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Risk aversion connectedness in developed and emerging equity markets before and after the COVID-19 pandemic

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ABSTRACT

This study investigates the dynamic connectedness across the variance risk premium in international developed and emerging equity markets based on a Bayesian time-varying parameter vector autoregressive methodology. The empirical results indicate that the total spillover index is on average 65.6%, indicating a high, albeit declining, level of interconnectedness across the investor sentiment in the three markets under review until early 2020. Following the COVID-19 outbreak though, the total investors' risk aversion connectedness – as expected – strengthens, but more importantly, its dynamics alter, indicating that the risk aversion of emerging markets is an important contributor to the connectedness of international markets.

1. Introduction

This paper investigates the relationship between investors' risk aversion in developed and emerging equity markets over the last decade including the recent global coronavirus pandemic. In particular, we examine the variance premia spillovers among developed markets (as proxied by MSCI EAFE Index), emerging markets (as proxied by MSCI Emerging Markets Index) and the US market (as proxied by S&P500 index). Although the empirical finance literature abounds with studies of cross-border stock market links, this study is among the rather limited attempts to investigate the connectedness in terms of investors' risk aversion. It has now become increasingly commonplace to assume that risk aversion and sentiment dynamics are significant contributing factors of risky assets prices (Bekaert and Hoerova, 2014). Furthermore, studying how market participants react as a global crisis unfolds is particularly interesting. The central finding of our analysis is that the COVID-19 pandemic has altered the connectedness dynamics across investors' risk aversion in the three markets under study, as emerging markets investors' sentiment becomes the main transmitter of shocks during the crisis.

This research is mainly inspired by one strand of behavioral finance literature that investigates the relationship of investor sentiment on asset price dynamics (Baker and Wurgler, 2007; Da et al., 2015; Kumar and Lee, 2006; Stambaugh et al., 2012; Tetlock, 2007). As investor preferences cannot be observed directly, researchers often rely either on market-based or survey-based measures; Brown and Cliff (2004) include a comparative analysis of the two approaches. We follow the first approach and proxy investors' risk aversion by the variance premium, which is the spread between realized and implied variance, and has been empirically established in the academic literature – among others, by Rosenberg and Engle (2002) and Bakshi and Madan (2006) – as an aggregate market risk aversion. An implied volatility index is directly derived from option prices and essentially reflects the risk-neutral expectation of realized volatility of the underlying asset for the next thirty days. It incorporates any event (either positive or negative) that affects underlying spot prices, as any positive shock will raise investors' bullish outlook and will move call options prices higher and put options prices lower and vice versa. In order to derive information about the risk parameters, Bekaert et al. (2013) suggest that the volatility index should be cleansed of the normal volatility dynamics and uncertainty influence by calculating the variance risk premium, which is the difference between the realized return variance of the underlying equity index and the implied volatility index squared.

The particular paper relates to the empirical literature that studies the return and volatility dynamics of emerging equity markets and their

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linkages with those of developed markets. Spillover effects from both the same, and different, geographical regions have been analyzed extensively regarding the origins and the intensity of information transmission across markets (see Yarovaya et al., 2017 and the references therein), but this paper contributes to existing literature by presenting empirical results from the analysis of the relatively unexplored concept of risk aversion integration. The closest studies to ours is that of Cipollini et al. (2018), who analyze total and directional connectedness in risk aversion in five European stock markets (the UK, Germany, Switzerland, France and the Netherlands) in the period 2000–2013 and Badshah (2018), who studies linkages among the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), CBOE EFA ETF Volatility Index (VXEFA) and CBOE Emerging Markets ETF Volatility Index (VXEEM).

This paper extends and complements the previous literature in three major ways: first, by providing a novel perspective on the interdependence among equity markets as it studies the dynamic connectedness across the variance risk premium in the US and international developed and emerging equity markets during an unprecedented global crisis, such as the COVID-19 pandemic. Recent studies find increased systematic risk and volatility in response to the pandemic (indicatively, Albulescu, 2020; Baig et al., 2020; Zaremba et al., 2020; Zhang et al., 2020); however, none of these studies analyze spillovers of investors' sentiment. Second, by using the variance risk premium as a proxy of risk aversion (instead of the model-free implied volatility that the overwhelming majority of existing studies use), we are able to measure risk aversion more effectively, as an implied volatility index proxies investors' risk aversion, but mainly indicates the expected stock market uncertainty (Low, 2004). Finally, methodologically, the employed Bayesian time-varying parameter vector autoregressive (TVP-VAR)[1] suggested by Antonakakis and Gabauer (2017) improves the widely-used methodology of Diebold and Yilmaz (2012; 2014; 2015), since it doesn't need an arbitrarily-set rolling window-size and thus, there is no loss of observations (which is crucial for a monthly frequency dataset as ours). To the best of our knowledge, this is the first attempt to analyze investors' risk aversion across major equity markets using a TVP-VAR based connectedness approach.

In sum, this study aims to answer the following questions: (1) how do investors in emerging equity markets respond to wavering US and international developed market investors' sentiment? (2) How quickly and strongly is market participants' sentiment in developing stock markets, as reflected in the variance premium, transmitted to developed markets? (3) Which markets are most responsive in terms of investors' risk aversion during the last decade and especially during the recent COVID-19 pandemic? Answering these questions would certainly be of great value to global investors as recent studies (see Fassas and Papadamou, 2018a and the references therein) have emphasized the potential role of investor sentiment in determining asset returns. Furthermore, as Ramelli and Wagner (2020) note, the COVID-19 crisis serves as a natural experiment that offers a cleaner setting for these research questions to be addressed. Our empirical results show that the US, as it was probably expected, is the largest transmitter of sentiment connectedness over the last decade, but emerging markets became a transmitter of spillovers during the recent global pandemic.

The remainder of the paper is organized as follows. Section 2 includes a review of the relevant literature, while Section 3 provides a detailed analysis of the dataset of this study. Section 4 discusses the employed methodology and Section 5 includes the empirical findings and presents a discussion of the results. Finally, Section 6 presents a summary of our findings and the concluding remarks.

[1] See Antonakakis et al. (2020) and the references therein for a comprehensive review of the empirical literature regarding TVP-VAR models.

2. Related literature

The present study relates to three strands of the empirical finance literature. The first strand investigates information flow from developed stock markets and strategic commodities (gold and oil) to emerging stock markets; see, among others Mensi et al. (2017; 2016; 2014), Sarwar and Khan (2017), Bhuyan et al. (2016), Jin and An (2016), Kenourgios and Dimitriou (2015), Syriopoulos et al. (2015), Gilenko and Fedorova (2014), Bianconi et al. (2013), Dimitriou et al. (2013), Zhang et al. (2013), Samitas and Tsakalos (2013), Kenourgios and Padhi (2012), Kenourgios et al. (2011), Beirne et al. (2010). A more recent strand of this spillover literature uses implied volatility indices in order to examine the linkages between financial markets and assets. Several studies document the existence of implied volatility spillovers across developed equity markets, mainly among the US and European countries, using equity-based volatility indices (Nikkinen and Sahlström, 2004; Skiadopoulos, 2004; Wagner and Szimayer, 2004; Äijö, 2008; Konstantinidi et al., 2008; Jiang et al., 2012; Peng and Ng, 2012; Siriopoulos & Fassas, 2012, 2013; Chen, 2014; Kenourgios, 2014; BenSaïda et al., 2018).

Research into cross-border links in emerging markets implied volatility was fueled by the introduction of respective volatility indices covering these markets. More specifically, Maghyereh et al. (2016) investigate the directional connectedness between oil and eleven stock exchanges using implied volatility indices and find evidence that the bulk of association is largely dominated by the transmissions from the oil market to equity markets and not the other way around. Bouri et al. (2017a) investigate the interactions of the Indian stock market with oil and gold using implied volatility indices, while Bouri et al. (2017b) use implied volatility indices and examine short-term and long-term causality dynamics between gold and the Chinese and Indian stock markets. Dutta (2018) investigates stock market integration among the U.S. and China and Brazil using their volatility indexes published by the CBOE. Ji et al. (2018) examine the information flow across US equities, strategic commodities (oil and gold) and Brazil, Russia, India, China and South Africa equities through the implied volatility channel. Furthermore, Bouri et al. (2018) examine the relationship of implied volatility in the commodity and major developed stock markets with the implied volatility in individual BRICS stock markets and conclude that the predictability of BRICS implied volatilities is generally a function of both global and within the group stock market implied volatilities, but the role of commodity market volatility is minimal. Separately, Badshah et al. (2018) examine the relationship between changes in VIX and the Chinese and Brazilian equity markets and VXEEM volatility index, while Badshah (2018) investigates cross-market volatility linkages among the VIX, the developed-market volatility index (VXEFA) and the emerging-market volatility index (VXEEM), by employing a VAR-DCC-GARCH model, and finds strong spillover effects from the US fear index to both VXEFA and VXEEM (while the spillovers from the developed and emerging markets implied volatilities to the US index are negligible). Lastly, Sharma et al. (2019) study the interaction of implied VIX across different equity markets of the BRICS countries and their results suggest bi-directional causality for most of the BRICS VIX sample series. The results of these earlier studies, based on implied volatility indices, should be interpreted with caution, because an implied volatility index reflects not only investors' risk aversion, but also investors' expectation regarding future realized volatility.

The second strand of literature has to do with market-based measures of risk aversion. Even though the terms “risk aversion”, “risk appetite,” and “risk premium” are very often used interchangeably, they are distinctive notions; Gai and Vause (2006) explain in detail the differences. Estimating market participants' risk aversion has a long history (see Bliss and Panigirtzoglou, 2004 for a relevant discussion), but it is relatively recently that academic literature has begun using options data to do so (Ait-Sahalia and Lo, 2000; Jackwerth, 2000; Rosenberg and Engle, 2002; Bliss and Panigirtzoglou, 2004; Bakshi and Madan, 2006; Kang et al., 2010; Bekaert and Hoerova, 2014; Bekaert et al., 2013;

Bollerslev et al., 2009, 2011; Bollerslev and Todorov, 2011; Carr and Wu, 2009; Drechsler and Yaron, 2010; Drechsler, 2013; Faccini et al., 2019; Fassas et al., 2019). As a measure of risk aversion, we employ the variance risk premium since it gauges how much market participants are willing to pay to hedge against increases in variance (Carr and Wu, 2009). Studying risk aversion at an aggregate level – rather than at the individual (or household) level – enables us to determine whether the effect of the pandemic on risk aversion are pervasive enough to affect financial markets dynamics.

The particular study contributes to the extant spillover literature by demonstrating that spillovers exist not only in returns and volatility of financial assets, but also in market participants' sentiment. This finding is important as market participants and analysts frequently cite market sentiment as a key determinant of asset prices. As Gai and Vause (2006) note, market prices very often move together, even though many of the valuation determining factors can be quite different in different financial markets. Recently, risk aversion has also been included in monetary economics empirical research investigating the connection between accommodating monetary policy and greater appetite for risk by market participants (indicatively, Borio and Zhu, 2012; Bekaert et al., 2013; Fassas and Papadamou, 2018b).

Finally, the third relevant strand includes the contemporaneous, but exponentially growing, literature on the impact of COVID-19 on financial markets (Akhtaruzzaman et al., 2020; Ashraf, 2020; Conlon and McGee, 2020; Corbet et al., 2020a, 2020b; Goodell and Huynh, 2020; Ji et al., 2020a,b; Ramelli and Wagner, 2020; Sharif et al., 2020; Zaremba et al., 2020; Zhang et al., 2020) and more specifically, the research examining the impact of COVID-19 on sentiment (Baker et al., 2020; Bouri et al., 2020; Buckman et al., 2020; Papadamou et al., 2020a; 2020b). Goodell (2020) sketches a useful taxonomy of the emergent empirical research on pandemics and finance. Since global macroeconomic and financial crises cause considerable shifts in economic and corporate fundamentals, as well as in the level of investors' risk aversion, a large number of studies investigate financial markets correlations in the context of crises (see Ji et al., 2020a,b; Yarovaya and Lau, 2016 for a relevant discussion).

3. Data and preliminary analysis

Our empirical dataset covers three major segments of the international equity markets and their implied volatilities indices; in particular, we study the S&P500 and VIX tracking the US market, the iShares MSCI EAFE Index Fund (EFA)[2] and CBOE EFA ETF Volatility Index (VXEFA) covering developed markets and the iShares MSCI Emerging Markets Index Fund (EEM)[3] and CBOE Emerging Markets ETF Volatility Index (VXEEM) tracking emerging markets. VIX (the CBOE Volatility Index) was the first volatility index introduced by Chicago Board Options Exchange (CBOE) in 1993 and re-launched in 2003 based on the concept of the fair value of variance swap developed by Demeterfi et al. (1999). In March 2011, CBOE introduced the CBOE Emerging Markets ETF Volatility Index (VXEEM) based on iShares MSCI Emerging Markets Index Fund (EEM) options, while in June 2013 began disseminating the CBOE EFA ETF Volatility Index (VXEFA) based on iShares MSCI EAFE Index Fund (EFA) options (with historical data going back to 2008).

In line with Carr and Wu (2009), we define the variance risk premium (VRP) as the difference between the ex-post realized return variation and the ex-ante risk-neutral expectation of the future return variation, as proxied by the respective implied volatility index. The ex-post realized variance ($HV_{i,t-1}$) is calculated according to the following equation:

$$HV_{i,t-1} = \frac{365}{n_{t-1}} \sum_{t=1}^{n_{t-1}} (R_i)^2 \tag{1}$$

in which, R_i is the daily return of the underlying asset i (with i = S&P500, EFA and EEM) and n_{t-1} is the number of calendar days in month t-1. We follow the common practice of not de-meaning squared returns and annualizing the volatility based on the 365/actual day convention. We calculate non-overlapping monthly observations, computing realized variance separately for each calendar month, since the use of daily data, may be non-synchronous and thus, may potentially lead to serious econometric problems of errors in variables. In this setting, we remove any serial correlation within the error term, enhance the predictive power of implied volatility and avoid overestimating historical realized variability, by calculating the variance premium as follows:

$$VRP_{i,t} = 100^*(HV_{i,t-1} - IV^2_{i,t-1}) \tag{2}$$

in which, $IV^2_{i,t-1}$ denotes the implied volatility index squared recorded on the last trading day of month t-1 and essentially represents the market-based forecast of realized volatility of the underlying asset i in month t.

Our dataset covers the period from April2011[4] until May 2020 and thus, contains 110 non-overlapping monthly observations. Table 1 includes the descriptive statistics of the three variance premium series, while Figure 1 presents their evolution over the sample period. The average estimates in Table 1 represent the average dollar profit or loss for each $100 notional investment in the variance swap contract (Carr and Wu, 2009). This means that if an investor holds until maturity a 30-day variance swap contract with a notional of $100 on the S&P 500 index, the iShares MSCI Emerging Markets Index Fund (EEM) and the iShares MSCI EAFE Index Fund (EFA), the average return per $100 notional investment, during the period under examination, is -$0.387, -$0.508 and -$0.97 respectively. This finding confirms existing empirical evidence that the variance premium is significantly and systematically negative, indicating that index options buyers are willing to pay a hedging premium (Drechsler, 2013). The emerging markets fund exhibits the highest VRP (in absolute terms), while the US market exhibits the lowest one; this finding is anticipated, as it suggests that investors require more compensation for bearing the same risk in emerging market equities than in the US or developed stock markets. Remember that as Bakshi and Madan (2006) show the variance risk premium is driven by the desire of risk-averse market participants to acquire protection against extreme events. Finally, the reported ADF tests show that all three series are stationary and thus, can be used in the TVP-VAR analysis.

4. Methodology

In order to explore the risk aversion transmission mechanism across the three markets in a time-varying fashion, we employ the TVP-VAR methodology of Antonakakis and Gabauer (2017) that extends the originally proposed connectedness approach of Diebold and Yılmaz (2014)[5]. This framework allows the variances to vary via a stochastic volatility Kalman Filter estimation with decay factors following Koop and Korobilis (2014). The Bayesian information criterion (BIC) suggests that a TVP-VAR(1) model is appropriate. Therefore, the TVP-VAR(1) model for the variance premia in the US, developed markets (DM) and emerging markets (EM) is specified as follows:

$$y_t = \beta_t y_{t-1} + \varepsilon_t \quad \varepsilon_t | F_{t-1} \sim N(0, S_t) \tag{3}$$

[2] EFA tracks a market-cap-weighted index of 21 developed markets based in Europe, Australia and the Far East (MSCI EAFE Index); it excludes the US and Canada and small-caps. It is the sixth-largest U.S. ETF according to market capitalization, as of December 2018.

[3] The iShares MSCI Emerging Markets ETF (EEM) tracks the MSCI Emerging Markets Index, which is a market-cap-weighted index designed to represent performance of the large and mid-cap stocks across 24 emerging equity markets.

[4] The starting date is determined by the availability of data, since VXEEM historical data is available since mid-March 2011.

[5] In this paper, we use the Dynamic Connectedness Approach Based on TVP-VAR code provided by Antonakakis and Gabauer (2017).

Table 1. Summary statistics for monthly Variance Risk Premia.

	US	DM	EM
Mean	-0.387***	-0.508***	-0.970***
Median	-0.976	-0.864	-1.567
Maximum	59.33	49.22	55.68
Minimum	-9.95	-16.17	-17.30
Std. Dev.	6.170	5.718	6.318
Skewness	8.38	6.18	6.64
Kurtosis	81.62	54.73	61.14
ADF t-test	-11.32***	-12.43***	-13.23***

Notes: This table reports summary statistics for monthly variance premia for the United States (US), developed markets (DM) and emerging markets (EM). The dataset includes 110 observations (for the period April 2011–May 2020). In addition, the Augmented Dickey Fuller Test (ADF) t-statistics are reported.
*** Denotes significance at the 99% confidence level.

$$vec(\beta_t) = vec(\beta_{t-1}) + \nu_t \; \nu_t|F_{t-1} \sim N(0, S_t) \tag{4}$$

in which, y_t and y_{t-1} represent vectors that contain the variance risk premia of the three markets under review (therefore N = 3), F_{t-1} represents all information available until t-1, while β_t is an N x N dimensional time-varying coefficient matrix and $\in_t$ is an N x 1 dimensional error disturbance vector with an N x N time-varying variance–covariance matrix, S_t. $vec(\beta_t)$, $vec(\beta_{t-1})$ and ν_t are N^2 x 1 dimensional vectors and R_t is an $N^2 \times N^2$ dimensional matrix. For the initialization of the Kalman filter, we are using empirical Bayes prior parameters (β_0 and Σ_0) in which the priors are equal to the estimation results of a VAR estimation based on the first 20 months[6]: $\beta_0 \sim N(\beta_{ols}, \Sigma\beta_{ols})$, $\Sigma_0 = \Sigma_{ols}$. The Kalman Filter estimation relies on forgetting factors that control how fast the estimated coefficients vary over time. If the forgetting factor is set equal to 1, then the specification collapses to a constant parameter VAR. In our case, since we assume that parameters are not changing dramatically from one period to the other, we set forgetting factor equal to 0.99.

After we have estimated the time-varying parameters, we need to transform the TVP-VAR to a moving average representation the TVP-VMA can be written as:

$$y_t = \sum_{t=0}^{\infty} A_j \varepsilon_{t-j} \tag{5}$$

in which, the NxN coefficient matrices Ai meet the following recursive equation:

$$A_i = \varphi_1 A_{j-1} + \varphi_2 A_{j-2} + \ldots + \varphi_p A_{j-p} \tag{6}$$

with A_0 being the N x N identity matrix and $A_j = 0$ for j < 0.

Following the presentation by Diebold and Yilmaz (2014), the H-step-ahead generalized forecast-error variance decomposition is computed as follows:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)} \tag{7}$$

in which, Σ is the variance matrix of ε_t, σ_{jj} is the standard deviation of the of the error term of the j^{th} equation, while e'_i is a vector containing zeros, with one on the i^{th} element.

Since these $\theta_{ij}(H)$ do not sum to one under the generalized decomposition, each entry of the variance decomposition matrix is rescaled to range between 0 and 1. These rescaled quantities are denoted as $\tilde{\theta}_{ij}(H)$ and computed as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{8}$$

Note that by construction, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$, in which N is the total number of time series considered. These $\tilde{\theta}_{ij}(H)$ can be considered as a measure of the pairwise directional connectedness from market j to market i at horizon H.

Correspondingly, we also compute the pairwise directional connectedness in the opposite direction, from market i to market j and by taking their difference, we compute the net pairwise directional connectedness, which essentially identifies the market that is playing the dominant role in the information transmissions between the two markets under review. Following a similar rationale, we can also compute how all markets are jointly contributing to a single market i:

$$S_{i\leftarrow}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 \tag{9}$$

and also, how a particular market i is contributing to the shocks of all other markets:

$$S_{i\rightarrow}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}(H)} \times 100 \tag{10}$$

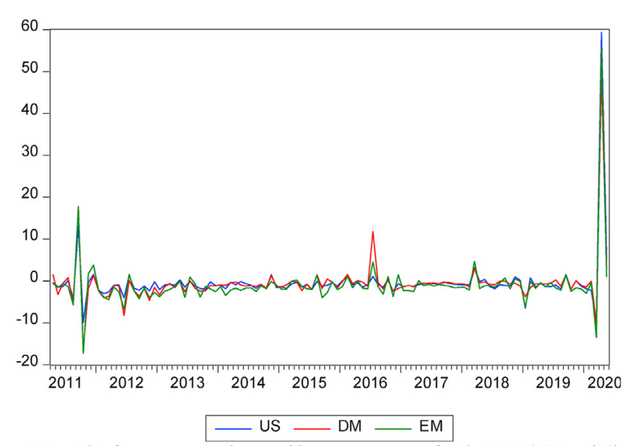
Thus, from these two measures we can compute the net total directional connectedness as follows:

$$S_i(H) = S_{i\rightarrow}(H) - S_{i\leftarrow}(H) \tag{11}$$

Finally, the total aggregation of the variance decompositions across all markets measures the system-wide connectedness and is calculated as follows:

$$S_{i\rightarrow}(H) = \frac{\sum_{i,j=1, j\neq i}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ii}(H)} \times 100 \tag{12}$$

This index captures the total information flow among all markets under examination and ranges between 0 and 100. When the markets/assets under review have a strong exchange of spillovers, this spillover index is high and vice versa. In concluding, we should note that the generalized framework employed here is not able to identify any



Notes: This figure presents the monthly variance premia for the United States (US), developed markets (DM) and emerging markets (EM) for the period April 2011 – May 2020.

Figure 1. Variance risk premia.

[6] Antonakakis et al. (2019) show that the prior specification is only influencing the few observations until they are squeezed out of the system, which in turn leads to the convergence of the TVP-VAR dynamic connectedness results.

structural channels, rather it captures how connected the risk aversion measures are (Antonakakis et al., 2019).

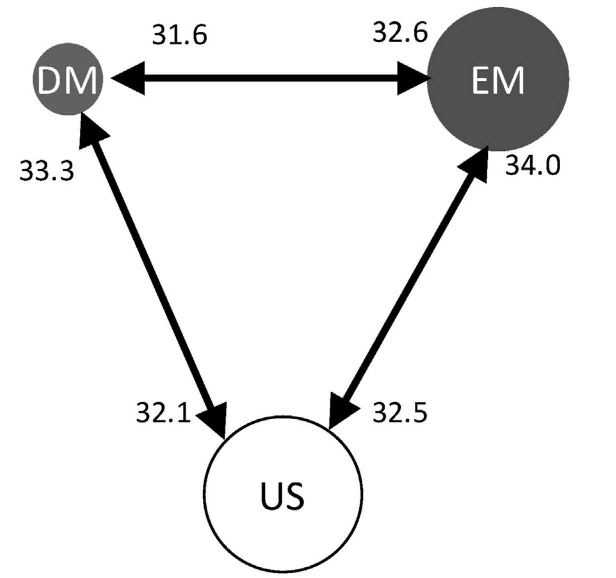
5. Empirical results

Table 2 reports the full sample cross-market connectedness across the level series of the variance premia of the three equity markets. We focus on the off-diagonal elements as they measure the pairwise volatility directional connections. The highest variance premium pairwise connectedness measure observed is from US to Emerging Markets (EM) equities hovering around 34% (third column, first row), while the second highest number also stems from the US; that is, the US→DM measure, which is 33.8%. In addition, the pairwise directional volatility connectedness from Developed Markets (DM) to the other markets is higher than the respective pairwise directional volatility connectedness from EM.

Accordingly, and based on the net connectedness (which is reported in the last row of Table 2 and graphically portrayed in Figure 2), which is the total sum of net directional pairwise spillovers, expressed as a negative value (net recipient) and a positive value (net transmitter) respectively, it seems that, on average, the volatility of Emerging Markets is the largest net receiver (-2.93%), while the US market is the largest net transmitter (+3.1%). These statistically significant relationships between developed and emerging markets investors' risk aversion directly suggests less diversification opportunities.

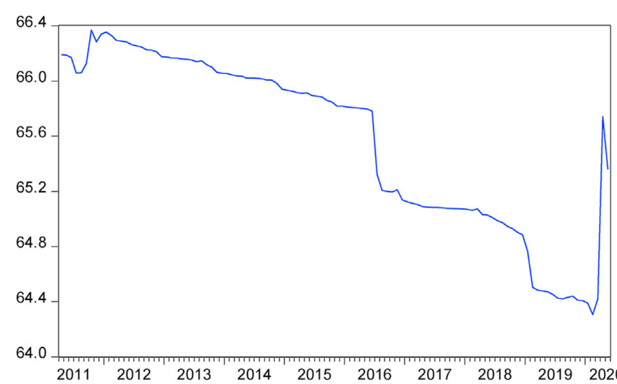
The total spillover index in all three markets is 65.6% (presented in Table 2), suggesting a sizable degree of interdependence among the three variance premia. Therefore, our empirical results indicate that emerging markets have significantly converged with equities from the developed markets in terms of investors' sentiment, confirming existing empirical evidence regarding integration of these markets into world markets in terms of returns, risk and valuation ratios (see Bekaert and Harvey, 2017 for a relevant discussion). Nevertheless, the period under review includes many market-moving events, with the COVID-led market sell-off being the most significant one. Therefore, a static measure of volatility spillovers may not describe adequately the true dynamics of the equity markets under investigation. Thus, we turn our attention to the analysis of the time-varying estimate of the dynamic total connectedness index plotted in Figure 3. Although the total connectedness index is estimated to be 65.6%, Figure 3 shows that there was a gradual decrease in total connectedness of the three markets under review over the last decade, only to skyrocket again after February 2020, when the global pandemic started to unfold.

We also report results related to the time-variability in net pair-wise directional connectedness among the variance premium series, which actually exhibit the most interesting empirical finding of this study. According to Guiso et al. (2018), aggregate risk aversion fluctuates either because typical investor's risk aversion changes or because the distribution of wealth among investors with different risk aversion changes. There are several competing theories attempting to explain changes in risk aversion (see Guiso et al., 2018 for a comprehensive review). The net directional connectedness indices (presented in Figure 4) provide



Notes: Filled nodes correspond to net recipients, while empty node corresponds to net transmitter.

Figure 2. Net pairwise directional network across three markets.



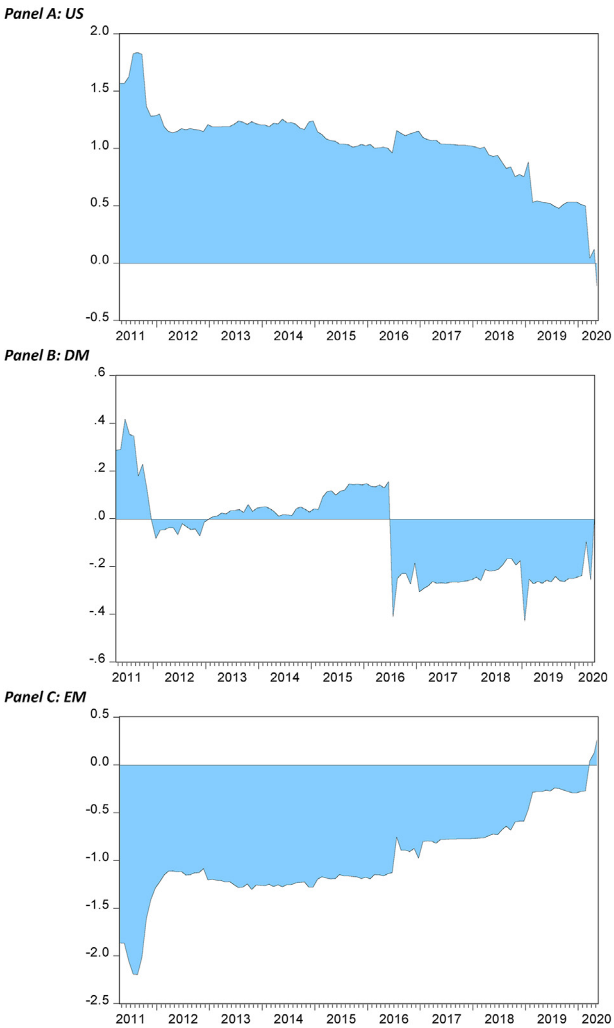
Notes: this graph presents the net total directional connectedness based on the TVP-VAR model for the period April 2011–May 2020.

Figure 3. Net spillover index over time.

Table 2. Directional spillovers (in %).

To market i	From market j			
	EM	DM	US	From Others
EM	33.335	32.636	34.029	66.665
DM	31.603	34.641	33.756	65.359
US	32.135	32.541	35.324	64.676
Contribution to others	33.335	32.636	34.029	66.665
				65.57%
Net Contribution (To – From) Others	-2.926	-0.182	3.109	

Notes: This table reports the variance decompositions for estimated TVP-VAR model. Variance decompositions are based on 10-step-ahead forecasts with the ordering as shown in the column heading, i.e. the (i, j) value is the estimated contribution to the variance of variance premium forecast error of market i coming from innovations to variance premium of market j. A lag length of order 1 was selected by the Bayesian information criterion.
The lower right corner (in bold) indicates the level of the total spillover index in %. The last row 'Net Contribution' indicates the total sum of net directional pairwise spillovers, expressed as a negative value (net recipient) and a positive value (net transmitter), respectively.



Notes: The net directional connectedness indices indicate the total sum of net directional pairwise spillovers, expressed as a negative value (net recipient) and a positive value (net transmitter).

Figure 4. Net directional connectedness plots.

information about how much each market's volatility contributes in net terms to other market's volatilities. The analysis of the net volatility spillovers shows that emerging equity markets have been net receivers of risk until early 2020, while the US, as probably expected, has been steadily, for the whole decade under review, a net transmitter of investor sentiment uncertainty. Finally, in the case of developed markets, as proxied by the iShares MSCI EAFE Index Fund, we notice that developed markets, with the Euro-debt crisis and the Brexit referendum, were basically net transmitters until mid-2016 and became net receivers after that period of turmoil.

Interestingly, when the COVID pandemic started to unravel in February 2020, the US risk aversion proxy became a net receiver of shocks from the other two markets, while emerging markets investors' sentiment became the main transmitter of shocks during the global pandemic crisis. These findings are somehow intuitive and confirm the evolution of the COVID outbreak around the world, as emerging markets were the first to be exposed, followed by Europe. Actually, this finding confirms the recent results by Bouri et al. (2020) who find that the US dollar is a primary transmitter of shocks before the outbreak, whereas it becomes a net receiver of shocks from other assets during the COVID outbreak period.

Our empirical findings have significant implications for emerging market investors as they indicate varying degree of contagion effects between emerging and developed markets and suggest that risk aversion should be included in models of contagion as well as in the design of effective asset allocations (Demirer et al., 2018).

6. Conclusion

The role of emerging markets in the world economy has been growing at a rapid pace over the past decades[7]. In parallel, academic research on emerging markets has also been booming since the data on emerging markets became available in the mid-1990s. This study extends existing attempts by analyzing the connectedness in investor sentiment as proxied by the variance premium of developed and emerging equity markets. In addition, in this paper, we contribute to existing empirical literature by investigating, for the first time, how the time-varying dynamics of investors' risk aversion reacted to the unprecedented catastrophic shocks of the COVID-19 pandemic.

Risk-neutral probability measures of expected volatility, such as the VIX, VXEFA and VXEEM, are considered a gauge not only for investors' expectations regarding uncertainty of future equity returns, but also for investors' risk aversion. By measuring the variance premium as the difference between the realized return variance (the physical probability measure) and the implied volatility index squared (risk-neutral probability measure), we are able to separate implied volatility from the effect of physical volatility dynamics and uncertainty and thus, derive a measure directly related to risk aversion (Bekaert and Hoerova, 2014).

The empirical analysis employs the TVP-VAR methodology of Koop and Korobilis (2014) and combine it with the connectedness measures proposed by Diebold and Yılmaz (2014), which are based on a generalized VAR model and have been actively employed in the finance literature to investigate spillover effects across various financial markets (see Batten et al., 2014; 2019 and Yarovaya and Lau, 2016 for a relevant discussion). The empirical methodology used permits the variances to vary over time and thus, overcomes the limitation of the arbitrarily chosen rolling-window-size, that can potentially result in erratic or flattened parameters and loss of valuable observations (Antonakakis and Gabauer, 2017; Antonakakis et al., 2018, 2019; Gabauer and Gupta, 2018; Korobilis and Yilmaz, 2018).

Our findings suggest that the US has been the largest contributor to the risk of other two markets until the COVID outbreak, which actually altered the network of connectedness across the investor sentiment in the three markets. The most important finding of this empirical analysis is that emerging equity markets, although are net receivers of risk until the start of 2020, they become net transmitters during the global pandemic. In comparison with the related literature, our findings are consistent with the bulk of literature that confirms the US leading role, but this is the first study to show that developed and emerging equity markets also have information content for the US equity market. These findings are of great importance as it is well documented in empirical literature (Philippas and Siriopoulos, 2013; Bekaert and Hoerova, 2016; Chen et al., 2016) that changes in risk appetites are an important determinant of asset returns. Additionally, understanding the drivers of investors' sentiment co-movements is not only a topic of interest for asset pricing, but also has implications for portfolio diversification and investment strategies. To that end, a connection of investors' risk aversion/appetite changes and the popularity of risky trades can been established, as existing empirical evidence indicates a close link between investor sentiment to herding and speculative behavior in financial markets (e.g. Blasco et al., 2012). Finally, policymakers, in order to safeguard financial stability more effectively, can observe and influence the direction of risk aversion spillovers across countries by closely monitoring the role of each country in the risk aversion transmission process.

[7] See Bekaert and Harvey (2017) for a comprehensive review of the emerging markets characteristics.

Declarations

Author contribution statement

A.P. Fassas: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data associated with this study has been deposited online at Mendeley data at 10.17632/7mym92twyp.3.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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