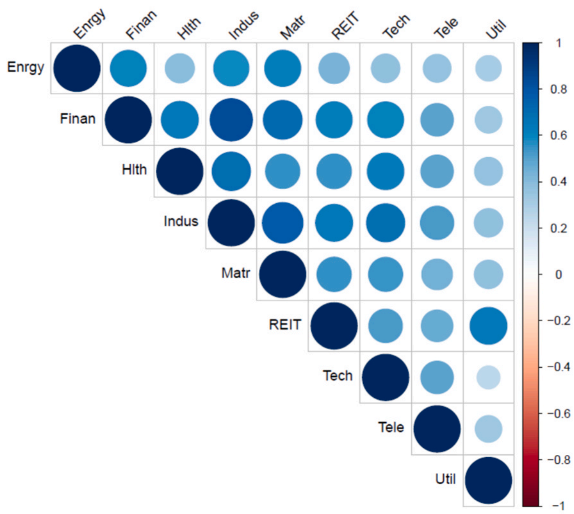
The empirical methodology incorporates analyses of volatility connectedness across nine (9) US industry sectors: namely, Energy (Enrgy), Financials (Finan), Health Care (Hlth), Industrials (Indus), Materials (Matr), Real Estate Investment Trust (REIT), Technology (Tech), Telecommunication (Tele), and Utilities (Util). The purpose of volatility is to ascertain the direction and magnitude of information flow between assets/markets. Ross (1989) argues that the volatility of asset prices is under the direct influence of the rate of information flow. Transmission of volatility across markets occurs when common information as well as hedging strategies are shared, simultaneously shaping agent beliefs and expectations (Fleming et al., 1998).

The flow of information in extreme situations (i.e., shocks or "innovations" to the market such as the GFC) can be observed as 'financial contagion'. Financial contagions are often manifest in the price of one asset fluctuating abnormally due to a shock in another asset, and this phenomenon passing from asset/market to asset/market (Allen and Gale, 2000). Such phenomena, according to Kodres and Pritsker (2002), are due to agents holding 'rational expectations' and reducing their exposure to macroeconomic risks by revising their portfolios (containing multiple assets). This concept is easily extendable to sectors and regions with one specific country, as well as those across borders facing similar macroeconomic risk or not (Allen and Gale, 2000; Kodres and Pritsker, 2002). This motivates an

a) Realized Volatility (RV)



b) Realized Skewness (RS)



c) Realized Kurtosis (RK)

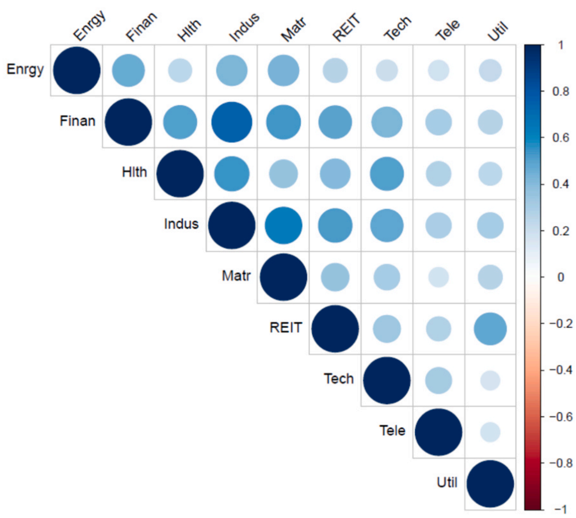


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Fig. 1. Correlation matrix a) Realized Volatility (RV), b) Realized Skewness (RS), c) Realized Kurtosis (RK), Note: This figure shows the correlation matrix among US industries using RV, RS, and RK.

empirical analysis of sectoral higher moment connectedness as it promises to provide valuable insights about the rate and magnitude of information flow, volatility and shock transmission, and risk and propagation of financial contagion across the US industries.

We use 'high frequency' firm-level data to estimate higher moment connectedness measures: Realised Volatility (RV) as well as such as Realised Skewness (RS) and Realised Kurtosis (RK). Developed concurrently by Andersen et al. (2001a),b) and Barndorff--Nielsen and Shephard (2001), (2002), the realised volatility/variance is an observed (*ex post*), unbiased estimator of the 'underlying latent volatility' of a time series process. It is often computed by summing the squared returns (r) and cross-products of high frequency, intra-day returns data (Andersen et al., 2001b). The resultant daily covariance matrix for the 1-minute returns can be outlined as,

$$\mathrm{Cov}_t = \sum_{j=1}^{\frac{1}{\Delta}} r_{t+j\Delta,\Delta} r'_{t+j\Delta,\Delta} \tag{1}$$

here, Δ is the number of 1-minute transactions recorded in one day. The daily realised variances—the proxy for RV—can be obtained from the diagonal elements of this covariance matrix, $RDVar_t = v_{j,t}^2 = \{Cov_t\}_{j,j}$. The relevant logarithmic standard deviations are given by $lv_{j,t} = \log(v_{j,t})$. The realised volatility estimates have the advantage of being free from model specification and measurement errors (Andersen et al., 2001a, b). The RV can be used to measure, model, forecast stochastic volatilities of high frequency returns (Andersen et al., 2003; Barndorff-Nielsen and Shephard, 2002).

There are often abnormal fluctuations observed when new information (shocks) hits the markets (i.e., the GFC, COVID-19 pandemic, Russian invasion of Ukraine, etc.) (. This phenomenon is described as a jump process and follows a non-continuous trajectory due to the information's 'non-marginal impact' (Merton, 1976). Bates (1991) posits that the distributional attributes of stocks indicate a 'marked change' at the onset of a crash—in particular, the October 1987 stock market crashes across the globe. A jump (or crash) risk is often exhibited by substantial positive magnitudes of skewness and excess kurtosis in the immediate pre- as well as post-crash periods (Bates, 1991, 1996).

Thus, it is useful to analyse the third and fourth moments—skewness and kurtosis—to gain insights on their inherent jump risks, especially for asset pricing (Neuberger, 2012). However, the third and fourth moments are often difficult to measure precisely. To overcome this, Amaya et al. (2015) formulate the realized or *ex post* measures of the skewness and kurtosis of the intra-day stock returns. The realised daily skewness—the third moment—is computed by standardising the intra-day returns using the realised variance ($RDVar_t$).

$$RDSkew_t = \frac{\sqrt{\frac{1}{\Delta}} \sum_{j=1}^{\frac{1}{\Delta}} r_{t+j\Delta,\Delta}^3}{RDVar_t^{\frac{3}{2}}} \tag{2}$$

The realised daily kurtosis ($RDKurt_t$) measures allows us to gauge the extremes of the returns distribution as well as ex post market perception of jump/crash risk. Computation of $RDKurt_t$ also involves standardisation of the intra-day returns using the realised variance ($RDVar_t$), albeit differently.

$$RDKurt_t = \frac{\frac{1}{\Delta} \sum_{j=1}^{\frac{1}{\Delta}} r_{t+j\Delta,\Delta}^4}{RDVar_t^2} \tag{3}$$

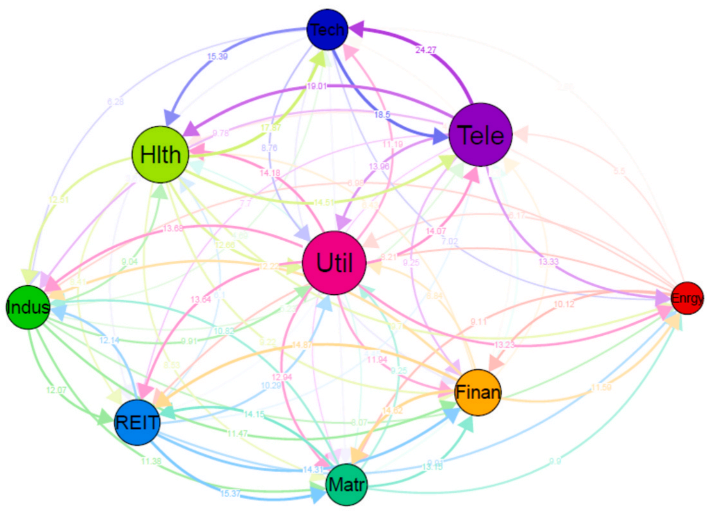
The computed realised daily higher moments are then used to perform connectedness analysis using the methodologies of Diebold and Yilmaz (2012), (2014). The basis of the connectedness measures involves estimating a generalised N-variable Vector Autoregression (VAR) model. The N-variable VAR(p) is covariance stationary and expressed as $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$ where error term $\varepsilon \sim (0, \Sigma)$ is identically and independently distributed (iid). The resulting Moving Average (MA) process from this VAR(p) model incorporates infinite lags: $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$. Here, A_i is an $N \times N$ coefficient vector satisfying the recursive process $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 as an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. Diebold and Yilmaz (2012) argue that deciphering the underlying dynamics of the system are based largely on the moving average coefficients.

The orthogonality of the VAR model innovations are achieved through availing the generalised VAR framework of Koop et al. (1996) and Pesaran and Shin (1998). The *cross-variance shares*, or *spillovers*, are denoted as the fraction of H-step-ahead forecast error variance of x_i that originate from the shocks in x_j, where $i, j = 1, 2, \ldots, N$ and $i \neq j$. The forecast error variance decomposition ($\theta_{ij}^g(H)$)—based on Koop et al. (1996) and Pesaran and Shin (1998)—for the H-steps-ahead is identified as,

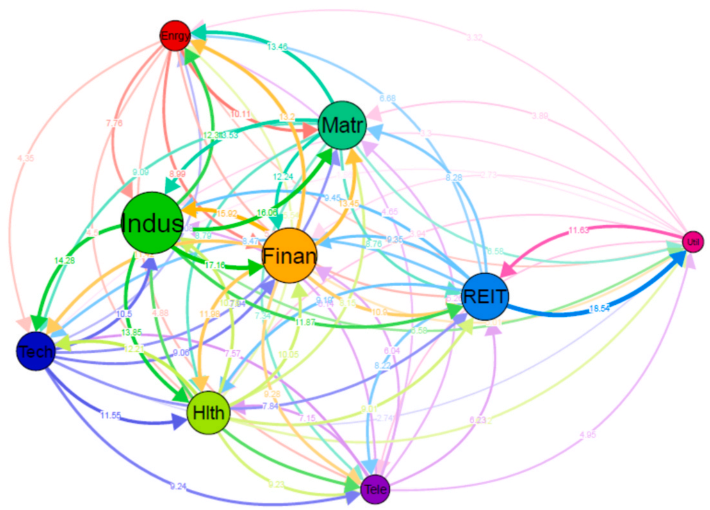
$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)^2} \tag{4}$$

here, Σ represents the variance matrix of the error vector ε, σ_{jj} represents the jth equation's error term's standard deviation, and e_i

a) Realized Volatility (RV)



b) Realized Skewness (RS)



c) Realized Kurtosis (RK)

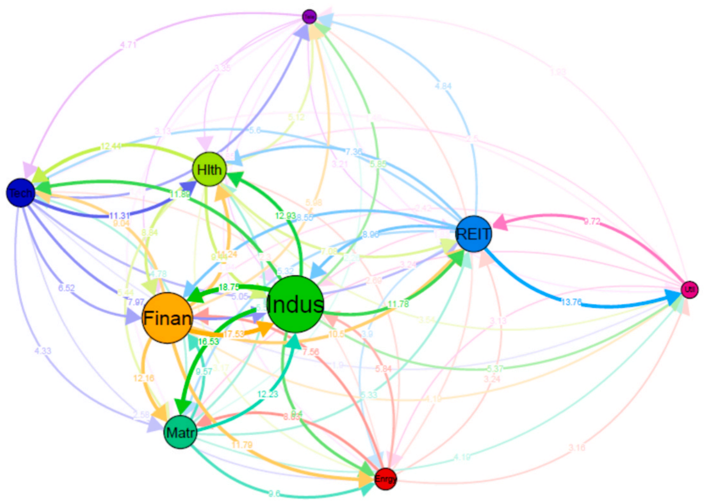


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Fig. 2. Static connectedness in US industries, a) Realized Volatility (RV), b) Realized Skewness (RS), c) Realized Kurtosis (RK), Note: The figures illustrates the static connectedness estimates for RV, RS, and RK for 9 US Industries. Energy (Enrgy), Financials (Finan), Health Care (Hlth), Industrials (Indus), Materials (Matr), Real Estate Investment Trust (REIT), Technology (Tech), Telecommunication (Tele), and Utilities (Util) for the full sample period. The size of the node indicates the extent of spillovers To Others. Additionally, thicker and darker arrows represent higher pairwise spillovers in US Industries.

represents the selections where the ith element takes the value of one and zero otherwise. The row elements of Eq. (4) do not add up to one: $\sum_{j=1}^{N}\theta_{ij}^{g}(H) \neq 1$. This is useful as these row element sums can be used to normalise the variance decomposition matrix,

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{5}$$

where, $\sum_{j=1}^{N}\widetilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H) = N$ due to specification. The normalised variance decomposition matrix can then be used to compute the spillover index. The total volatility spillover index is computed as,

$$S^{g}(H) = \frac{\sum_{i,j=1\ i\neq j}{}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)}\cdot 100 = \frac{\sum_{i,j=1\ i\neq j}{}^{N}\widetilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{6}$$

The total volatility index delineates the impact of the volatility shock spillovers across the system of US industries on the total forecast error variance. The directional volatility spillovers market i gains from the remaining markets j are calculated by,

$$S_{i\cdot}^{g}(H) = \frac{\sum_{j=1\ j\neq i}{}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)}\cdot 100 = \frac{\sum_{j=1\ j\neq i}{}^{N}\widetilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{7}$$

Similarly, the directional volatility spillovers market i provides to the remaining markets j are measured by,

$$S_{\cdot i}^{g}(H) = \frac{\sum_{j=1\ j\neq i}{}^{N}\widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ji}^{g}(H)}\cdot 100 = \frac{\sum_{j=1\ j\neq i}{}^{N}\widetilde{\theta}_{ji}^{g}(H)}{N}\cdot 100 \tag{8}$$

Eqs. (7) and (8) can be used to compute the difference between the gross volatility shocks market i transfers to other markets j and the gross volatility shocks market i collects from other markets j:

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H) \tag{9}$$

The spillover analyses are extended by estimating the determinants of the Realised Higher Moments (*RHM*) using different specifications incorporating micro- (firm level) as well as macro-economic factors.

$$\begin{aligned} RHM_t = {} & \beta_0 + \beta_1 RPM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 MOM_t + \gamma_1 VIX_t + \gamma_2 OVX_t + \gamma_3 GVZ_t + \gamma_4 EVZ_t + \gamma_5 MOVE_t \\ & + \gamma_6 TED_t + \gamma_7 EPU_t + \gamma_8 EMV_t + \gamma_9 GPR_t + \varepsilon_t \end{aligned} \tag{10}$$

The firm level factors include the theoretical five factors model of the Fama and French (1993), (2015) asset pricing model: the Returns Difference Between Value-Weighted Market and Risk-free Portfolios (*RPM*), Returns Difference Between the Diversified Portfolios of Small and Big Stocks (*SMB*), Returns Difference Between the Diversified Portfolios of High and Low B/M (ratio of average returns and price) Stocks (*HML*), Returns Difference Between Robust and Weak Profitability Diversified Stock Portfolios (*RMW*), and Returns Difference Between Low and High Investment Firms Diversified Stock Portfolios (*CMA*). These factors are designed to explain the variations in average returns pertaining to ***Size***, B/M, profitability, and investment. Fama and French (2015) note that the five factors explain some 71–94 percent of firm-level (cross-section) variance in expected returns. We include an additional firm-level factor—Carhart's (1997) One-Year Return Momentum Portfolio—to capture the short-term persistence in stock returns. The Momentum factor is a strategy for "buying past winners and selling past losers" and resultant portfolios manifest in 'abnormal returns'. This phenomenon generally involves sluggish response of prices to firm-specific information (Jegadeesh and Titman, 1993).

The regression model incorporates nine country-level 'uncertainty' factors: namely the CBOE Volatility (VIX), Crude Oil Volatility (OVX), Gold Volatility (GVZ), and Eurocurrency Volatility (EVZ) Indices, the Merrill Lynch Option Volatility Estimate (MOVE), the T-Bill and Eurodollar Spread (TED), Economic Policy Uncertainty (EPU), the Daily Infectious Disease Equity Market Volatility Tracker (EMV), and the Geopolitical Risk Index (GPR). The motivation for the inclusion of these macroeconomic (uncertainty) factors is the state-space framework in which the asset prices—and by extension their realized higher moments—are dependent on the relevant macroeconomic fundamentals and publicly available information (Andersen et al., 2005; Fleming et al., 2006). The literature finds state-space variables including priced factors (such as the risk factors, including the monetary variables, outlined above) are better capable of predicting (forecasting) the variations in stock market returns (Chen, 1991; Flannery and Protopapadakis, 2002).

The realised higher moments are first modelled using the micro- and macro-economic factors separately (i.e., estimating the β's and γ's on their own) and then using the full model comprising all firm- and country-level factors (i.e., estimating the β's and γ's together). The former approach allows us to observe the estimated effects avoiding multicollinearity between the micro- and macro-economic factors. The fully specified model prevents any omitted variable bias in the estimated coefficients.

3. Data and descriptive statistics

We avail returns data from nine US industries, provided by the Wharton Research Data Services, at 1-minute frequency from 02 January 2014–30 September 2021. This high frequency returns data is used to compute the daily realised higher moments—RV, RS, & RK. The firm-level factors—the Fama and French (1993), (2015) five factors and Carhart's (1997) Momentum—are computed using the data provided by Kenneth French, Tuck School of Business, Dartmouth College. The country-level (macroeconomic) uncertainty factors are obtained from the Economic Policy Uncertainty data portal maintained by Scott R Baker, Nick Bloom, and Steven J Davis (Baker et al., 2016). The above variables are all computed at a daily frequency for conformity in the regression analysis.

a) Realized Volatility (RV)

b) Realized Skewness (RS)

c) Realized Kurtosis (RK)

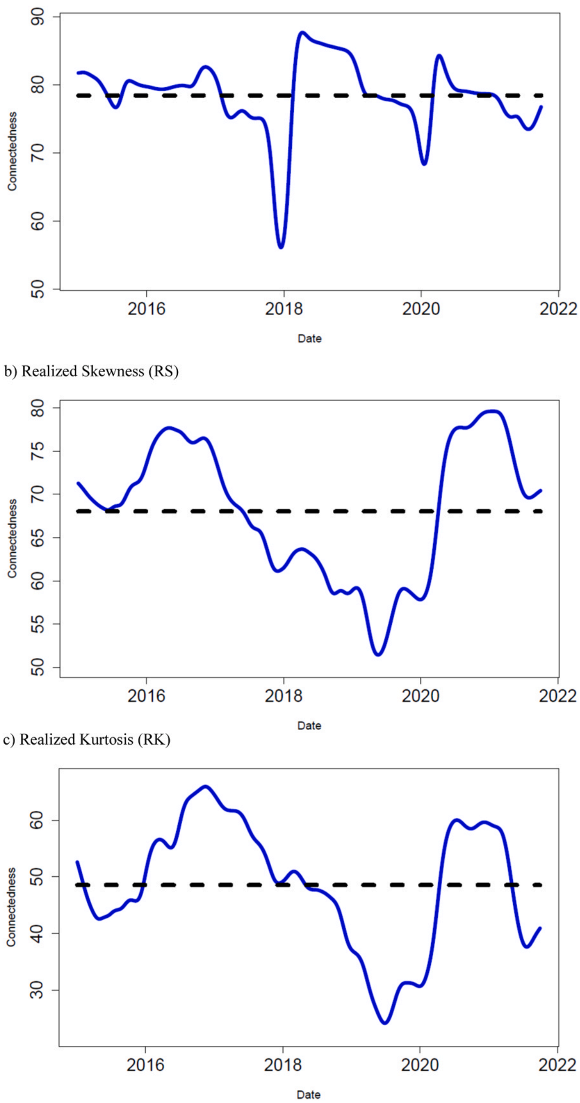

Fig. 3. Time-varying total connectedness in US industries, a) Realized Volatility (RV), b) Realized Skewness (RS), c) Realized Kurtosis (RK), Note: These figures represent the time-varying Total connectedness in the RV, RS, and RK of US Industries. A rolling window of 250 days is used along with the lag 1 and 10 day ahead forecast.

Table 1 provides the descriptive statistics for the *RV*, *RS*, and *RK* grouped by the nine major industry sectors of the US. As can be seen, the mean of *RV* is virtually zero for all industry sectors. The *RVs* exhibit positively skewed as well as leptokurtic distributions in all nine instances—and, unsurprisingly, non-normally distributed at 1 percent level of significance. The mean *RS* is positive for all nine broad industry sectors while the skewness and kurtosis values are also positive—except for telecommunications. These distributions are not normal at 1% level. The *RK* values have positive means and large magnitudes (>1000) in the nine US industries. The nine distributions of RK are positively skewed and leptokurtic and, as such, are non-normal. The Autoregressive Conditional Heteroskedasticity (ARCH) and Ljung-Box test statistics indicate presence of the ARCH effect and autocorrelation in the nine industry sectors for all moments (*RV*, *RS*, and *RK*) at the 1% level.

Fig. 1 presents the correlation matrix of the realized volatility, skewness, and kurtosis for the nine US industry sectors. In terms of the RVs (Fig. 1(a)), the pairwise correlation coefficients can be found between the Financials sector with the Industrials, Materials, and Real Estate Investment Trust sectors. The latter three sectors are also highly correlated with each other. Health Care is also highly correlated with Technology, Telecommunications, and Utilities. In addition, the Energy and Utilities are also found to be highly correlated with the other industry sectors.

The plot of realised skewness (in Fig. 1(b)) depicts a similar scenario with the Financials sector recording some of the highest correlation coefficients the Industrials, Materials, and Real Estate Investment Trust sectors. The RS of the latter three are also high correlated. However, the Energy and Utilities sectors are not as correlated via this higher moment, as they were with the RV. Lastly, the realised kurtosis correlation plot (Fig. 1(c)) continues to paint a picture similar to that of the RS. The Financials are again highly correlated with the Industrials, Materials, and Real Estate Investment Trust—with the latter being highly correlated in this higher moment. The highest pairwise RK of the Energy sector is with Financials and that of Utilities is with Real Estate Investment Trust—virtually identical to that of the RS in part (b) of Fig. 1.

4. Empirical findings

Fig. 2 plots the full sample static connectedness in the nine US industries. As can be seen from part (a), the Telecommunications, Health Care, and Utilities sectors are most connected in terms of realised volatility spillovers. Utilities appear to provide most of the RV spillovers—doing so almost equally—to the other eight markets. In contrast, the bulk of RV spillovers from Telecommunications go to Utilities, Technology, and Health Care sectors. The energy sector remains the least RV-connected to the remaining markets. Overall, Fig. 2(a) demonstrates that most of the realised volatilities from a particular sector go to related sectors: e.g., most RV transmissions from Real Estate Investment Trust are to Financials, Materials, and Industrials. In essence, 'related' industries, within the US, tend to be more volatility connected, implying 'strong ties' within such industries. This may be attributed to the risks and shocks—macroeconomic and otherwise—faced by the industry sector in question as well as sharing of common information (Fleming et al., 1998; Diebold and Yilmaz, 2015). The concept of common information relates to the theoretical discussions (and empirical observations) of the impact of information (flow) on market movements as well as co-movements (information exchange or common information) between markets (Ederington and Lee, 1993).

Part (b) of Fig. 2 provides a contrasting picture—the Industrials, Financials, and Real Estate Investment Trust sectors are most connected with respect to realised skewness spillovers. In contrast to the RV spillover, the origins of the RS spillovers are more concentrated from these three sectors. Moreover, the RS connectedness of the other industries are directed towards these three sectors. Beyond these three sectors, Materials and Healthcare are the most RS-connected. The Utilities and Telecommunications industries remain the least connected, in terms of RS spillovers. The scenario is virtually identical when considering the Realised Kurtosis in Fig. 2 (c). However, the RK connectedness among the remaining six markets are further reduced. In sum, it highlights the important of these three sectors in defining the distributional connectedness of the sample industries as well as the jump risk spillovers between them. It also underscores the predominance of financial markets, often more susceptible to shocks, driving the 'extreme event-induced' risk spillovers across the various industry sectors within the US economy—i.e., 'financial contagion' (Allen and Gale, 2000; Billio et al., 2012). In sum, the brunt of the extreme news (or shocks) is generally borne by the Industrials, Financials, and Real Estate Investment Trust sectors, and then dissipated (as financial contagion) to the other industries by way of 'cross-market rebalancing' (Kodres and Pritsker, 2002). The 'cross-market rebalancing' is a theorised channel of contagion in financial in which agents react to shocks in one market by re-optimising their portfolios in the remaining markets that they operate in.

Fig. 3 plots the total connectedness across the nine US industries over time. As can be seen from Part (a), there is a greater extent (above the long-run average/mean) of volatility spillover in the aftermath of global disruptive events: such as the oil shale revolution of 2014–16, the Brexit referendum of 2016, the Chinese economic slowdown of 2015–16, breakdown of the Iran nuclear deal and former US President Trump's trade war in 2018, and the COVID-19 pandemic in 2020. The increased volatility connectedness of US industry sectors in response to these global shocks is reasonable and generally in line with recent empirical literature on volatility connectedness, such as Naeem et al. (2022). This finding remains conformant with the underpinnings of increased (common) information flow and contagion during shocks—in line with the theoretical predictions and empirical observations by Ederington and Lee (1993), Fleming et al. (1998), Allen and Gale (2000), Kodres and Pritsker (2002), inter alia. The above empirical findings also highlight the continued 'centrality' of the US foreign policy in the international financial markets—which in turn has a profound impact on the former's industries output (Rapach et al., 2013). Fig. 3(a) also shows that these global events culminated in the greatest extent of realized volatility connectedness as compared to other events. These extreme events are likely to have transpired against agents' expectations/preferences (causing harm to US industries) and the market movements culminated in 'cross-market rebalancing' (as predicted by theory), including corrections, co-movements, and contagion (Kodres and Pritsker, 2002; Egger and Zhu, 2020).

Parts (b) and (c) of Fig. 3 paint a contrasting picture to that of Part (a). There is greater (> long run mean) connectedness in the higher realised moments (realised skewness and kurtosis) after the 2016 Brexit referendum and 2015–16 Chinese economic slowdown, and the 2020 onset of the COVID-19 pandemic. These observations are similar for both the RS and RK, despite the RK fluctuations being more pronounced with respect to its long-run average. These observations highlight the soaring jump/crash risk in US industries as connectedness of realised skewness and kurtosis rise following extreme, unprecedented, and/or unpredictable overseas (and after hours) news. While the realised volatility connectedness (in Fig. 3(a)) increased following global events (which may have been expected/predicted), the higher moment connectedness only 'over-reacted' to external and extreme/unprecedented/unpredictable shocks, due to largely unquantified consequences (to date) to real economic sectors. In particular, the higher moment connectedness falls post-2018. The duration of these heightened 'jump/crash risks' (RS and RK spillovers) also appear to linger further in contrast to their RV counterparts.

Our empirical findings are in concordance of theoretical prognosis and observed changes to the distributional characteristics of assets/stocks/markets—such as increased positive magnitudes of skewness and excess kurtosis—in the immediate pre- and post-crash/

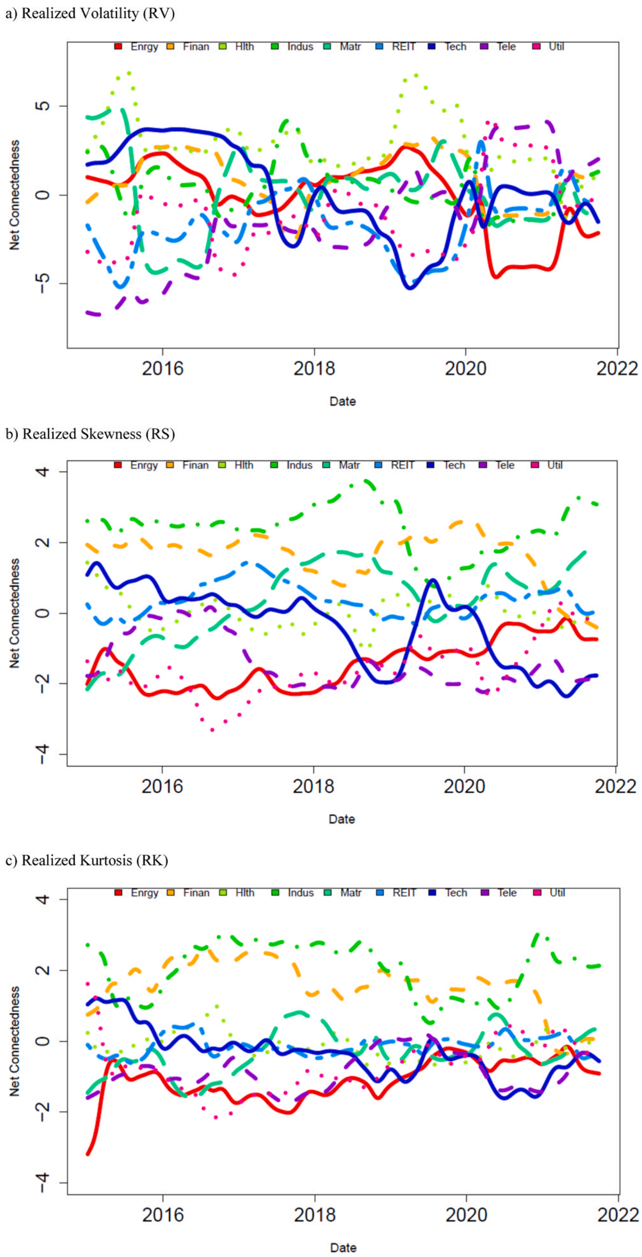

Fig. 4. Time-varying Net connectedness in US industries, a) Realized Volatility (RV), b) Realized Skewness (RS), c) Realized Kurtosis (RK), Note: These figures represent the time-varying Net connectedness in the RV, RS, and RK of US Industries. A rolling window of 250 days is used along with the lag 1 and 10 day ahead forecast.

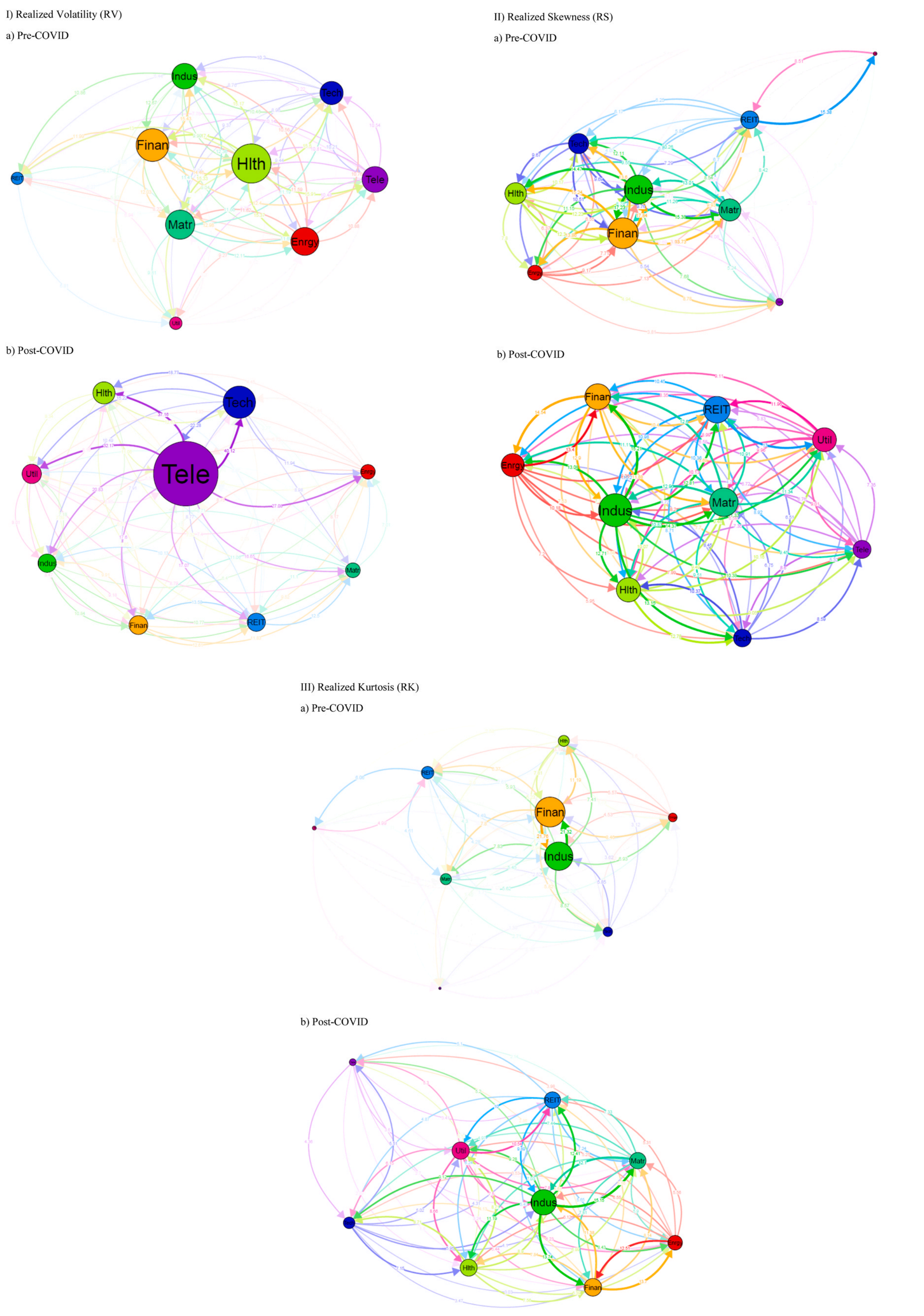

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Fig. 5. Static connectedness in US industries – Pre and Post COVID-19, I) Realized Volatility (RV), a) Pre-COVID, b) Post-COVID, II) Realized Skewness (RS), a) Pre-COVID, b) Post-COVID, III) Realized Kurtosis (RK), a) Pre-COVID, b) Post-COVID, Note: Refer to note with Fig. 2. Pre-COVID (1/06/2018–31/01/2020) and Post-COVID (3/02/2020–30/09/2021).

extreme event periods, manifesting as jumps-in-volatility or jump risk (Merton, 1976; Bates, 1991, 1996). The observed increased jump risk in the US industry sectors, albeit novel, also remains in agreement with Gong et al. (2020) who observe greater jump risk in Chinese financial and commodities markets at extreme/crisis events. We also observe a difference between volatility and jump/crash risks (Part (a) vs Parts (b) & (c) of Fig. 3), indicating a dichotomy in agents' pricing of such risks.

Fig. 4 plots the time-varying net connectedness values of realised volatility, skewness, and kurtosis with respect to each of the nine US industry sectors. The time-varying RV plots in Part (a) exhibits that the Energy, Financials, and Health Care industries are net transmitters of volatility throughout most of the sample time period. The Real Estate Investment Trust, Telecommunications, and Utilities industries are generally net receivers of volatility during this time. Other sectors such as Industrials, Materials, and Technology alternate between being net receivers or transmitters, especially during extreme events. The 'mean reversal' of these industries is especially prominent in the wake of the 2014–16 oil shale revolution, 2015–16 Chinese economic slowdown, and the onset of the COVID-19 pandemic in 2020. The industry sectors that alternate in net RV connectedness are also composed largely of the 'real sectors' of the economy. In contrast, the US industries that are stable in their net connectedness status generally fall under services, including financial as well as commodities. This reiterates the financial and associated industries' preeminent role in propagating risk spillovers and/or financial contagion among US industry sectors—in line theories of financial contagion/connectedness by Allen and Gale (2000) and Billio et al. (2012).

However, the key novelty of the net RV connectedness plots (Fig. 4(a)) lies in the increasing prominence of the Technology, Telecommunications, Health Care, and Utilities sectors in transmitting the volatilities following the initial wave of the COVID-19 pandemic. At the same time, Energy and, to a lesser extent, Financials become net recipients of volatility. This highlights the impact of the varying impacts of the COVID-19 pandemic on different US industry stocks. The services sector experiences a boom in the post-pandemic era and drive much of the volatility in the equity markets. This may be attributed to the health and travel restrictions imposed worldwide to contain the pandemic as well as 'remote work' becoming the norm for most firms as well as markets.

The relative importance of energy and financials subsided due to reduced demand and economic activities following COVID-19 restrictions as well as reduced investment in an uncertain environment—i.e., demand and supply shocks (Fahlenbrach et al., 2021). Shortly after the first global wave of COVID-19 in March 2020, the US stock and oil markets reached record lows in a matter of weeks as well as facing liquidity crises (Haddad et al., 2021; Naeem et al., 2022). The relative unimportance of the financial and related industries during this timeframe may indicate lowered risk spillover and/or financial contagion during the onset of the COVID-19 pandemic. This is likely due to the unprecedented mobilisation of fiscal and stimulus packages, by the US government as well as worldwide, to counteract the adverse effects of the pandemic (Augustin et al., 2022). This also demonstrates the interlinkage between financial markets and economic growth that is proven theoretically as well as empirically in the extant literature (see e.g., Beck et al., 2000; Shafiullah et al., 2022).

Parts (b) and (c) of Fig. 4 depict connectedness of the nine US industries in the third and fourth moments (realised skewness and kurtosis). While the movements in the RS and RK remain similar, the fluctuations in the jump/crash risk connectedness appear more pronounced in the former compared to the latter. The Financials and Industrials sectors are generally the largest transmitter of RS and RK. However, following the first wave of the COVID-19 pandemic, the RS and RK connectedness of Financials declines sharply while that of Industrials rise. This indicates the opposing jump/crash risks faced by the different sectors of the US economy. The US government COVID-19 stimulus packages are observed to lower the risk of financial contagion through bailouts while unable to avert one of the largest recessions in some nine decades—perhaps, due to multiple rounds of lockdowns in the US and globally (Acemoglu et al., 2021; Elenev et al., 2022). This is indicative of the theorised, and empirically observed, impact of economic stimulus on the financial markets as well as contagion (Allen and Gale, 2000; Shafiullah et al., 2022).

The Energy, Telecommunications, and Utilities industries are some of the biggest recipients of the realised skewness and kurtosis spillovers. However, following the onset of the COVID-19 pandemic, the RS and RK connectedness of the Energy and Utilities industries rise considerably, whereas the realised kurtosis of Telecommunications fell. This indicates an increase in jump risk and is consistent with the post-pandemic troubles/booms/troughs faced in these markets. The higher moment connectedness of the Technology industry follows a decreasing trend while that of Materials exhibits an increasing one. In addition, the RS and RK of Technology experiences a sharp decline after COVID-19 lockdowns came into effect in March 2020, responding to higher for demand for technology hardware and services as remote work became virtually ubiquitous—i.e., pandemic mitigation strategy (Jones et al., 2021). The realised skewness and kurtosis of Health Care and Real Estate Investment Trust are somewhat stable throughout the sample time period—with both industries seeing slight declines in RS and RK shortly after the first wave of COVID-19.

The above discussion provides novel observations regarding the stock markets of the US industry sectors. It is evident that the impact of COVID-19 has been profound and variegated across US industries. The time-varying higher moment connectedness measures indicate a greater magnitude of jump/crash following COVID than any other crisis within the sample timeframe—such as Brexit, Chinese slowdown, former US President Donald Trump's trade war, etc. The risk profiles of some sectors of the US economy improved—such as Technology and Financials and, to a lesser extent, Health Care, Real Estate Investment Trust, and Telecommunications. Other sectors saw a worsening of the risk profiles—such as Industrials, Materials, Energy, and Utilities. This uneven impact on various industries indicates the demonstrate the unprecedented shock from this ongoing pandemic and corrections in the markets (including the 'cross-market rebalancing' theory) that introduced a 'new normal' to business transactions—be it investment or production (Kodres and Pritsker, 2002; Ramelli and Wagner, 2020; Fahlenbrach et al., 2021; Haddad et al., 2021; Jones et al., 2021). The industries with improved post-pandemic crash risk profiles are generally the ones that continued to conduct transactions (i.e., benefitted) under COVID restrictions—and vice-versa. The latter also demonstrates the economic growth-financial market linkage—as predicted by theory, and observed empirically (Beck et al., 2000; Shafiullah et al., 2022).

The time-varying connectedness moments (Fig. 4) demonstrate that COVID-19 has had a tremendous and mottled impact on the risk profiles of different US industry sectors. This motivates us to analyse the connectedness networks in the pre- and post-COVID-19 pandemic era. Fig. 5 presents the static connectedness measures for the three higher moments (RV, RS, & RK) in the pre- and post-pandemic periods for the US industries. Both the pre- and post-COVID periods are comprised of 420 days to allow for sample equivalence and comparability. Part I of Fig. 5 displays the static realised volatility connectedness in US industries before and after COVID. In the pre-COVID period (Fig. 5(I)(a)), the Health Care and Financials industries are the most volatility connected. The volatility connectedness of the Materials, Industrials, Energy, Telecommunications, and Technology sectors are more uniform, with virtually identical magnitudes of connectedness. The transmission and receipt of realised volatilities are also uniform between these seven industries. The Real Estate Investment Trust and Utilities industries are the least connected and, on the periphery considering its transmission and receipt of volatilities. We continue to observe the pre-eminence of the financial (and related) industries in transmission of information (i.e., volatility risk) across the US industry sectors.

In the post-COVID period (Fig. 5(I)(b)), the Telecommunications industry takes 'centre-stage' in volatility connectedness, with the Technology industry being the second-most connected. The magnitudes of RV-connectedness of Health Care, Utilities, Industrials, Financials, and Real Estate Investment Trust are similar in magnitude. The Materials and Energy industries are least connected in the post-pandemic period. Much of RV transmissions originate in the Telecommunications industry, with Technology being the second-largest origin. The volatility spillovers from the remaining seven industry sectors pale in comparison. This is an accurate representation of the new normal of 'remote work' after the onset of the first wave of COVID-19 and technology stocks dictating the markets—i.e., how business is conducted in the post-pandemic era (Dingel and Neiman, 2020; Ramelli and Wagner, 2020; Jones et al., 2021; Elenev et al., 2022).

The realised skewness plots (in Fig. 5(II)) for the pre- and post-COVID periods depicts a somewhat similar scenario. The pre-COVID RS-connectedness is again seen to be concentrated within four sectors—Financials, Industrials, Health Care, and Materials. Three other sectors have considerable higher moment (RS) connectedness: Technology, Real Estate Investment Trust, and Energy. Here too, we observe the prominent role of the financial and related industries in propagating jump/crash risk in the pre-COVID-19 period. The Telecommunications and Utilities industries are the least connected, with the latter being only connected to the Real Estate Investment Trust. Fig. 5(II)(b) shows a contrasting scenario with the RS-connectedness becoming more uniform—with regard to magnitude and interconnectivity—in the post-COVID era. This is in spite of the same four industry sectors dominating both the pre- and post-pandemic time periods. The US industries also become more connected with each other—as opposed to relative isolation of Telecommunications and Utilities post-COVID.

The realised kurtosis connectedness plots in Fig. 5(III) illustrate an even starker scenario. The Financials and Industrials sectors are insurmountable regarding their RK-connectedness in the pre-COVID era. The remaining industries are in relative isolation with the Utilities and Telecommunications sectors being the least connected and most isolated. In the post-COVID period, this higher moment (realise kurtosis) connectedness measures are distributed more evenly across the industries and the latter are more inter-connected. However, Telecommunications industry is the least RK-connected and exists in relative isolation from the remaining industries—as much of it benefitted from the COVID-19 restrictions.

The increased connectedness in realised skewness and kurtosis demonstrates the heightened jump/crash risk in the post-COVID markets. It also likely exhibits reorientation (including 'cross-market rebalancing') of network connectedness across the US industries in the post-pandemic era (Kodres and Pritsker, 2002; Billio et al., 2012). The jump/crash risk (transmission) also becomes more widespread across the nine US industries—except for Telecommunications when considered the post-COVID realised kurtosis values. This rebalancing/reorientation is likely due to looming fears of recession as well as the fears being realised in one of worst recession in decades soon afterwards (Acemoglu et al., 2021). The recession can be attributed to demand and supply shocks (disruptions) as opposed to a financial—as observed by the relative unimportance of the financial and associated industries (Acemoglu et al., 2021; Fahlenbrach et al., 2021). The findings from the time-varying net connectedness estimates in Fig. 4 appear to agree with that of the static pre- and post-COVID-19 static connectedness estimates in Fig. 5.

It is evident from the above analyses and discussion that there are both micro- and macro-economic factors in play regarding the connectedness (including the static and dynamic equilibria) of the US industry sectors. We proceed with our modelling of the connectedness higher moments—realised volatility, skewness, and kurtosis—onto the aforementioned six micro-economic and nine macro-economic factors. Table 2 provides the estimates for the realised volatility connectedness. Model 1 contains the firm-level factors only and we find none of the coefficients (β's) statistically significant at the usual levels of significance (1 & 5 percent). Model 2 incorporates the nine country-level 'uncertainty' factors only and six coefficients (γ's) are found to be significant—namely the CBOE Gold Volatility and Eurocurrency Volatility Indices, the Merrill Lynch Option Volatility Estimate, the T-Bill and Eurodollar Spread, Economic Policy Uncertainty, and the Daily Infectious Disease Equity Market Volatility Tracker. Model 3 incorporates both micro- and macro-economic factors and its estimated coefficients (the β's & γ's) are virtually identical—in magnitude and sign—to that of Model 1 & 2.

The estimated signs of the macro-economic coefficients agree with *a priori* expectations—and underscore better predictive capacity of the priced factors (Chen, 1991; Flannery and Protopapadakis, 2002). Higher uncertainty from internal sources—such as the US interest rate, credit risk, and economic policy risks—as well as Gold are found to reduce the realised volatility connectedness of US industries. In contrast, increased external risks (to the US economy) such as uncertainty originating from the Eurocurrency and

Infectious Diseases increase volatility connectedness within US industries. This presents an interesting scenario as inflated internal (macro-economic) fundamentals eventuate in a reorientation (including 'cross-market rebalancing') in the interconnected network(s) of the US industry sectors (Andersen et al., 2005; Fleming et al., 2006). This has also been evident from the static connectedness plots from Fig. 5. In contrast, external risks have relatively limited impacts on industry stocks—merely exacerbating the (volatility) contagion across industries as future expectations (may) about market conditions (and demand) take a bleak turn (Rapach et al., 2013).

The adjusted-R^2 of the three estimated models in Table 2 indicate that much of the variations that can be predicted by the model are largely due to the macro-economic factors. None of the firm-level factors—such as the Fama and French (1993), (2015) 'five factors' and Carhart's (1997) Momentum (four factors) based on respective theoretical models—are found to affect (realised) volatility connectedness in the US industries. This is further corroborated by the statistically significant constant term (C) in Model 3—as the five factors fail to capture all the variations in expected returns (Fama and French, 2015). This implies that volatility in the US industry sectors is largely contributed by macro-economic (state-space) uncertainties concerning inflated internal fundamentals and external/exogeneous risks—vindicating Chen (1991) and Flannery and Protopapadakis (2002), inter alia.

Some of the firm-level factors appear significant considering the higher moment connectedness estimates in Table 3 & 4. In Table 3, the Returns Difference Between the Diversified Portfolios of Small and Big Stocks (SMB) and the Returns Difference Between the Diversified Portfolios of High and Low B/M Stocks (HML) from the Fama and French (1993), (2015) three and five factor models are statistically significant (Model 3)—at 5 and 10 percent levels of significance, respectively. The micro-economic factors are not significant when estimated without the macro-economic factors (Model 1, Table 3). Of the macro-economic factors (in Table 3), the CBOE Volatility, Crude Oil Volatility, Gold Volatility, and Eurocurrency Volatility Indices, the Merrill Lynch Option Volatility Estimate, and the T-Bill and Eurodollar Spread are statistically significant.

Table 4 presents the realised kurtosis connectedness regression estimates. The estimated coefficients in Table 4 are similar to that of Table 3 as the firm-level factors yield a statistically significant coefficient only when combined with the macro-economic (risk) factors (Model 3). However, in contrast to Table 3, only one of the micro-economic factors—the SMB—is significant in Table 4. The coefficient of the SMB is negative in both Table 3 & 4 but is considerably larger in magnitude in Table 4. We find the Economic Policy Uncertainty coefficient to be significant in Table 4 (at the 10% level) in addition to the macro-economic factors that remain significant in Table 3.

The overall findings from the realised skewness and kurtosis regressions (in Table 3 & 4) demonstrate that the jump/crash risks—theorised as a jump-in-volatility by Jin (2015) —operate via different data generating processes to that of (realised) volatility. The jump/crash risk across the US industry sectors are transmitted and received via both the micro- and macro-economic channels—as

Table 2
Impact of firm-level and macroeconomic factors on the connectedness of Realized Volatility.

	Model 1	Model 2	Model 3
C	78.408	89.240***	89.326***
	(0.403)	(2.598)	(2.582)
RPM	-0.124		-0.139
	(0.085)		(0.142)
SMB	-0.397		-0.381
	(0.334)		(0.277)
HML	0.168		-0.076
	(0.310)		(0.288)
RMW	0.233		0.066
	(0.375)		(0.363)
CMA	-0.581		-0.313
	(0.482)		(0.467)
MOM	0.202		-0.027
	(0.231)		(0.220)
VIX		-0.053	-0.069
		(0.087)	(0.095)
OVX		0.027	0.029
		(0.020)	(0.019)
GVZ		-0.321***	-0.318***
		(0.097)	(0.098)
EVZ		0.417***	0.414***
		(0.142)	(0.142)
MOVE		-0.076**	-0.076**
		(0.037)	(0.037)
TED		-0.113***	-0.112***
		(0.031)	(0.031)
EPU		-0.019***	-0.019***
		(0.007)	(0.007)
EMV		0.156**	0.159**
		(0.062)	(0.063)
GPR		0.005	0.005
		(0.004)	(0.004)
Adjusted-R^2	0.443%	15.362%	15.645%

Note: Standard errors are in (). *, **, *** indicates significance at 10, 5, 1%, respectively.

predicted by the common information flow theory (Ederington and Lee, 1993). Some two of the 'three factors' theoretical model of Fama and French (1993) are found to determine higher moment connectedness across the nine US industries. Size (SMB) reduces the industry jump/crash risk while book-to-market equity (HLM) aggravates it. The negative impact of size (SMB) is in accordance with that of Fama and French (1993)—especially for big firms (and aggregations such as industries)—as the former is expected to provide some shielding to crash risk due to challenging events (i.e., GFC, COVID-19, etc.). The jump risk-aggravating effect of book-to-market equity (HLM) is also in line with a priori expectations as well as that of Fama and French (1993), (2015). This is because higher book-to-market equity (undervalued) industries face a greater risk of jump/crash than otherwise. However, the positive and statistically of the intercept coefficient in all three models of Table 3 & 4 indicate that not all the variations in the jump/crash risk connectedness can be explained by the 'Five Factors' theoretical model of Fama and French (1993), (2015) and 'Momentum' of Carhart's (1997) 'four factor' theoretical model.

The macro-economic (risk) factors capture much of the variations in jump/crash risk connectedness (in Table 3 & 4). Between 52.539 and 63.753 percent of all variations in the realised kurtosis and skewness are explained by the macro-economic factors in the estimated regression Model 2 in Table 4 and Model 3 in Table 3, respectively. Among the macro-economic factors, we observe the contribution of CBOE Volatility and Crude Oil Volatility to jump/crash risk in the US industry stocks. The negative impact of VIX on industry jump risk can be explained due to the 'counter-cyclicality' of stock market (returns) volatility (Andersen et al., 2005). The counter-cyclicality of VIX is channelled through the positive risk premiums borne by markets to offset the macro-economic fluctuations (risks) (Corradi et al., 2013). The positive impact of Crude Oil Volatility on jump/crash risk is unsurprising as the energy market volatility adversely affects production, supply chains, expected inflation, etc.

The coefficients of the remaining, significant macroeconomic factors on the third and fourth moment connectedness are generally opposite—except for the TED spread. This provides further evidence of jump/crash risk (realised skewness and kurtosis) connectedness network being structurally different to that of realised volatility. The negative coefficients on the CBOE Eurocurrency Volatility Index and the T-Bill and Eurodollar Spread are reflections of adverse market expectations and common information sharing that is discussed and observed in both theoretical and empirical literature—i.e., fear and/or contagion (Ederington and Lee, 1993; Fleming et al., 1998; Allen and Gale, 2000; Kodres and Pritsker, 2002). The positive coefficients of CBOE Gold Volatility Index and Merrill Lynch Option Volatility Estimate indicate greater crash risk contagion in response to volatility in gold and US interest rate(s). Abnormal fluctuations in these indices generally imply expectations of economic slowdown/contraction in the US and global economy(ies) as well as other economic/financial turmoil. Gold is observed to act as a safe haven in times of crises and, as such, expectedly associates positively with

Table 3
Impact of firm-level and macroeconomic factors on the connectedness of Realized Skewness.

	Model 1	Model 2	Model 3
C	68.032***	56.852***	56.860***
	(0.536)	(1.993)	(1.983)
RPM	-0.065		-0.019
	(0.170)		(0.126)
SMB	-0.415		-0.471**
	(0.332)		(0.231)
HML	-0.322		0.449*
	(0.367)		(0.266)
RMW	-0.009		-0.322
	(0.503)		(0.310)
CMA	-0.196		-0.217
	(0.715)		(0.441)
MOM	-0.132		0.208
	(0.247)		(0.164)
VIX		-0.278***	-0.281***
		(0.070)	(0.074)
OVX		0.083***	0.085***
		(0.024)	(0.024)
GVZ		0.375***	0.374***
		(0.104)	(0.103)
EVZ		-0.394*	-0.394*
		(0.216)	(0.216)
MOVE		0.298***	0.298***
		(0.035)	(0.035)
TED		-0.263***	-0.263***
		(0.021)	(0.021)
EPU		-0.002	-0.002
		(0.004)	(0.004)
EMV		0.005	0.004
		(0.080)	(0.084)
GPR		-0.006	-0.006
		(0.006)	(0.006)
Adjusted-R^2	0.219%	63.769%	63.972%

Note: Standard errors are in (). *, **, *** indicates significance at 10, 5, 1%, respectively.

jump/crash propagation across the US industries (Baur, McDermott, 2010). Dahlquist and Hasseltoft (2013) observe short-term interest rate expectations and risk premia to move in opposite in response to fluctuations in 'international' macro-economic factors. Thus, interest rate risk culminates in a 'pro-cyclical' contagion of crash risk in the US industries. The US Economic Policy Uncertainty is negatively associated with higher moment connectedness, but the evidence is weak. This indicates that industry (stock) jump/crash risk is largely unaffected by Economic Policy Uncertainty.

Overall, the superior capacity of the priced factors (such as the risk factors including monetary variables) in explaining jump/crash risk continues to be apparent. The US industries appear to face greater jump/crash risk (transmission) with respect to commodities (especially gold and oil) but less so with respect to the other financial variables. This is reminiscent of the dual impact of the stimulus packages—the financial industry benefits from the bailouts but a recession cannot be averted in the remaining industry sectors (Acemoglu et al., 2021; Elenev et al., 2022; Shafiullah et al., 2022). higher moment connectedness of Financials declines sharply while that of Industrials rise. This indicates the opposing jump/crash risks faced by the different sectors of the US economy. The US government COVID-19 stimulus packages are observed to lower the risk of financial contagion through bailouts while unable to avert one of the largest recessions in some nine decades—perhaps, due to multiple rounds of lockdowns in the US and globally (Acemoglu et al., 2021; Elenev et al., 2022). The latter is reminiscent of the interplay—described by both theory and empirics—between the real sectors of the economy and financial markets (Beck et al., 2000; Shafiullah et al., 2022).

5. Conclusion

We provide the first analysis of higher moment connectedness of nine US industry sector returns using high frequency data between January 2014 and September 2021. Our 'static connectedness' analysis indicates 'strong ties' in volatility connectedness between 'related' industries. We observe the prominence of the financial and related industries in jump/crash risk transmission to other, 'real' industries of the economy. The 'time-varying total connectedness' analysis increase information flow (volatility risk) and contagion during disruptive global events (such as the GFC, Brexit referendum of 2016, first wave of the COVID-19 pandemic, etc.) (Arif et al., 2021, 2022a, 2022b; Arfaoui et al., 2023; Balli et al., 2022; Bouri et al., 2022; Hasan et al., 2022; Mbarki et al., 2022; Mirza et al., 2023; Naeem and Arfaoui, 2023; Naeem et al., 2023a, 2023b, 2023c; Rehman et al., 2023; Umar et al., 2022). This finding is hardly surprising and involves a correction/reorientation (including 'cross-market rebalancing') in the interconnected network(s) of the US industry sectors. However, the jump/crash risk transmission during such extraordinary global events appear to linger further than that

Table 4
Impact of firm-level and macroeconomic factors on the connectedness of Realized Kurtosis.

	Model 1	**Model 2**	**Model 3**
C	48.577***	21.529***	21.673***
	(0.763)	(2.936)	(2.943)
RPM	-0.193		-0.242
	(0.228)		(0.215)
SMB	-0.388		-0.713**
	(0.429)		(0.328)
HML	0.177		0.535
	(0.501)		(0.398)
RMW	-0.373		-0.418
	(0.729)		(0.495)
CMA	-0.260		-0.052
	(0.984)		(0.679)
MOM	0.019		0.358
	(0.368)		(0.274)
VIX		-0.671***	-0.698***
		(0.128)	(0.136)
OVX		0.181***	0.186***
		(0.054)	(0.055)
GVZ		0.653***	0.656***
		(0.180)	(0.180)
EVZ		-0.520*	-0.523*
		(0.291)	(0.292)
MOVE		0.471***	0.471***
		(0.045)	(0.046)
TED		-0.110***	-0.110***
		(0.035)	(0.034)
EPU		-0.011*	-0.010*
		(0.006)	(0.006)
EMV		-0.147	-0.141
		(0.094)	(0.097)
GPR		0.001	0.001
		(0.009)	(0.009)
Adjusted-R^2	0.087%	52.626%	52.934%

Note: Note: Standard errors are in (). *, **, *** indicates significance at 10, 5, 1%, respectively.

of volatility risk. The discrepancy between volatility and jump/crash risks implies a dichotomy in agents' pricing of such risks.

The 'time-varying net connectedness' analysis by industry reiterates the financial and associated industries' preeminent role in propagating volatility risk spillovers and/or financial contagion among US industry sectors. However, following the initial wave of the COVID-19 pandemic, an increasing prominence of the Technology, Telecommunications, Health Care, and Utilities sectors in transmitting the volatilities is observed. The relative unimportance of the financial and related industries during this timeframe due to the unprecedented mobilisation of fiscal and stimulus packages, by the US government as well as worldwide. The jump/crash connectedness of the Financials sector declines sharply while that of Industrials rise, indicating the opposing jump/crash risks faced by these sectors in the wake of the pandemic. This is due, in part, to COVID-19 stimulus packages averting crises in the financial sector but failing to avert pandemic induced recession. In sum, the industries with improved post-pandemic crash risk profiles are generally the ones that continued to conduct transactions (i.e., benefitted) under COVID restrictions—and vice-versa.

An evaluation of the 'static connectedness' of the higher moments reveal virtually identical observations. The volatility and jump/crash risk connectedness becomes more aggravated and widespread in the post-COVID period, with the Telecommunications industry remaining virtually unscathed in relative isolation.

The regression analyses indicate that the volatility risk of the US industries is determined solely by macro-economic factors. The internal (macro-economic) fundamentals of the US are more to blame for a reorientation (including 'cross-market rebalancing') in the interconnected network(s) that their external (international) counterparts. The jump/crash risks are determined by different factors (such as firm-level factors) than that of (realised) volatility. The priced factors (such as the risk factors including monetary variables) are found to better explain the jump/crash risk of the nine US industry sectors. The commodities (such as gold and oil) appear to worsen jump/crash risk other financial variables—implying, perhaps, the dual impact of the stimulus packages.

The above findings hold important implications for a multitude of stakeholders, such as investors, fund managers, policymakers, and financial regulators—in the US as well as the rest of the world. The identification of crash risks transmission from financial to real economic sectors can provide motivation and guidance to investors and fund managers in 'cross-market rebalancing' in portfolio formulation and management. A 'cross-market rebalanced' portfolio is likely to assist in financial risk management of US industries, especially in times of disruptive global events.

Our findings also provide insights into the asset pricing mechanisms that (virtually all) stakeholders of US industry sectors may exploit. The relative importance of firm-level factors, vis-à-vis industry-specific uncertainty, in influencing jump risk can be used by investors and fund managers to manage risk for their customers. In contrast, policymakers and financial regulators may use this information to assess over- or under-pricing of assets in specific industries and manage financial contagion within and across industry sectors of the US. The relative importance of macroeconomic factors in determining industry-level volatility may assist policymakers and financial regulators to determine the impact of global shocks on US industry sectors. In addition, this finding may be exploited, by virtually all stakeholders, to anticipate the US industries' response to global macroeconomic shocks. This will further boost financial risk management in US industries—both at the micro- as well as macro-economic levels.

Stakeholders in other jurisdictions—such as those in Europe and other OECD economics—to formulate and customise their financial risk management and gauging asset pricing mechanisms in response to the happenings in the US industries.

CRediT authorship contribution statement

Muhammad Naeem: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – review & editing. **Brian M. Lucey:** Supervision, Writing – original draft, Writing – review & editing. **Arunachalam Senthilkumar:** Writing – original draft, Writing – review & editing. **Muhammad Shafiullah:** Methodology, Writing – original draft, Writing – review & editing.

Data Availability

Data will be made available on request.

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