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Revisiting the pricing impact of commodity market spillovers on equity markets☆

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ABSTRACT

This paper revisits the dynamics of pricing relationships between commodity and equity markets in a sample of commodity-exporting economies between 2000–2023. We confirm the correlation between these asset prices increases around episodes of financial distress. Prior research attributes this increase to the effects of contagion initiated by commodity price shocks. However, we find that after controlling for the effect of time varying risk aversion and investor sentiment, there is no evidence that the documented correlation increase originates from commodity market shocks. Indeed, we are unable to reject the hypothesis of no contagion. We maintain that controlling for the influence of time varying risk aversion and investor sentiment, together with other factors which potentially cause common variation across price movements in commodity and equity markets, is essential to accurately capturing the relationship between asset prices in these markets.

1. Introduction

An extensive literature documents financial contagion in asset markets, covering a variety of financial instruments. These studies incorporate a variety of empirical approaches to assess the degree to which price shocks propagate across different asset classes. One relatively neglected area comprises the relationship between international commodity markets and equity returns, in particular those in emerging economies, and we believe it offers a particularly interesting scenario for further examination. Recent papers (see Creti et al. (2013), Roy and Roy (2017), Xu et al. (2019), Ahmed and Huo (2021), Hung and Vo (2021) and Mensi et al. (2022)) analyse the issue from the perspective of commodity-exporting emerging economies, finding evidence of what they maintain is a contagion effect between these markets. Later, we survey this literature in detail, but one recurring characteristic is the tendency in certain studies to confound distinct concepts such as interdependence, comovement, volatility spillovers and synchronisation when assessing the evidence for cross-market contagion. However, previous literature demonstrates that a critical distinction exists between documenting evidence of market comovement or synchronisation, and concluding that contagion is present (Forbes and Rigobon, 2002; Corsetti et al., 2005).

This situation underpins the central contribution of our paper, which is to revisit the pricing impact of commodity market spillovers on equity markets by explicitly considering the impact of important systemic global factors. Our primary motivation is to ascertain whether the evidence for contagion claimed in prior studies still prevails after controlling for such systemic global

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components. Specifically, our contributions can be summarised as follows. First, building upon the extensive methodological discussion and evidence we survey below, we include controls for the presence of: time variation in global risk aversion, global investor sentiment, financial stress, and economic policy uncertainty in our empirical specifications. Such factors are known to be responsible for generating comovement between asset returns in various markets, and we seek to determine if evidence of contagion between commodity and equity returns is robust to their inclusion. This contributes to overcoming the limitations and biases inherent in previous studies which omit such variables. Second, many studies analysing contagion and spillovers across commodity markets and other asset classes either focus upon the role of oil returns in transmitting shocks to advanced domestic stock markets, or analyse markets within a single emerging economy. We extend the scope of previous analysis by examining the most relevant commodity export market in nine commodity exporting countries. Our sample includes both developed and emerging economies. This facilitates comparisons and allows us to develop a more structured narrative when discussing the transmission channel through which shocks to internationally traded commodities affect domestic equity returns.

The key results of our study are as follows. In contrast to papers that fail to control for those systemic global factors documented to be important for explaining the dynamics of asset prices, we find no evidence of contagion between international commodity markets and the domestic equity returns in our nine commodity-exporting economies. The findings are consistent across developed and emerging economies. These results corroborate evidence from other studies examining related issues from the perspective of advanced economies, many of which also control for the presence of systemic global factors. We conclude that simply documenting comovement in asset returns between commodity and equity markets is insufficient basis for claiming the presence of contagion effects across markets unless the findings are robust to the inclusion of global factors.

Our study also provides context and informs certain existing debates in the literature which analyses asset price comovement in financial markets. Does such comovement provide sufficient evidence to claim some degree of interdependence between markets? Can we interpret any interdependence as indicating the presence of financial contagion being transmitted between markets? The seminal work of Forbes and Rigobon (2002) illuminates these issues by contributing fundamental theoretical foundations to underpin this debate. They demonstrate that empirically testing for contagion is not equivalent to documenting comovement between asset prices across financial markets, showing that a high pairwise correlation between markets provides no evidence of either interdependence or contagion. Karolyi and Stulz (1996) emphasise the role of global and domestic factors in explaining financial contagion, finding that global shocks exhibit a central role in explaining the comovement between the U.S. and Japanese equity returns. Several related studies also highlight the relevance of controlling for underlying global systemic factors or other common external elements that may explain the observed comovement across markets, a literature extensively surveyed by Karolyi (2003) and Dungey et al. (2005). These studies show that accounting for the presence of confounding factors is a necessary condition for distinguishing between mere correlation and financial contagion. More recently, the findings in Wang et al. (2023) confirm the importance of controlling for additional global factors, showing investors' risk aversion is a relevant channel influencing the relationship between equity markets in the U.S. and China and a set of commodity markets. Our paper complements and extends their analysis by studying the impact of commodity markets on a different, broader sample of both emerging and advanced commodity-exporting economies. Furthermore, our extended sample allows for a more comprehensive global coverage of the COVID-19 pandemic.

Our study of commodity and equity markets interprets financial contagion to be documented additional comovement between asset prices that extends beyond the acknowledged influence of time variation in global factors. To enhance the robustness of our conclusions, we use various proxies for global factors, including variables capturing risk aversion, investor sentiment, financial distress, and economic policy uncertainty. Specifically, the VIX index (VIX), the Put-Call Ratio (PCR), the St. Louis Fed Financial Stress (SLFFE) index and the Economic Policy Uncertainty (EPU).[1] We revisit the analysis of contagion between international commodity markets and a set of emerging and developed market equity returns, focusing on the role of these global factors in analysing the propagation of shocks. In particular, we investigate if there is any additional role for commodity markets in transmitting shocks to equity returns in commodity-exporting economies beyond the global factor channel.

Our definition of financial contagion closely follows the interpretation of prior literature describing financial contagion as market comovement which cannot be explained by fundamentals (Pindyck and Rotemberg, 1993; Dornbusch et al., 2000; Bekaert et al., 2005), and is adopted by much recent literature (Karolyi, 2003; Dungey et al., 2005). Under this interpretation, the fact two markets exhibit a high degree of comovement provides no evidence of financial contagion if there exists a third underlying factor which is responsible for the observed correlation. Building upon these foundations, controlling for global common factors is a fundamental part of any analysis detecting evidence of contagion rather than merely empirically documenting market comovement.

An increasing number of studies focus on the financialisation of commodity markets in an attempt to understand the economic relationship between international commodity markets and other asset classes. Boyd et al. (2018) survey the recent literature analysing the role of investors in commodity markets. The authors find speculative activity strengthens the link between commodity and equity markets by providing liquidity to commodity market participants. Previous research in this field analyses the role of investment capital, emphasising investors' exposure to commodity price fluctuations and portfolio capital flows. Cheng and Xiong (2014) survey these studies, analysing how investors' commodity market perceptions have evolved during the last two decades. They

[1] The VIX index estimates the implied market volatility obtained from option prices of S&P 500 traded equities. The Put-Call Ratio is computed as the ratio between the trading volume of put options and the trading volume of call options traded at the Chicago Board Options Exchange (CBOE). The St. Louis Fed Financial Stress (SLFFE) index tracks financial stress levels using a set of U.S. financial indicator variables. The Economic Policy Uncertainty (EPU) index measures economic uncertainty based on the content of news reports relating to economic uncertainty and the extent of disagreement evident across economic forecasts.

show how investors interpret commodity markets as an additional asset class which is available to diversify risk, and analyse the implications in terms of price discovery mechanisms. Tang and Xiong (2010) argue that the recent phenomenon of financialisation has increased the correlation between commodity and equity returns, especially in emerging markets.

We believe that extending the scope of previous analysis to incorporate commodity-exporting, emerging economies is worthwhile, since international commodity markets are often claimed to be a relevant channel through which external shocks affect such economies. This is particularly noteworthy in countries where a significant proportion of economic activity is associated with the performance of the commodity sector.

In relation to the financialisation of commodity market phenomenon, the economic intuition underpinning the link between commodity and stock markets may lie in the former's ability to capture expectations about the economic outlook for the latter, particularly in commodity-exporting economies. This transmission mechanism is consistent with the asymmetric information channel in King and Wadhwani (1990), where less informed investors use price changes in related asset markets to extract information concerning the economic prospects in another market of particular interest. In this context, if the commodity sector is an accurate gauge of domestic economic activity, then investors may interpret current economic conditions as a function of commodity sector activity. Therefore, changes impacting commodity markets may trigger changes in the composition of investors' equity market portfolios within commodity-exporting economies. This logic highlights the commodity channel as a relevant factor for explaining changes in stock returns in commodity-exporting economies. Several studies build upon this idea and document the transmission mechanism. For instance, Cheng and Xiong (2014) claim that copper and oil, among other commodities, are useful barometers for tracking economic activity during recent business cycles. Similarly, Hamilton (2009) maintains that oil demand shocks correlate with high levels of business sentiment. Kilian and Park (2009) show that positive oil demand shocks correlate with positive shocks to U.S. equity returns. In this sense, enhanced commodity market returns may translate into favourable news for domestic equity returns, as investors interpret commodity prices as an instrument to gauge future domestic economic prospects. The motivation of the present study is to determine whether such a commodity channel still accounts for evidence of contagion after controlling for channels linked to relevant global factors.

2. Literature review

The majority of research analysing financial contagion focuses on equities, currencies, government debt indicators and credit markets. A relatively less explored area examines the interrelationship between commodity and equity markets. Due to the importance of mature financial markets for global finance, the prevalence of much research is upon advanced economies, and utilises the international oil price as a focal point for commodity markets. Relatively few studies investigate the situation in emerging equity markets. In particular, with a focus on oil prices, Kilian and Park (2009) analyse the relationship with U.S. equity markets while Zhang (2017), Hatemi-J et al. (2017), and Apergis and Miller (2009) examine it with stock prices of the six, seven and eight major economies, respectively. Other authors, such as Hammoudeh and Choi (2006) and Janabi et al. (2010) investigate the relation between the oil market and equity market performance with an emphasis on oil-exporting economies. On the other hand, while retaining a focus on the U.S. equity market, Silvennoinen and Thorp (2013) expand the coverage of commodities to include oil, metals and food sectors. One common result across all these studies is that while commodity and equity markets exhibit some degree of pricing interrelationship, in general other financial and global factors exhibit a higher degree of comovement with equity markets.

In terms of empirical methodology, many studies capture the comovement between commodity and equity returns using the estimated conditional correlations from conditional volatility models, most commonly DCC-GARCH models. They maintain that observing increases in these correlations provides evidence of financial spillovers and contagion between markets, especially during episodes of acute financial stress, such as the 2007–2009 global financial crisis (GFC). For instance, Creti et al. (2013) use data from 25 commodity markets and S&P 500 returns over the period 2001 to 2011 and Mensi et al. (2013) examine the S&P 500 index and a set of commodity markets (energy, food, gold and beverages) from 2000–2011. Both studies document significant interdependence across markets between equity and commodity returns which tends to intensify during the GFC, and interpret this as evidence of a strengthening of respective market links as a result of the financialisation of commodity markets. Similar findings are also established for emerging markets. Sadorsky (2014) analyses the relationship between an aggregate, emerging market equity index and a set of commodity markets (oil, copper and wheat) over the period between 2000 and 2012, documenting an intensification of the comovement (spillovers) between stock returns and commodity markets, which is notably enhanced after the GFC. Further, Roy and Roy (2017) analyse the comovement between an aggregate commodity index, the Indian foreign exchange rate and the Indian equity market, concluding that the documented increase in correlations during the GFC provides evidence of contagion across markets.

Another family of related studies employs a vector autoregressive (VAR) approach, introduced in Diebold and Yilmaz (2009) and revised in Diebold and Yilmaz (2012), to analyse the dynamics of comovement between commodity market prices and equity returns. Bouri et al. (2021) examine the spillovers between S&P 500 returns and oil and gold markets using high-frequency observations, documenting that the links between these markets tend to intensify during episodes of financial distress. Analysing the dynamic relationship between Chinese stock returns and a set of commodity markets including, oil, gold, industrial metals, and agricultural commodities, Ahmed and Huo (2021) find increased spillovers in both return and volatility between stocks and the commodities under analysis, interpreting the findings as evidence of market contagion. Dey and Sampath (2020) focus on the spillovers between the gold price and the real estate and banking equity sectors in India. They conclude there is an increasing link between their chosen sectors and the gold price, although, importantly, they note some omitted global factors, such as U.S. financial shocks, may play a more relevant role in explaining the link between these markets. Evidence that links tend to intensify during periods of distress such as the GFC is also provided by Xu et al. (2019) who examine volatility spillovers between oil and equity returns in China and the U.S., and Awartani and Maghyereh (2013) who document the spillovers between oil and equity returns in the Gulf Cooperation Council Countries.

All the previous studies report a significant empirical relationship between equity and commodity returns, interpreted as evidence of either market contagion or spillovers. However, we posit that certain limitations in the methodological procedure(s) adopted, in particular, the failure to control for underlying global variables that may initiate the comovement across markets, calls into question the conclusions advocating the presence of contagion or spillovers effects. Following Karolyi (2003) and Dungey et al. (2005), controlling for such systemic global factors is crucial when characterising how shocks propagate across markets and, therefore, is a necessary condition for identifying the presence of contagion by allowing one to differentiate between simple asset price comovement and contagion proper. Consequently, we cannot dismiss concerns that the increase in asset market comovement documented in the previous studies arises as a result of omitted global factors, leading to concerns that the findings are not robust. This task is a key element motivating the present study.

Indeed, this critical issue is again highlighted by a set of recent studies exploring the relationship between commodity and stock markets, which document increasing links between markets, particularly during the period of financial turmoil initiated by the COVID-19 pandemic. The finding is consistent across different regions and commodities. However, once again, these studies typically fail to control for relevant systemic global factors, which may account for the documented increase in the links between markets. For instance, with respect to European equity sectors and the oil and gold markets, Mensi et al. (2022) demonstrate that there is an intensification of the links between these markets, particularly during financial distress episodes. Younis et al. (2023) document similar increased synchronisation between oil and gold markets and the stock returns of the BRICS countries (Brazil, Russia, India, China, and South Africa). A number of articles (Dutta et al., 2021; Hung and Vo, 2021; Liu et al., 2022; Zapata et al., 2023) find evidence that links between the S&P 500 returns and different commodity markets tend to intensify during episodes of financial distress, including the recent global pandemic. While Qi et al. (2022) and Chen et al. (2022) provide evidence on the links between Chinese equities and commodity markets and Sahadudheen and Kumar (2023) document increased links between oil and gold and the Indian equity and foreign exchange markets.

Existing research which incorporates additional financial channels and global factors when examining evidence of asset market contagion is often narrowly focused on its objectives. While the evidence highlights the relevance of such global factors, prior studies either address solely oil price shocks, focus upon a single country, or exclude the GFC. In contrast, the analysis in this paper provides more scope and generality. Hammoudeh and Choi (2006), using data from 1994 to 2004, find a limited effect of oil prices on the domestic equity returns of five oil exporting-countries from the Gulf Cooperation Council (GCC). Notably, they find that the impact of other international financial shocks, such as those emanating from U.S. equity returns and interest rates, account for most of the measured effect upon the domestic equity returns of the oil exporting-countries. Apergis and Miller (2009) examine the relationship between oil prices and stock returns using data from 1981 to 2007 for eight advanced economies. While they document a significant effect from oil prices transmitting shocks to equity markets, this effect tends to be quite small in comparison to the idiosyncratic shocks originating in the financial sector. Similarly, Kilian and Park (2009) conclude that oil price shocks explain around 20 percent of the variability of U.S. equity returns, while non-oil related shocks emanating from the U.S. financial market explain the remaining 80 percent of equity return variability. Each of these studies examines periods of more tranquil markets where as this paper explores periods of acute global financial market stress when contagion effects are documented to be at their peak.

In contrast to the uniformity of evidence in earlier studies, more recent evidence on the intensity of links between commodity markets and stock markets is mixed. Silvennoinen and Thorp (2013) estimate the correlation of a wide number of commodity markets with U.S. stock returns, using a smooth transition DCC-GARCH model including the VIX as a threshold variable to capture the effect of global risk aversion. Though the study finds that U.S. equity and commodity returns are related, this relationship is not universal across all commodity markets and depends on the period under analysis. For example, their results show that there is an increase in correlation between stock returns and oil returns during the GFC, there is a more modest increase in correlation between metal prices and equity returns, albeit this is not associated with the GFC, and there is no correlation evident between food prices and equity returns. Zhang (2017), using the Diebold–Yilmaz approach, documents that the effect of oil market price dynamics on a set of the major equity market returns appears very limited in comparison to the effect of other financial market variables in their sample and, more recently, Zhang and Hamori (2021) find a less prevalent role for commodity markets, in particular oil, in conveying shocks to U.S., Japan, and German stock returns during the recent COVID-19 pandemic. They argue that spillovers between these stock markets are largely explained by financial shocks, with a role evident for a systemic factor tracking global equity market volatility associated with infectious diseases. Conversely, oil shocks explain only a marginal proportion of the spillovers to stock markets. The findings in Zhang and Hamori (2021) emphasise the importance of controlling for global factors in any effort to capture the impact of commodity price fluctuations on stock returns.

3. Methodology and data

To capture potential contagion effects between pricing dynamics in commodity and equity markets, we utilise two empirical methodologies. This choice generates enhanced confidence in our findings, as when considered individually, though each approach possesses certain advantages it is also subject to certain drawbacks. The strengths manifest by each individual approach serve to overcome any inherent weaknesses in the other, as we discuss below. Specifically, the first approach adopts a Multivariate DCC-GARCH model originally formulated by Engle (2002). Our second specification follows the Diebold and Yilmaz (2012) methodology employing a generalised forecast error variance decomposition obtained from a vector autoregression model. We believe using both methodologies allows us to obtain a clearer perspective when interpreting both the current and prior results, yielding greater confidence in the conclusions of our analysis.

3.1. Multivariate DCC-GARCH

The multivariate DCC-GARCH methodology estimates the time-varying correlation between commodity and equity returns in order to better understand the evolution of their relationship over time. This approach facilitates the analysis of non-linearities in the covariance matrix of log-returns. Importantly, the methodology also controls for the presence of heteroscedasticity in log-returns which Forbes and Rigobon (2002) demonstrate imparts bias to any correlation estimates during periods of high return volatility. By using this multivariate GARCH framework, the analysis can incorporate the effect of time-varying return volatility and avoid problems relating to the presence of bias in the correlation estimates. The approach's main limitation is that it only provides an indicator capturing market comovement, and is unable to identify the origin of any shock(s) which causes returns in the two markets to move together.

Following Engle (2002), the DCC-GARCH model implemented in this paper is as follows:

$$r_t = u_t \tag{1}$$

$$u_t = H_t^{1/2}\epsilon_t \tag{2}$$

Let r_t be a $n \times 1$ vector of asset returns at time t, while u_t is a $n \times 1$ vector of residuals that follow a conditionally normal distribution, with mean equal to zero and covariance matrix H_t, such that:

$$u_t|\Omega_{t-1} \sim N\left(0, H_t\right) \tag{3}$$

where Ω_{t-1} represents the information set at time $t-1$. The covariance matrix is given by:

$$H_t = D_t R_t D_t \tag{4}$$

where D_t is a $n\times n$ diagonal matrix of time-varying standard deviations with the term in the diagonal corresponding to $\sqrt{h_{i,t}}$, where i = [equity returns, country-specific commodity returns], with estimates undertaken using the following univariate GARCH model:

$$h_{i,t} = \alpha_{0,i} + \alpha_{1,i}u_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{5}$$

R_t is a $n\times n$ matrix containing the time-varying conditional correlations. The dynamics of the conditional correlation matrix $\left(R_t\right)$ are given by:

$$R_t = diag\left(Q_t\right)^{-1} Q_t diag\left(Q_t\right)^{-1} \tag{6}$$

where $diag\left(Q_t\right)$ is a $n \times n$ diagonal matrix in which the ith diagonal element corresponds to the ith diagonal element of matrix Q_t given in Eq. (7).

$$Q_t = \left(1 - \lambda_1 - \lambda_2\right)\overline{Q} + \lambda_1\epsilon_{t-1}\epsilon_{t-1}' + \lambda_2 Q_{t-1} \tag{7}$$

In Eq. (7), λ_1 and λ_2 are coefficients to be estimated. $\epsilon_{i,t} = \frac{u_{i,t}}{\sqrt{h_{i,t}}}$ corresponds to the standardised residual obtained by dividing the residual term by the square root of the univariate time-varying variance in Eq. (5). $\overline{Q} = T^{-1}\sum_{t=1}^{T}\epsilon_t\epsilon_t'$ is the $n \times n$ unconditional covariance matrix of ϵ_t.

We estimate the multivariate DCC-GARCH model using quasi-maximum likelihood procedures in three different stages to avoid computational issues arising from the number of coefficients to be optimised.[2] The first stage estimates the univariate mean and volatility equations. In the second stage, we estimate the DCC coefficients given the first stage results. The final stage uses the first and second stage findings as initial values, and estimates the entire model simultaneously. This process guarantees better algorithm convergence when optimising the maximum likelihood function, and avoids generating inconsistent estimates of the conditional correlation matrix (Engle and Sheppard, 2008).

3.1.1. Estimating time-varying correlations

Our baseline model specification excludes global factors and involves replacing the generic mean equation of the DCC-GARCH model (Eq. (1)) with the following functional form for each country:

$$r_{1,t} = \gamma_{0,1} + \gamma_{1,1}r_{1,t-1} + u_{1,t} \tag{8}$$

$$r_{2,t} = \gamma_{0,2} + u_{2,t} \tag{9}$$

where $r_{1,t}$ and $r_{2,t}$ denote equity and country-specific commodity returns, respectively. We include the one period lag of equity returns in its own-return equation to capture the effect of any persistence in returns.[3] We model the univariate volatilities for equity

[2] Cappiello et al. (2006) show that even when assumptions concerning the normal distribution of the error term are invalid, the results of the model still have a valid quasi maximum likelihood estimation interpretation.

[3] The lack of any measured persistence in commodity returns enables us to exclude their lagged values from the specification in Eq. (9). See table B.1 in the online appendix.

and commodity returns as indicated by Eq. (5) which employs a GARCH(1,1) formulation. Using these specifications, we proceed to estimate the time-varying correlation (ρ_{it}), expressed as a percentage displaying values in the interval (−100,+100), for country i at time t as follows: $\rho_{i,t} = \{cov(r_{i,1}, r_{i,2})_t / [\sigma(r_{i,1})_t \cdot \sigma(r_{i,2})_t]\} \cdot 100$, where $r_{i,1}$ denotes equity returns of country i, and $r_{i,2}$ represents the country-specific commodity returns of country i. $cov(.)_t$ and $\sigma(.)_t$ represent the time-varying covariance and time-varying standard deviation, respectively, obtained from the covariance matrix in Eq. (4).

Our second specification amends the model incorporating the effect of global factors. Under this amended specification incorporating the effect of the global factor, we replace the generic mean equation of the DCC-GARCH model (Eq. (1)) with the following functional form for each country:

$$r_{1,t} = \gamma_{0,1} + \gamma_{1,1} r_{1,t-1} + \gamma_{2,1} F_t + u_{1,t} \tag{10}$$

$$r_{2,t} = \gamma_{0,2} + \gamma_{2,2} F_t + u_{2,t} \tag{11}$$

where F_t denotes the global factor. Initially, the global factor corresponds to global risk aversion as captured by the VIX index. We subsequently replace the VIX index with the Put-Call Ratio to control for global investor sentiment.[4] Considering this amended specification, we estimate the time-varying correlation for each country in analogous fashion to the previous specification.

3.2. Diebold and Yilmaz approach

Our second methodological approach is developed by Diebold and Yilmaz (2012) and offers a flexible way to model the pricing relationship between markets. Based on a generalised VAR model formulation, this approach offers a number of advantages. First, it generates a measure of the spillovers from one market to another. Second, it facilitates identification of the direction of the shock and an understanding of which asset is the source of any shocks transmitted across markets. Third, the estimated spillovers are not affected by the ordering of the VAR variables. Fourth, the nature of the VAR approach ensures endogeneity is not an issue. Its downside is that it only captures linear effects between markets. The reduced form of our VAR models is as follows:

$$Y_t = AY_{t-1} + u_t \tag{12}$$

We adopt two model specifications. Our initial baseline model formulation omits controls for the effects of global factors, and is given by:

$$Y_t = [r_{1,t}, r_{2,t}] \tag{13}$$

where $r_{1,t}$ and $r_{2,t}$ denote the time-series of stock and commodity returns, respectively.

The second model specification controls for the presence of global factors, and it is represented as:

$$Y_t = [r_{1,t}, r_{2,t}, F_t] \tag{14}$$

where F_t represents the global factor. As with the DCC-GARCH analysis, initially, we use the VIX index as a global factor, subsequently re-estimating the model after replacing it with the Put-Call Ratio.

Following Diebold and Yilmaz (2012), we compute the spillover indices obtained from the generalised forecast error variance decomposition (FEVD) of the VAR model. The generalised FEVD corresponds to the percentage of the variance of the forecast error which is explained by shocks orthogonal to the variables in the VAR model. A natural interpretation of the generalised FEVD relates to the key question of interest, namely the manner in which shocks originating within one asset market impact the other (i.e., the spillover effect). Specifically, we estimate a VAR model of order 2, with the generalised FEVD horizon set to 12 periods ahead. We use a rolling window length of 1000 observations when undertaking the forecasts. The model structure is comparable to those in related studies adopting similar estimation procedures (see Diebold and Yilmaz (2012)). Computing the VAR using a sample of rolling windows enables us to calculate the spillovers between markets through time. Adopting this methodology also enables us to identify the source of shocks, so it becomes possible to specify which asset market, if any, impacts the other.

3.3. Global factors

Initially, we employ risk aversion and investor sentiment proxies, namely the VIX index (VIX) and the Put-Call Ratio (PCR), respectively, to control for these global factors. Subsequently, in robustness exercises, we use the St. Louis Fed Financial Stress (SLFFE) index as a measure of financial distress, and the Economic Policy Uncertainty (EPU) index to capture disagreement over the impact of macroeconomic policy. Following Bekaert et al. (2011), we interpret the VIX index as a variable that captures common time variation in global risk aversion. During episodes of acute financial stress the VIX index tends to be high, uncertainty increases and the performance of financial markets deteriorates. As a consequence, risk-averse investors become more reluctant to expose their wealth by investing in risky assets. This logic underpins the colloquial term for the VIX index, the "fear index" (see Diebold and Yılmaz (2014)) and may explain its link to the comovement in returns documented in financial markets. Related studies that focus on controlling for the effect of global factors pay particular attention to the effect of global risk aversion in financial markets. Passari

[4] In further robustness checks we also consider the St. Louis Fed Financial Stress index and the Economic Policy Uncertainty index.

and Rey (2015) argue the VIX index is a key element in characterising the dynamics of risky returns, documenting that a single factor, which correlates highly with the VIX index, explains a high proportion of the volatility exhibited by risky assets. Coudert and Gex (2008) further support this idea, highlighting that key indicators of changes in investor risk aversion, such as the VIX, help predict episodes of equity market stress.

Several studies of commodity and international equity markets share this approach, documenting that links between them increase during episodes of financial distress. Cheng et al. (2014) demonstrate that a fall in commodity futures prices correlates with financial market downturns during times when the VIX is high. Similarly, Silvennoinen and Thorp (2013) conclude that the correlation between the U.S. equity market and commodity returns is enhanced during periods of financial and investor stress.

In addition, several articles utilise trading patterns in the options market to capture investor sentiment motivating our use of the Put-Call Ratio (PCR). For instance, Easley et al. (1998) theoretically demonstrate an informational link between options market trading volume and stock prices, suggesting investor trading behaviour plays a role in explaining future equity returns. Pan and Poteshman (2006) show that options trading volume contains relevant information for predicting future U.S. equity returns, arguing that market sentiment of informed option market investors is the source of this predictability. Further, Dennis and Mayhew (2002) utilise the PCR as a proxy for investor sentiment, to explain the skewness of stock option prices traded on the Chicago Board Options Exchange (CBOE) while Bandopadhyaya and Jones (2008) find that CBOE option trading volume explains components of S&P returns which are unrelated to market fundamentals and demonstrate that the PCR is a suitable measure to capture such market sentiment. Broadening the analysis, Bathia and Bredin (2013) highlight the relevance of investor sentiment, proxied by the PCR, to explain stock market returns in the G7 countries.

To ensure the robustness of our findings, in addition to the VIX and the PCR, we also include two alternative empirical measures used in prior literature to capture the effect of systemic global factors identified as being of particular relevance during times of financial stress: the St. Louis Fed's Financial Stress (SLFFE) index and the Economic Policy Uncertainty (EPU) index proposed and computed by Baker et al. (2016). Both indices are global in their orientation, attempting to capture the effect of systemic shocks which impact the international economy. This makes them appropriate candidates for indicating the influence of any common factors on the dynamics of returns in both equity and commodity markets. Moreover, Kliesen et al. (2012) provide a comprehensive comparison of the SLFFE index with other financial stress indicators, including the VIX, and confirm its appropriateness for capturing episodes of financial distress. Baker et al. (2019) discuss differences between the EPU index and other financial risk and sentiment related indices documenting that while the EPU index effectively captures global economic-related uncertainty it appears relatively less sensitive to financial market developments in comparison to financial stress indices. This is unsurprising since the SLFFE and the EPU indices differ in their focus. The SLFFE index is constructed using a principal components methodology and captures variation in a set of indicators relating to the overall financial health of the U.S. economy. The EPU index employs a text search methodology with the objective of capturing the level of global economic uncertainty. It appears to perform well, accurately tracking episodes of economic crisis and financial distress, such as the GFC, the 2009–12 European Sovereign Debt Crisis (ESDC) and the global COVID-19 pandemic. Several studies incorporate the EPU index to reflect how the economic uncertainty affects macroeconomic performance, especially in relation to a countries' economic growth (Aisen and Veiga, 2013), equity market returns (Antonakakis et al., 2013), oil prices (Antonakakis et al., 2014), and output, employment and investment (Baker et al., 2016).

3.4. Contagion test

Earlier, we raise issues surrounding the validity of certain existing approaches which analyse asset market contagion. Since certain model specifications fail to control for the influence of important external systemic factors that may be responsible for any measured correlations, their omission may lead to a misleading attribution of contagion between asset returns. This issue arises both when evaluating the dynamic correlations of the DCC-GARCH model and any spillover effects apparent when using the Diebold and Yilmaz methodology. Furthermore, as Diebold and Yilmaz (2009) emphasise, their spillovers measure is only designed to capture interdependence between markets. Indeed, they explicitly reject considering it to be a contagion measure. Our approach to mitigating these drawbacks involves incorporating the effect of global risk aversion and global investor sentiment as potentially important determinants of the documented correlation/spillovers between equity and commodity markets. We analyse whether the measured patterns of comovement between these markets around episodes of crisis can be accounted for the presence of these underlying systemic factors.

Employing the DCC-GARCH model, we compare the time-varying correlation between two specifications of the mean equation. One specification (Eqs. (8) and (9)) excludes, while another (Eqs. (10) and (11)) includes the global factor. Subsequently, we compute the average correlation between each specification during sub-samples covering three episodes of financial distress that we further outline below. When applying our second approach, the Diebold–Yilmaz variance decomposition framework, we compute the spillovers emanating from returns in the country-specific commodity market to the associated domestic equity market. As with the DCC-GARCH, we compute two specifications of the model, one excluding and the other including the global factor in the VAR model, as shown in Eqs. (13) and (14), respectively. Again, we calculate the average spillovers during crisis episodes from each specification.

This comparison is undertaken for three recent major episodes of financial market turmoil, the global financial crisis in the period 2007–09 (GFC), the European sovereign debt crisis during 2009–12 (ESDC), and the COVID-19 global pandemic during 2020–21 (COVID-19 pandemic). Two criteria motivate this selection. First, our focus is upon periods of financial vulnerability, which are precisely the times at which previous literature documents that the correlation or spillovers between asset markets tend to increase. It is during such episodes that we wish to discern if there is any additional impact of price changes originating in commodity markets exerting an influence on equity returns beyond the impact of factors influencing global investor sentiment. In addition, by analysing these episodes, we are able to benchmark our results against other studies which analyse the same periods. Second, most related studies evaluate the effect of commodity markets on the relevant domestic equities during the GFC. Therefore, by extending the analysis of contagion to the ESDC and the COVID-19 pandemic, we broaden the scope of the existing evidence that relates equity return movements to those in commodity markets.

We date the beginning of the GFC to 17 July 2007, when Bear Stearns discloses information alerting markets to the collapse in value of its investment funds (a precursor to the company's bankruptcy days later). We set the end date of the GFC crisis to 31 August 2009, when according to the U.S. Financial Crisis Inquiry Commission, asset markets have stabilised. According to the U.S. National Bureau of Economic Research, this end date is also consistent with the end of the U.S. recession. Following relevant milestones in the crisis timeline, we date the beginning of the ESDC to 2 October 2009, when the Greek government reveals that the nation's budget deficit is twice its expected level and represents 12.5% of Greek GDP. Its end date corresponds to 26 July 2012 when the incumbent European Central Bank president, Mario Draghi, announces the Outright Monetary Transactions programme in the context of the now famous "we will do whatever it takes to save the Euro" statement. This programme enables the ECB to purchase eurozone member countries sovereign bonds in the secondary market, following which sovereign bond spreads associated with the most severely impacted eurozone economies began to exhibit a pronounced downward trend, relieving pressures in European sovereign debt markets and helping to alleviate negative investor perceptions of the Eurozone's prospects. For the case of the COVID-19 global pandemic, we set the beginning of the crisis to 2 January 2020 following the World Health Organization declaration of the COVID-19 outbreak as a public health emergency of international concern. We date the end of the pandemic crisis on 31 May 2021 when the vast majority of the countries lift their last lockdown measures, with no further forced governmental interventions put in place to contain the spread of the pandemic.

To establish the basis for our test for contagion between asset markets, we follow Celik (2012) and perform a test for differences in means in order to conduct a time comparison of the model-determined time-varying correlations and the spillovers obtained from the DCC-GARCH model and the Diebold–Yilmaz approach, respectively. This enables us to statistically evaluate whether the observed increase in correlation/spillovers during financial stress episodes reflects a direct transmission channel between commodity and equity returns, or if it is simply the manifestation of omitted factors, such as global risk aversion and investor sentiment, exerting a common influence across markets. For each of our chosen empirical approaches (the DCC-GARCH model and the Diebold–Yilmaz variance decomposition approach), the contagion test is a two-sample test for equality of the means derived from the estimation of the two methodologies (time-varying correlation or spillovers) under our two alternative specifications, namely excluding and including the global factors. We run the contagion test for each methodology by comparing the mean of the time-varying correlations/spillovers with and without controlling for the effect of global factors. We compute the difference in means, focusing on the GFC, the ESDC, and the COVID-19 pandemic sub-sample crisis episodes. The null and alternative hypothesis of the contagion test are as follows:

$$\begin{aligned} &\mathrm{H}_0 : \mu_F \leq \mu_{no\ F} \quad (no\ \ contagion) \\ &\mathrm{H}_a : \mu_F > \mu_{no\ F} \quad (contagion) \end{aligned} \tag{15}$$

where μ_F and $\mu_{no\ F}$ represent the means of the sample correlation/spillover we compute during the relevant financial crisis episode using the model specification with and without incorporating the effect of global factors. Under the null hypothesis, the average correlation/spillover obtained from the model including the global factor is less than or equal to that arising from the model excluding the global factor. We interpret this to imply that the effect of the global factor accounts for the increase in correlation/spillovers between markets during crisis episodes, meaning there is no evidence of contagion between commodity and equity markets. The alternative hypothesis states the average correlation/spillover emanating from the model including the effect of the global factor is strictly greater than the one we derive from the model excluding the effect of the global factor, suggesting there is an additional link between commodity and equity markets extending beyond the manifestation of systemic global factors. We interpret any such finding as evidence of contagion across markets. The test statistic (t) is as follows:

$$t = \frac{\bar{\rho}_F - \bar{\rho}_{no\ F}}{\sqrt{s_F^2/n_F + s_{no\ F}^2/n_{no\ F}}} \tag{16}$$

where $\bar{\rho}_F$ and $\bar{\rho}_{no\ F}$ are the means of the sample correlation/spillovers during each crisis episode using the specifications with and without the global factor, respectively. s_F^2 and $s_{no\ F}^2$ are the sample variances and n_F and $n_{no\ F}$ are the sample sizes. We reject H_0 at α% significance level if $t > t_{(1-\alpha,\upsilon)}$, where we calculate the degrees of freedom (υ) as:

$$\upsilon = \frac{\left(s_F^2/n_F + s_{no\ F}^2/n_{no\ F}\right)^2}{\left(s_F^2/n_F\right)^2 / \left(n_F - 1\right) + \left(s_{no\ F}^2/n_{no\ F}\right)^2 / \left(n_{no\ F} - 1\right)} \tag{17}$$

Other studies use the same logic to test for asset market contagion, but follow a slightly modified approach. For instance, when comparing returns during times of financial distress and more tranquil periods, Longin and Solnik (1995) test for statistical differences in the elements of the respective variance–covariance matrices.

Table 1
Commodity exporting economies.
Source: United Nations Conference on Trade and Development (UNCTAD) website (https://unctadstat.unctad.org/EN/Index.html).

Country	Main export	Commodity exports (% of total exports)				Commodity exports (% of GDP)				Main commodity export (% of commodity exports)			
		2000–05	2006–11	2012–17	2018–22	2000–05	2006–11	2012–17	2018–22	2000–05	2006–11	2012–17	2018–22
Brazil	Oil	46	58	64	73	5	6	6	11	9	16	13	13
Canada	Oil	36	49	50	51	11	12	12	14	22	33	37	25
Chile	Copper	84	87	86	86	24	31	23	25	55	70	63	61
Colombia	Oil	65	71	81	81	9	11	11	11	43	46	55	53
Mexico	Oil	18	26	21	17	4	7	7	7	59	59	42	34
Norway	Oil	79	82	80	83	25	26	22	29	64	54	44	58
Peru	Copper	83	88	89	91	13	23	18	20	42	49	46	41
Russia	Oil	76	83	81	70	22	20	18	19	57	64	63	56
S. Africa	Gold	49	55	57	66	9	12	14	24	51	62	59	37

Column "main export" shows the main commodity export by country. The rest of the columns in the table report the average percentage value of exports for each of the following four periods: 2000-2005, 2006-2011, 2012-2017, and 2018-2022 for each country.

3.5. Data

The data consists of daily observations of country-specific commodity and equity returns, from 7 January 2000 to 31 May 2023 from the following nine commodity-exporting economies, with the major country-specific export-commodity given in parentheses: Brazil (oil), Canada (oil), Chile (copper), Colombia (oil), Mexico (oil), Peru (copper), Norway (oil), Russia (oil), and South Africa (gold). We select countries according to two criteria: first, commodities must constitute a significant percentage of the country's exports (see Table 1), and second, the country must adopt either a "floating" or a "free-floating" exchange rate regime throughout the sample period.[5] The equity, commodity, VIX index, and PCR data is sourced from Bloomberg. We obtain the St. Louis Fed Financial Stress index data from the Federal Reserve Economic Data website and the Economic Policy Uncertainty index from Baker et al. (2016)'s website.[6] To avoid introducing confounding factors associated with fluctuations in the value of the U.S. dollar, we compute equity returns from equity indices measured in local currency and obtain commodity returns from commodity price indices denominated in U.S. dollars.

Given the relevance of commodity exports for the selected countries, we analyse potential contagion between a particular country's equity market and the international price of its major export-commodity. Our goal is to assess how specific commodity shocks to economically important, country-specific commodity markets influence domestic equity returns. This focus is dictated by the evidence documenting differentiated price dynamics across international commodity markets. For instance, Daskalaki et al. (2014), maintain that commodity markets are segmented from one another, with each commodity following its own pricing dynamics evolving independently of the patterns exhibited by other commodity types. Similarly, Erb and Harvey (2006) and Kat and Oomen (2007) document that the evolution of commodity prices displays heterogeneity through time. They conclude that acknowledging the differentiated dynamics of commodity prices substantially improves portfolio diversification using commodity assets. In addition, Adams and Glück (2015) show that commodity prices exhibit differential responses to the effects of the financialisation of commodity markets. They find that since 2008, oil and copper prices increasingly relate to price changes in the U.S. equity market, while others, such as aluminium and wheat prices, show no increase in correlation with U.S. equity returns. The documented heterogeneity of pricing dynamics characterising international commodity markets, together with the economic relevance and importance of a particular commodity market within a specific country, motivates our focus upon a single country-specific export commodity price for each economy in the sample.

4. Results

4.1. DCC-GARCH model

This section presents the estimates of the time-varying correlations based on the DCC-GARCH model we introduce in Section 3.1. We present two different model specifications, namely without and then with controls for the effect of variations in global factors.[7]

4.1.1. Time-varying correlations

Fig. 1 displays the plots of the conditional correlations. For each plot, the grey (black) line represents the conditional correlation estimates using the model excluding (including) the global factor. As we use two different global factor proxies, the figure presents

[5] The regimes we employ correspond to the most flexible exchange rate categories under "De Facto Classification of Exchange Rate Arrangements" elaborated by the International Monetary Fund. See International Monetary Fund (2019).

[6] Federal Reserve Economic Data website: https://fred.stlouisfed.org. Economic Policy Uncertainty website https://www.policyuncertainty.com.

[7] Tables B.2 and B.3 in the online appendix present the estimation results of these models.

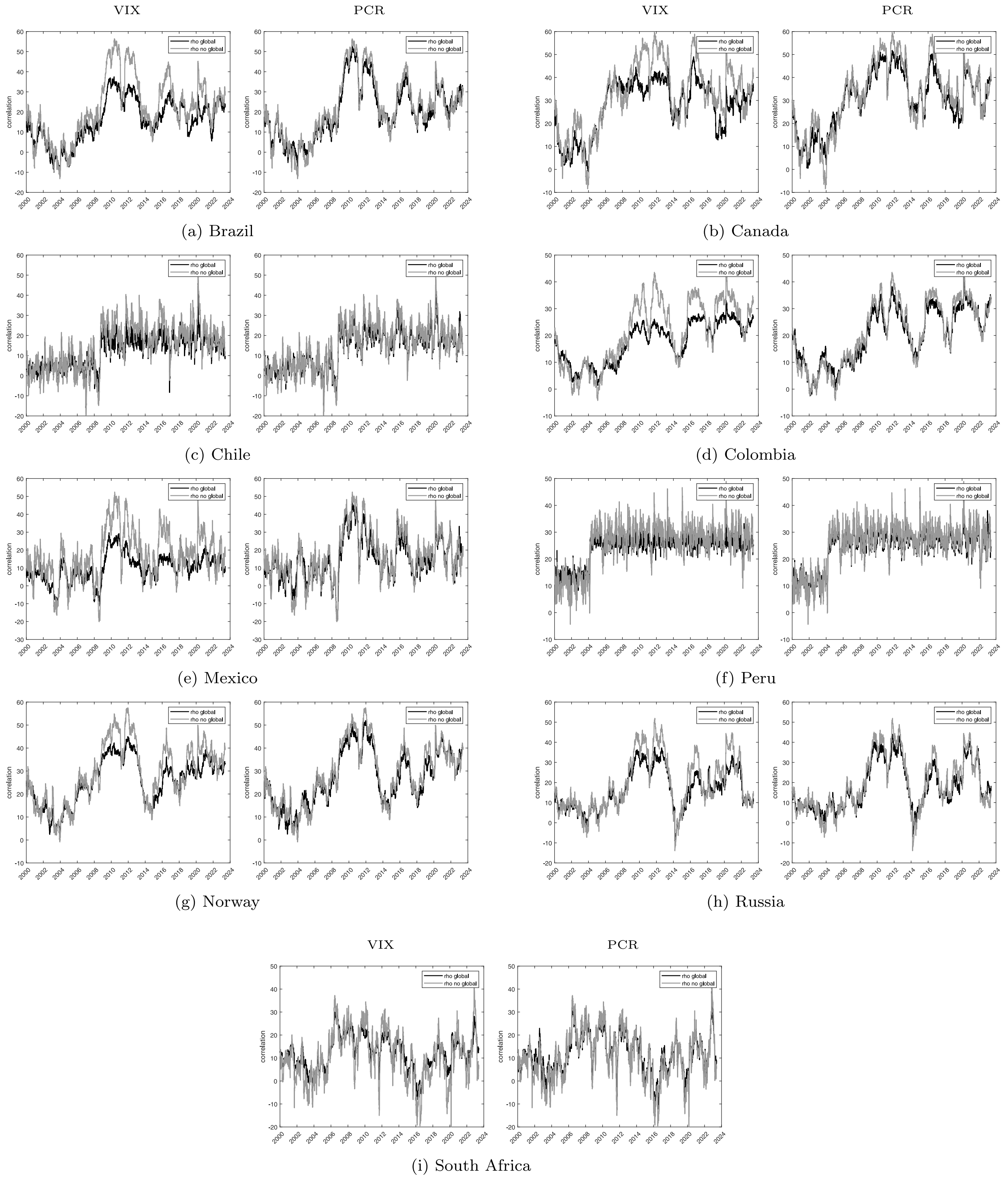

Fig. 1. Time varying correlation from DCC-GARCH model with and without global factor. The grey (black) line corresponds to the time-varying correlation computed using the DCC-GARCH model introduced in Section 3.1 excluding (including) the global factor in the model specification For each country, the global factor in the subplot in the left (right) column is proxied by the VIX index (PCR index) DCC-GARCH model estimated by maximum likelihood using a sample of daily observations from 07 January 2000 to 31 May 2023 Time-varying correlation (ρ_{it}), expressed as a percentage displaying values in the interval (−100,+100), for country i at time t obtained from the covariance matrix in Eq. (4) as follows: $\rho_{it} = \{cov(r_{i,1}, r_{i,2})_t / [\sigma(r_{i,1})_t \cdot \sigma(r_{i,2})_t]\} \cdot 100$, where $r_{i,1}$ denotes domestic stock returns of country i, and $r_{i,2}$ represents the country-specific commodity returns of country i. $cov(.)_t$ and $\sigma(.)_t$ represent the time-varying covariance and time-varying standard deviation, respectively.

two subplots for each country, with the left (right) figure depicting results when the VIX index (PCR) controls for the global factor. In almost all cases, we observe conditional correlations tend to increase during periods of financial distress, namely the GFC, the ESDC, and later during the COVID-19 pandemic. However, both correlations tend to exhibit discernible differences through time. In particular, the pattern of conditional correlation that includes the global factor (black line) tends to be lower in magnitude than the one which excludes it (grey line). The difference between the two conditional correlations is accounted by the influence of the global factors. These global components appear to explain a significant element of the co-movement between equity and commodity markets, and controlling for their effect the correlation between markets tends to be somewhat lower in magnitude (black line), particularly around the time of the three crisis episodes we analyse. We interpret this pattern as a manifestation of the importance of recognising the role played by global risk aversion and investor sentiment in the mechanism underlying the propagation of shocks across domestic asset markets.

The analysis to date maintains that conditional correlation dynamics are an appropriate measure to capture comovement between stock and commodity markets. Indeed, the documented pattern of comovement between commodity and equity markets is one that accords with intuition, given existing evidence that increased correlation between asset markets is characteristic of periods of financial turmoil. However, the presence of confounding systemic factors, in the form of time-varying risk aversion (reflected in VIX index) and investor sentiment (represented by the PCR), may be the underlying catalyst which underpins this pattern of movement in both markets. Consequently, we are unable to draw definitive conclusions regarding the degree of contagion across markets simply by comparing the evolution of their conditional correlations. This key difference distinguishes our results from those in related studies that omit controlling for the influence of global factors. We proceed to discuss this idea more formally in the next section.

4.1.2. Contagion test based on time-varying correlations

This section presents the results of the contagion test we outline in Section 3.4 for the three crisis episodes we investigate, namely the GFC, the ESDC, and the COVID-19 pandemic. Initially we control for global risk aversion and investor sentiment as global factors, and later include additional measures relating to financial distress and economic policy uncertainty as a robustness check.

Table 2 panel A displays the results of the contagion tests using the VIX index to control for the influence of global risk aversion for the three crisis periods. They reveal that for the majority of countries we cannot reject the null hypothesis of no contagion for the selected crisis episodes under analysis. The single exception is South Africa during both the GFC and the COVID-19 pandemic, where we find some statistical evidence of contagion. Table 2 panel B presents the findings from re-estimating the contagion tests after replacing the global factor VIX index with the PCR, thereby controlling for investor sentiment. As the results show, once again we are unable to reject the null hypothesis of no contagion for every country during the crises we analyse. Overall, we are led to conclude that for the vast majority of the countries in the sample, after accounting for the effect of the global risk aversion and investor sentiment channels, commodity markets appear to exert no additional influence inducing excessive comovement on equity returns. On the basis of this methodology, we reject the hypothesis of any evidence of contagion between commodity and equity markets for the majority of the countries in the sample.

4.1.3. Robustness to alternative global factors

This section examines the robustness of our findings by reformulating the previous specifications to include two alternative empirical measures as controls. Here, we consider the St. Louis Fed's Financial Stress (SLFFE) index, and subsequently with the Economic Policy Uncertainty (EPU) index as global factors.[8]

Table 2 panels C and D, present the results of undertaking contagion tests using the SLFFE and the EPU index, respectively. Employing the SLFFE index to capture episodes of financial distress (panel C), we cannot reject the null hypothesis of no contagion for any country in any of the crisis episodes under investigation. These findings again emphasise the relevance of controlling for global factors. In this case, the financial distress channel accounts for the increased correlation between stocks and commodity returns. Consequently, once we control for this global factor, we observe a substantially diminished role for shock transmission between commodity and stock markets, in other words, no evidence of contagion. These results corroborate our initial findings using both the VIX index (panel A) and the PCR (panel B) to measure global factors. Similarly, when we use the EPU index as the global factor to control for economic-related uncertainties (panel D), we cannot reject the no contagion hypothesis in the majority of countries during the crisis episodes we analyse, albeit occasional exceptions appear. These include Brazil during the GFC and the Covid-19 pandemic, South Africa in the GFC, and Mexico during both the ESDC and the Covid-19 pandemic, although the contagion evidence is only marginally significant in the former case. Overall, the substantial weight of evidence points towards no contagion between asset markets, and emphasises the importance and relevance of controlling for systemic factors. Here, the economic uncertainty channel explains the majority of the enhanced links between commodity and equity returns during financial crisis episodes. Overall, both alternative measures support the conclusions we obtain using both the VIX index and the PCR, namely that findings of contagious spillovers between commodity and equity markets in prior studies are not robust to the inclusion of controls for time variation in systemic global factors which exert a simultaneous influence upon all asset markets.

[8] Both indices, the SLFFE index and the EPU index, are available at a monthly frequency, so we conduct the robustness exercises using observations at monthly frequency for the same sample period as before, January 2000 to May 2023. Fig. A.1 in the Appendix A displays a comparison of the indices we employ to capture the effect of global factors. The correlation matrix in the appendix confirms the correlation between the VIX and SLFFE indices is high, while the association is manifestly weaker when comparing both these indices with the PCR and the EPU index, with the PCR and the EPU index exhibiting the lowest correlation.

Table 2
Contagion test based on the DCC-GARCH estimation.

Panel A: VIX as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	24.6	16.4	−8.2	1.0	45.4	30.9	−14.5	1.0	30.7	20.7	−10.0	1.00
Canada	37.0	36.7	−0.3	0.8	50.0	37.4	−12.6	1.0	39.9	27.7	−12.1	1.00
Chile	12.6	10.2	−2.4	1.0	23.0	16.9	−6.1	1.0	24.3	19.4	−4.9	1.00
Colombia	22.1	17.4	−4.7	1.0	32.3	22.2	−10.2	1.0	35.1	27.5	−7.6	1.00
Mexico	13.9	4.6	−9.3	1.0	35.3	21.4	−13.9	1.0	25.7	15.1	−10.6	1.00
Norway	33.7	31.6	−2.1	1.0	47.5	39.1	−8.4	1.0	40.2	32.8	−7.4	1.00
Peru	29.7	26.7	−3.0	1.0	29.9	26.3	−3.5	1.0	30.1	26.8	−3.3	1.00
Russia	22.9	20.3	−2.6	1.0	38.5	30.4	−8.1	1.0	35.0	26.8	−8.2	1.00
S. Africa	19.1	19.9	0.8**	0.02	17.5	16.2	−1.4	1.0	13.1	14.5	1.4***	0.00

Panel B: PCR as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	24.6	20.9	−3.7	1.0	45.4	42.0	−3.4	1.0	30.7	29.5	−1.2	1.0
Canada	37.0	34.3	−2.7	1.0	50.0	45.9	−4.1	1.0	39.9	38.8	−1.1	1.0
Chile	12.6	10.8	−1.8	1.0	23.0	19.9	−3.1	1.0	24.3	21.9	−2.4	1.0
Colombia	22.1	19.1	−3.1	1.0	32.3	29.2	−3.2	1.0	35.1	33.5	−1.6	1.0
Mexico	13.9	10.5	−3.4	1.0	35.3	31.1	−4.2	1.0	25.7	24.5	−1.3	1.0
Norway	33.7	30.8	−2.9	1.0	47.5	44.1	−3.4	1.0	40.2	39.2	−1.0	1.0
Peru	29.7	27.9	−1.8	1.0	29.9	27.8	−2.1	1.0	30.1	28.1	−2.0	1.0
Russia	22.9	19.7	−3.2	1.0	38.5	34.3	−4.1	1.0	35.0	32.4	−2.6	1.0
S. Africa	19.1	18.9	−0.2	0.7	17.5	16.9	−0.7	0.9	13.1	13.1	−0.003	0.5

Panel C: SLFFE index as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	33.5	24.1	−9.4	1.0	31.3	23.1	−8.2	1.0	34.0	19.5	−14.5	1.0
Canada	48.7	31.2	−17.6	1.0	47.3	31.5	−15.8	1.0	56.9	31.6	−25.3	1.0
Chile	27.3	16.3	−11.1	1.0	29.2	16.6	−12.6	1.0	31.3	16.8	−14.6	1.0
Colombia	27.9	13.6	−14.3	1.0	31.6	10.6	−21.0	1.0	53.8	17.9	−35.9	1.0
Mexico	29.7	19.2	−10.4	1.0	29.1	12.8	−16.2	1.0	24.9	14.2	−10.7	1.0
Norway	43.4	32.1	−11.3	1.0	52.1	32.4	−19.7	1.0	60.5	30.9	−29.6	1.0
Peru	30.4	28.2	−2.1	0.6	52.9	54.5	1.6	0.2	42.9	36.8	−6.2	1.0
Russia	34.1	24.6	−9.5	1.0	39.9	25.8	−14.0	1.0	35.4	17.9	−17.5	1.0
S. Africa	27.5	15.4	−12.1	1.0	34.8	18.4	−16.3	1.0	24.4	17.6	−6.9	1.0

Panel D: EPU index as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	33.5	39.6	6.1*	0.07	31.3	33.7	2.4	0.1	34.0	48.4	14.3**	0.0
Canada	48.7	49.5	0.7	0.3	47.3	47.6	0.3	0.4	56.9	59.8	2.9	0.2
Chile	27.3	26.9	−0.4	0.7	29.2	27.7	−1.5	1.0	31.3	28.3	−3.0	1.0
Colombia	27.9	27.1	−0.8	0.7	31.6	30.9	−0.8	1.0	53.8	52.7	−1.2	0.7
Mexico	29.7	28.0	−1.6	1.0	29.1	30.4	1.3***	0.0	24.9	34.4	9.5***	0.0
Norway	43.4	42.5	−0.9	0.7	52.1	47.3	−4.8	1.0	60.5	55.5	−4.9	1.0
Peru	30.4	32.9	2.6	0.4	52.9	54.1	1.2	0.1	42.9	44.9	1.9	0.2
Russia	34.1	31.9	−2.2	1.0	39.9	37.0	−2.9	1.0	35.4	34.5	−0.9	0.8
S. Africa	27.5	32.0	4.5**	0.04	34.8	36.6	1.8	0.2	24.4	26.2	1.7	0.2

Column 'No global factor' ('Global factor') corresponds to the average time-varying correlation during the selected crisis episodes computed using the DCC-GARCH model excluding (including) the global factor in the model specification Time-varying correlation (ρ_{it}), expressed as a percentage displaying values in the interval (−100,+100), for country i at time t obtained from the covariance matrix in Eq. (4) as follows: $\rho_{it} = \{cov(r_{i,1}, r_{i,2})_t / [\sigma(r_{i,1})_t \cdot \sigma(r_{i,2})_t]\} \cdot 100$, where $r_{i,1}$ denotes domestic stock returns of country i, and $r_{i,2}$ represents the country-specific commodity returns of country i. $cov(.)_t$ and $\sigma(.)_t$ represent the time-varying covariance and time-varying standard deviation, respectively Panel A, B, C and D depict the estimation results using the VIX index, the Put-Call Ratio (PCR), the St. Louis Fed Financial Stress (SLFFE) index, and the Economic Policy Uncertainty (EPU) index, respectively, as a proxy of the global factor Column 'Diff.' corresponds to the difference between the columns 'Global factor' and 'No Global factor' Column 'Cont. p-val' corresponds to the p-value of the contagion test of Section 3.4, where H_0: No contagion, and H_a: Contagion Global financial Crisis dates: 17 July 2007 to 31 August 2009. European Sovereign Default Crisis dates: 2 October 2009 to 26 July 2012. Covid pandemic dates: 2 January 2020 to 31 May 2021. (*), (**), (***) indicates statistical significance at 10, 5, and 1% level, respectively.

4.2. Diebold-Yilmaz approach

We now present the estimates of spillovers between commodity and equity markets we obtain using the Diebold–Yilmaz methodology we introduce in Section 3.2. In accordance with the previous approach, our Diebold–Yilmaz framework involves estimating two VAR specifications, with Eq. (13) excluding, and Eq. (14) including, the effect of global factors. We conduct both VAR specifications for every country in the sample. Initially, we employ the time varying risk aversion as captured by the VIX index to control for global factors. We subsequently replace the VIX index with our selected global factor proxies, namely, the PCR, the SLFFE index and the EPU index.

4.2.1. Spillovers between markets

Fig. 2 depicts the decomposition of the relevant shocks impacting equity markets. For each country, the subplot in the left (right) column adopts the VIX index (the PCR) to control for global factors. For each subplot, the measured shocks emanating from commodity markets when the model excludes (includes) the respective global factor are indicated by the grey (black) line. The dashed line captures the shocks attributable to the respective global factor when it is itself incorporated into the model in Eq. (14).

Our analysis yields the following findings. First, Fig. 2 reveals that for all countries in the sample, the spillovers transmitted from commodity to equity markets are indeed time varying. Before the GFC, such spillovers exhibit a similar evolution and tend to be close to zero under both model specifications, with and without either of the two global factors. Following the GFC, Fig. 2 indicates that commodity markets spillovers increase and appear greater in absolute magnitude in the absence of the global factors. This holds whether we use the VIX index or the PCR to control for these global factors. Second, the impact of the global factor exceeds that of commodity markets in absolute magnitude for most countries under analysis, with a few exceptions during the second half of the sample when using the PCR as the global factor. Moreover, global factor spillovers tend to strengthen after the GFC, and display additional increases during both the ESDC and the Covid-19 pandemic.

These results reflect the fact that prior to the GFC, with less evidence documenting financialisation of commodity markets, the relevance of time variations in global factors for commodities, such as risk aversion and investor sentiment, is diminished. This reflects the fact that during this period commodity markets are not widely considered to constitute an important asset class in the portfolio composition of international investors. This translates into the negligible differences we observe when measuring the impact of commodity market spillovers on equity returns, no matter whether or not we control for global risk aversion (using the VIX index) or investor sentiment (based on the PCR). This evidence is consistent with the prior narratives accompanying the financialisation of commodity markets documented in previous studies. For instance, Adams and Glück (2015) maintain there is a significant change in the relationship between commodity and stock markets after 2008 when commodity markets increasingly attract the interest of investors searching to diversify their portfolios. Consequently, the financial distress episodes experienced during the GFC not only negatively impact equities, but also exert an influence on investor perceptions' of commodity markets which are now seriously considered as an alternative asset class. In this context, Cheng and Xiong (2014) highlight investors' risk appetite as one of the main channels through which movements in commodity and equity markets relate to one another. Following the GFC, financialisation of commodity markets intensifies and controlling for risk aversion becomes more relevant, precisely, because it is during such financial distress episodes that these global factors play a role as an important transmission channel through which external shocks to major commodity export markets impact equity returns. These dynamics are highlighted by the fact that estimated global risk aversion spillovers, represented in Fig. 2 by the dashed line in the left-hand column of each country subplot, becomes a more relevant source of shocks during the crises we analyse. The difference between commodity market spillovers in both models (comparing the grey and black lines), also reveals the enhanced effect of global risk aversion. Following the GFC, in comparison to the case without the global factor (grey line), when we include the VIX index in the model (black line) we observe both a reduction in the impact of the magnitude of commodity market spillovers on equity markets and increases which are noticeably muted during episodes of financial distress. We observe similar patterns, although somewhat less pronounced in magnitude, when using the PCR to control for global factors. We interpret these observations as evidence of the importance of the global factor component in transmitting shocks. A corollary of this observation is that the commodity market channel appears less relevant once we include controls for risk aversion and investor sentiment in the analysis. In Section 4.2.3 we provide a formal tests of these findings in terms of evidence of contagion between markets.

4.2.2. Net spillovers between markets

Now we proceed to more formally analyse the net effect of spillovers between commodity and equity markets, defined as follows:

$$S_{net} = S_{comm\to stock} - S_{stock\to comm} \tag{18}$$

where S_{net} represents the net spillovers between commodity and domestic equity markets, $S_{comm\to stock}$ denotes the spillovers of commodity returns on equity returns (i.e., the percentage of the forecast error variance of equity returns explained by orthogonal shocks to commodity returns), and $S_{stock\to comm}$ corresponds to the spillovers of equity returns on commodity returns (i.e., the percentage of the forecast error variance of commodity returns explained by orthogonal shocks to equity returns).

Fig. 3 depicts the net spillovers between commodity and domestic equity markets. For each country, the subplot in the left (right) column includes the VIX index (PCR) to control for global factors. For each plot, the black (grey) line corresponds to the model which includes (excludes) the corresponding global factor. The findings are as follows: First, net spillovers which include the effect of the global factor (black line), computed using either the VIX index or the PCR, are time-varying and fluctuate from positive to negative

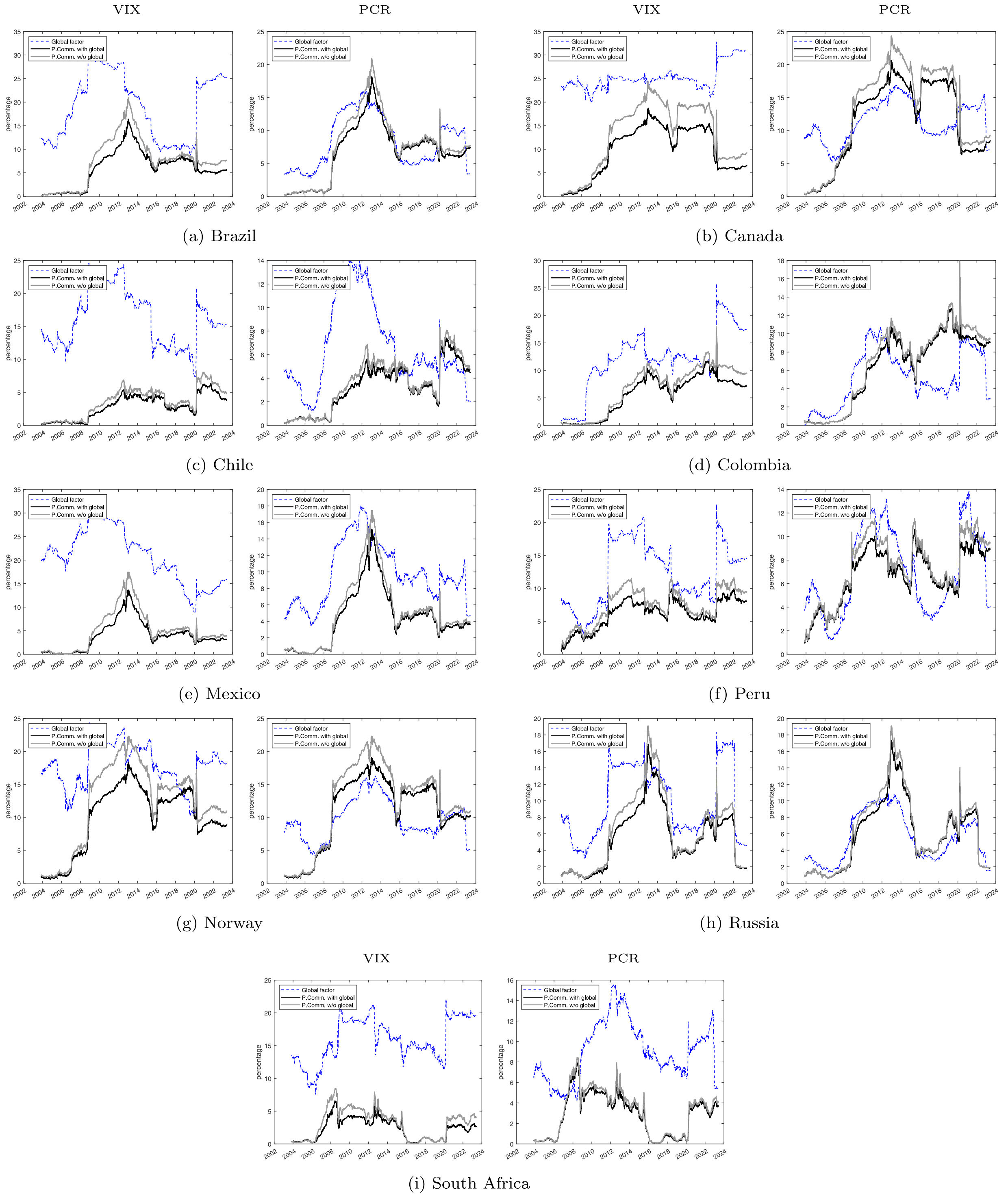

Fig. 2. Spillovers to domestic stock returns, based on the Generalised Diebold–Yilmaz approach, with and without global factor. The lines in the figure represent the decomposition of shocks (i.e.: spillovers) received by domestic stock returns y-axis measures the effect of each spillover as a percentage of the total spillovers received by domestic stock returns The dashed line depicts the spillovers of the global factor on domestic stock markets For each country, the global factor in the subplot in the left (right) column is proxied by the VIX index (PCR index) Spillovers of the global factor corresponds to the percentage of the forecast error variance of stock returns explained by orthogonal shocks of the global factor Black and grey lines represent the commodity market spillovers to domestic stock markets under two model specifications. The black (grey) line includes (excludes) the effect of the global factor in the model specification. Commodity market spillovers correspond to the percentage of the forecast error variance of stock returns explained by orthogonal shocks of commodity returns Spillovers obtained from the OLS estimation of the vector autoregressive model introduced in Section 3.2 using a sample of daily observations from 07 January 2000 to 31 May 2023.

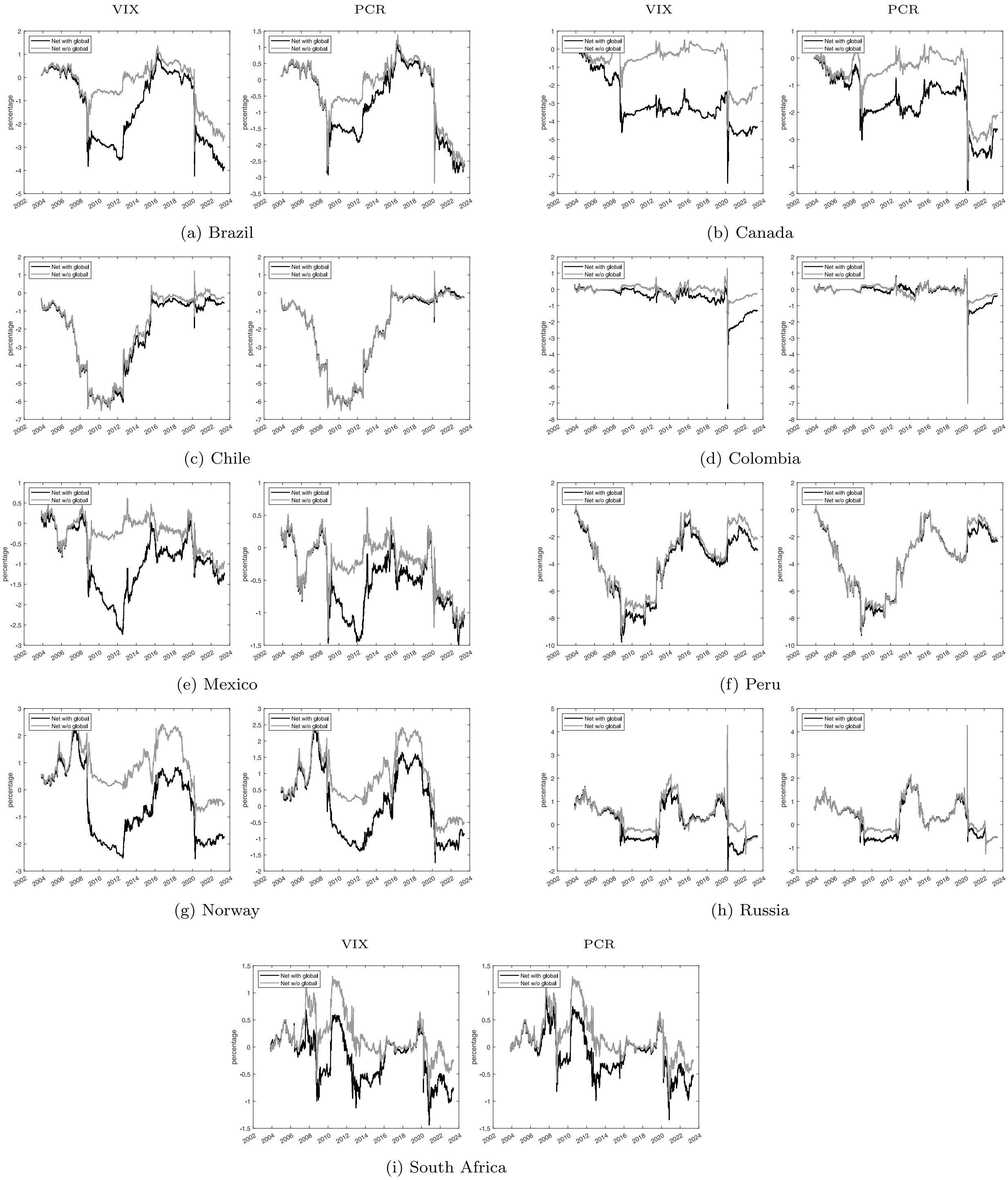

Fig. 3. Net spillovers between commodity and domestic stock markets. Lines represent the net spillovers between commodity and domestic stock markets under two model specifications: Black (grey) line represents the net spillover including (excluding) the effect of the global factor in the model specification For each country, the global factor in the subplot in the left (right) column is proxied by the VIX index (PCR index). y-axis measures the effect of each net spillover as a percentage of the total shocks received by domestic stock returns. Net spillovers between commodity and domestic stock markets are defined as follows: $S_{net} = S_{comm\rightarrow stock} - S_{stock\rightarrow comm}$, where S_{net} represents the net spillovers between commodity and domestic stock markets, $S_{comm\rightarrow stock}$ denotes the spillovers of commodity returns on stock returns (i.e.: the percentage of the forecast error variance of stock returns explained by orthogonal shocks of commodity returns), and $S_{stock\rightarrow comm}$ corresponds to the spillovers of stock returns on commodity returns (i.e.: the percentage of the forecast error variance of commodity returns explained by orthogonal shocks of stock returns). Spillovers obtained from the OLS estimation of the vector autoregressive model introduced in Section 3.2 using a sample of daily observations from 07 January 2000 to 31 May 2023.

values at different points through time. These results indicate that both stock and commodity markets are indeed net *providers* and *recipients* of shocks depending on the time span under analysis, and there is no clear pattern indicating that shocks originating in one specific market dominate shocks emanating from the other market across the entire sample. This evidence suggests that while equity and commodity returns exert a changing influence on each other, there is no dominant effect of one market over another.

Second, the common element across countries is that net spillovers display a sustained decline progressing to negative values during the GFC. Conversely, negative net spillovers appear diminished in magnitude during the ESDC, even displaying positive values in some countries. Finally, net spillovers exhibit further declines towards negative values during the Covid-19 pandemic.

Results which omit the effect of global factors (grey line) reveal similar patterns in comparison to the results described above, although the former are subject to the qualification they derive from a less robust approach, as the model specification excludes the effect of global factors.

4.2.3. *Contagion test of spillovers effects*

Finally, using the spillover estimates we introduce in Section 4.2.1, we investigate any evidence documenting the presence of contagion between commodity and equity markets. Specifically, using the contagion test described in Section 3.4, we compare the mean spillovers from commodity to equity markets obtained under our two familiar model specifications, including and excluding the global factors. Our initial global factor controls are for global risk aversion and investor sentiment, and subsequently, we replace them with alternative measures such as financial distress and economic policy uncertainty. Mean spillover comparisons and tests of contagion are undertaken during the three crisis episodes, specifically the GFC, the ESDC, and the Covid-19 pandemic. Our aim is to statistically evaluate whether the average spillovers obtained from the model excluding the global factor equal or exceed the average estimated spillovers from the model which includes it. Alternatively, the test evaluates the null hypothesis of no contagion between equity and commodity markets.

The findings in Table 3 panel A reveal that for all crisis episodes in all countries, the magnitude of the average commodity market spillovers without the global factor (column 'No global factor') are statistically greater than those including the risk aversion component, which in this case is proxied by the VIX index (column 'Global factor'). Thus, we cannot reject the null hypothesis of no contagion. Panel B depicts the contagion results controlling for investor sentiment, using the PCR as the global factor. Once again, we are unable to reject the no contagion hypothesis for any country in every crisis episode under analysis. This evidence emphasises once again the role of the global factor channel to account for the observed increased shock transmission from commodity to stock markets, particularly during episodes of financial crises.

4.2.4. *Robustness to alternative global factors*

To control for the effect of alternative global factors, we implement two separate robustness exercises, sequentially replacing the VIX index by the SLFFE and the EPU indices to control for financial distress and economic policy uncertainty, respectively. Table 3 panels C and D present the results using the SLFFE index and the EPU index, respectively. Once more, our findings are consistent across the majority of countries and for the three crisis episodes, namely we are almost universally unable to reject the no contagion hypothesis. The only two exceptions occur in the case of Mexico during the ESDC for both alternative definition of global factors. These results suggest that both the financial distress channel and the economic uncertainty channel account for most of the increased spillovers between commodity and stock markets during financial crisis episodes. Overall, the findings displayed in Table 3 signify there is a substantially diminished impact of commodity markets on equity returns after controlling for the effect of global factors. Collectively, our evidence suggests commodity markets play only a secondary role in transmitting shocks to domestic equity returns. Specifically, the measured impact of commodity market spillovers during episodes of financial crises become less relevant after incorporating controls for the time-varying influence of global risk aversion, investor sentiment, financial distress, and economic policy uncertainty. The conclusions of this section are consistent with the ones we previously obtain in Section 4.1.2 using the DCC-GARCH methodology. Overall, our results lead us to reject the hypothesis of the presence of any significant contagion effects between commodity and equity markets in the 2000–2023 period under analysis.

Finally, as an additional robustness exercise, we re-estimate the contagion tests using the Diebold–Yilmaz methodology, but now computing the spillovers from stock returns to the country-specific commodity returns. Table A.1 in the Appendix A depicts the results. The contagion tests based on this specification show the results are highly robust in comparison to our previous findings, as we are unable to reject the no contagion hypothesis for any country, any crisis episode and any global factor definition, the only exception being for South Africa during the ESDC when controlling for the PCR as the global factor.

5. Conclusions

This paper revisits the previous evidence and accompanying explanations for reputed contagion effects between commodity and equity markets documented in several studies. We analyse a sample of nine major commodity exporting economies, which includes both emerging market and advanced economies, covering the 2000 to 2023 period. Our main findings using both a DCC-GARCH model and the approach pioneered by Diebold and Yilmaz (2009) and revised in Diebold and Yilmaz (2012) are as follows: The conditional correlation/spillovers between commodity and equity returns are time varying, tending to increase during periods of

Table 3
Contagion test based on the Spillovers estimation.

Panel A: VIX as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	3.5	2.5	−1.0	1.0	12.5	9.0	−3.5	1.0	7.3	5.6	−1.7	1.0
Canada	10.3	7.8	−2.5	1.0	17.7	13.4	−4.3	1.0	8.7	6.5	−2.3	1.0
Chile	1.2	0.8	−0.5	1.0	4.2	3.2	−1.1	1.0	6.5	5.0	−1.5	1.0
Colombia	2.0	1.5	−0.4	1.0	7.4	6.1	−1.3	1.0	11.2	8.6	−2.5	1.0
Mexico	2.0	1.4	−0.6	1.0	9.2	6.7	−2.6	1.0	3.6	3.1	−0.5	1.0
Norway	9.4	7.3	−2.1	1.0	18.3	14.0	−4.3	1.0	10.7	8.8	−1.8	1.0
Peru	6.9	5.2	−1.7	1.0	10.1	7.9	−2.2	1.0	10.0	8.1	−1.9	1.0
Russia	3.9	3.1	−0.8	1.0	10.0	8.2	−1.8	1.0	8.5	7.3	−1.2	1.0
S. Africa	6.2	4.4	−1.8	1.0	5.1	3.8	−1.3	1.0	3.3	2.3	−1.0	1.0
Panel B: PCR as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	3.5	3.1	−0.4	1.0	12.5	10.7	−1.8	1.0	7.3	6.5	−0.8	1.0
Canada	10.3	9.2	−1.1	1.0	17.7	15.3	−2.4	1.0	8.7	7.5	−1.3	1.0
Chile	1.2	1.1	−0.2	1.0	4.2	3.5	−0.8	1.0	6.5	6.0	−0.5	1.0
Colombia	2.0	1.8	−0.2	1.0	7.4	6.6	−0.8	1.0	11.2	10.0	−1.2	1.0
Mexico	2.0	1.8	−0.3	1.0	9.2	7.7	−1.5	1.0	3.6	3.2	−0.4	1.0
Norway	9.4	8.4	−0.9	1.0	18.3	15.6	−2.6	1.0	10.7	9.6	−1.0	1.0
Peru	6.9	6.2	−0.7	1.0	10.1	8.9	−1.2	1.0	10.0	8.5	−1.4	1.0
Russia	3.9	3.5	−0.4	1.0	10.0	8.8	−1.2	1.0	8.5	7.8	−0.7	1.0
S. Africa	6.2	5.7	−0.4	1.0	5.1	4.7	−0.4	1.0	3.3	3.1	−0.2	1.0
Panel C: SLFFE index as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	12.5	10.6	−1.8	0.9	26.9	23.1	−3.8	1.0	16.6	13.4	−3.2	1.0
Canada	22.8	18.6	−4.3	1.0	32.2	25.8	−6.5	1.0	34.6	19.9	−14.7	1.0
Chile	5.5	4.8	−0.7	0.8	11.5	10.1	−1.4	1.0	15.2	12.3	−2.9	1.0
Colombia	5.5	5.2	−0.4	0.7	11.2	8.1	−3.2	1.0	25.2	20.0	−5.2	1.0
Mexico	8.1	8.1	−0.04	0.5	10.2	12.0	1.8**	0.03	15.9	16.1	0.2	0.4
Norway	16.7	14.8	−1.9	0.9	25.3	22.3	−2.9	1.0	30.6	22.9	−7.7	1.0
Peru	22.8	18.7	−4.1	1.0	29.9	25.1	−4.8	1.0	27.0	21.6	−5.4	1.0
Russia	16.9	15.9	−1.0	0.9	21.3	19.4	−1.9	1.0	15.5	13.2	−2.3	1.0
S. Africa	4.5	4.2	−0.3	0.7	3.9	3.0	−0.9	1.0	3.2	2.7	−0.5	0.9
Panel D: EPU index as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	12.5	11.1	−1.4	0.8	26.9	23.4	−3.4	1.0	16.6	15.4	−1.2	0.8
Canada	22.8	19.8	−3.1	1.0	32.2	26.1	−6.2	1.0	34.6	31.6	−3.0	1.0
Chile	5.5	4.7	−0.8	0.9	11.5	9.4	−2.1	1.0	15.2	13.7	−1.5	0.9
Colombia	5.5	4.0	−1.5	1.0	11.2	6.9	−4.3	1.0	25.2	21.6	−3.7	1.0
Mexico	8.1	8.4	0.3	0.4	10.2	11.9	1.7**	0.04	15.9	13.6	−2.3	1.0
Norway	16.7	13.8	−2.9	1.0	25.3	18.6	−6.6	1.0	30.6	27.7	−2.9	1.0
Peru	22.8	21.2	−1.6	0.8	29.9	27.2	−2.7	1.0	27.0	25.0	−2.0	1.0
Russia	16.9	14.1	−2.8	1.0	21.3	17.8	−3.5	1.0	15.5	14.0	−1.5	1.0
S. Africa	4.5	4.8	0.2	0.4	3.9	2.9	−1.0	1.0	3.2	2.5	−0.8	1.0

Column 'No global factor' ('Global factor') corresponds to the average spillover, expressed as a percentage, from country-specific commodity returns to domestic stocks returns during the selected crisis episodes computed using the Diebold–Yilmaz methodology excluding (including) the global factor in the model specification Country-specific commodity return spillovers correspond to the percentage of the forecast error variance of stock returns explained by orthogonal shocks of country-specific commodity returns Panel A, B, C, and D depict the estimation results using the VIX index, the Put-Call Ratio (PCR), the St. Louis Fed Financial Stress (SLFFE) index, and the Economic Policy Uncertainty (EPU) index, respectively, as a proxy of the global factor Column 'Diff.' corresponds to the difference between the columns 'Global factor' and 'No Global factor' Column 'Cont. p-val' corresponds to the p-value of the contagion test of Section 3.4, where H_0: No contagion, and H_a: Contagion Global financial Crisis dates: 17 July 2007 to 31 August 2009. European Sovereign Default Crisis dates: 2 October 2009 to 26 July 2012. Covid pandemic dates: 2 January 2020 to 31 May 2021. (*), (**), (***) indicates statistical significance at 10, 5, and 1% level, respectively.

acute financial distress, specifically the GFC, the ESDC, and the Covid-19 pandemic. This evidence applies to all sampled countries and corroborates previous findings. However, in contrast to many previous studies, our findings reveal that this is not evidence of contagion. Specifically, after accounting for the effect of time variation in global factors by including suitable proxies such as risk aversion, investor sentiment, financial distress, or economic policy uncertainty, we observe the impact of commodity markets pricing dynamics on equity returns is greatly diminished in magnitude, becoming largely insignificant for every country in the sample.

These findings lead us to conclude that there is a much more limited role for commodity markets in transmitting shocks which impact upon equity returns than previously maintained. Once we incorporate global factors in the guise of measures of global risk aversion, market sentiment, financial distress or uncertainties, we almost universally reject the hypothesis of market contagion. This conclusion stands in stark contrast to the findings of related studies which analyse such contagion effects in emerging equity markets but fail to control for the presence of time variation in global factors. We believe this omission leads to misleading conclusions in terms of falsely attributing the patterns observed in return dynamics to financial contagion. We further test for evidence of contagion by employing a statistically robust procedure and conclude there is a limited role for commodity markets in propagating shocks to the domestic equity markets of commodity exporting economies. This accords with the findings of related studies which control for the impact of time-varying global factors.

While our results lead us to reject the contagion hypothesis, we observe an increase in the correlation/spillovers between commodity and equity markets during episodes of financial distress, even after controlling for the effect of global factors. We interpret this as evidence of enhanced integration between markets, reinforcing a belief that commodities have become more important as a distinct asset class in the portfolios of international investors. In this context, our conclusions may be relevant in informing the investment policy of commodity market participants, especially institutional investors and hedge funds. Our results highlight an evolving dynamic pattern evident between market comovements over time. However, our interpretation does not support the existence of an additional component in risk transmission from commodity to equity markets that goes beyond the impact of systemic global factors during episodes of distress. The evidence in our study offers two practical implications for commodity market participants. First, unlike those studies which suggest employing additional hedging strategies related to those markets (see Choi and Hammoudeh (2010)), our analysis provides no basis for encouraging revisions to hedging strategies for investors with portfolios exposed to the commodity and equity markets in the countries we analyse. Second, given our rejection of any evidence of contagion, our findings suggest there is still an important role for portfolio diversification between the commodity and equity markets in the economies in our sample, a recommendation aligning with other prior studies (see Arouri and Nguyen (2010)).

CRediT authorship contribution statement

Francisco Pinto-Ávalos: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft. **Michael Bowe:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Stuart Hyde:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A

See Fig. A.1 and Table A.1.

Global factor correlation matrix

	VIX	SLFFE	EPU	PCR
VIX	100			
SLFFE	86	100		
EPU	25	9	100	
PCR	30	42	1	100

Correlation expressed as percentage. VIX corresponds to the volatility index computed by the CBOE. SLFFE index corresponds to the St. Louis FED Financial Stress Index. EPU corresponds to the Economic Policy Uncertainty index of Baker et al. (2016), available on https://www.policyuncertainty.com/. The Put-Call Ratio (PCR) is computed as the ratio between the trading volume of put options and the trading volume of call options traded at the CBOE. All indices measured in their original unit of measure.

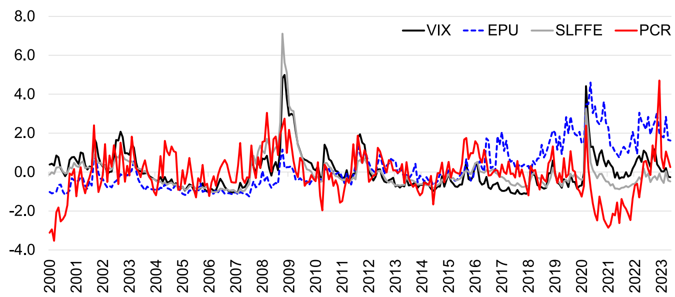

Fig. A.1. Comparison of global factor proxies. VIX corresponds to the volatility index computed by the CBOE. EPU corresponds to the Economic Policy Uncertainty index of Baker et al. (2016), available on https://www.policyuncertainty.com/. SLFFE index corresponds to the St. Louis FED Financial Stress Index. The Put-Call Ratio (PCR) is computed as the ratio between the trading volume of put options and the trading volume of call options traded at the CBOE. For comparison purposes, all series are standardised using their respective mean and standard deviation.

Table A.1
Contagion test based on the Spillovers estimation, commodity return decomposition.

	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Panel A: VIX as global factor												
Brazil	4.3	4.1	−0.2	0.9	13.1	12.1	−1.1	1.0	8.6	7.9	−0.7	1.0
Canada	10.8	10.4	−0.4	1.0	18.1	16.8	−1.4	1.0	11.3	10.9	−0.4	1.0
Chile	5.9	5.5	−0.4	1.0	9.9	9.0	−0.9	1.0	6.6	5.8	−0.8	1.0
Colombia	1.9	1.6	−0.3	1.0	7.2	6.3	−0.9	1.0	11.9	10.8	−1.1	1.0
Mexico	2.1	2.0	−0.1	0.9	9.5	8.8	−0.8	1.0	4.3	3.9	−0.3	1.0
Norway	8.0	7.1	−0.8	1.0	18.0	16.1	−1.9	1.0	11.2	10.6	−0.6	1.0
Peru	13.3	12.1	−1.1	1.0	17.1	15.5	−1.6	1.0	11.1	10.4	−0.7	1.0
Russia	3.7	3.1	−0.6	1.0	10.2	8.8	−1.4	1.0	8.4	8.1	−0.3	1.0
S. Africa	5.7	4.5	−1.1	1.0	4.4	3.7	−0.6	1.0	3.5	2.9	−0.6	1.0
Panel B: PCR as global factor												
	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	4.3	4.2	−0.2	0.8	13.1	12.3	−0.9	1.0	8.6	8.1	−0.5	1.0
Canada	10.8	10.5	−0.3	0.9	18.1	17.1	−1.1	1.0	11.3	10.6	−0.7	1.0
Chile	5.9	5.7	−0.2	1.0	9.9	9.2	−0.7	1.0	6.6	6.1	−0.5	1.0
Colombia	1.9	1.8	−0.1	1.0	7.2	6.6	−0.6	1.0	11.9	11.2	−0.7	1.0
Mexico	2.1	2.0	−0.1	0.8	9.5	8.8	−0.7	1.0	4.3	4.0	−0.3	1.0
Norway	8.0	7.7	−0.3	0.9	18.0	16.7	−1.3	1.0	11.2	10.7	−0.5	1.0
Peru	13.3	12.7	−0.5	1.0	17.1	16.0	−1.0	1.0	11.1	10.4	−0.7	1.0
Russia	3.7	3.4	−0.2	0.9	10.2	9.4	−0.8	1.0	8.4	8.0	−0.4	1.0
S. Africa	5.7	5.6	−0.1	0.9	4.4	4.5	0.2***	0.0	3.5	3.6	0.1	0.2
Panel C: SLFFE index as global factor												
	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	12.3	9.8	−2.4	0.8	35.7	28.5	−7.2	1.0	24.6	16.5	−8.1	1.0
Canada	21.7	18.8	−2.9	0.9	33.4	26.8	−6.6	1.0	38.3	22.3	−16.0	1.0
Chile	5.1	5.0	−0.1	0.6	8.7	7.4	−1.3	0.9	8.4	8.4	−0.0095	0.5
Colombia	4.9	4.4	−0.5	0.8	12.1	8.4	−3.7	1.0	31.7	21.2	−10.4	1.0
Mexico	5.8	5.0	−0.8	0.8	14.7	12.7	−2.0	1.0	20.7	16.3	−4.4	1.0
Norway	20.3	17.9	−2.5	0.8	34.0	27.2	−6.8	1.0	32.7	22.2	−10.5	1.0
Peru	21.5	18.4	−3.1	1.0	28.3	23.2	−5.2	1.0	23.0	20.4	−2.5	1.0
Russia	16.0	13.4	−2.6	0.9	32.0	25.0	−7.0	1.0	25.3	17.6	−7.7	1.0
S. Africa	8.9	7.9	−1.0	0.8	7.3	6.2	−1.2	1.0	5.2	6.3	1.1	0.1

(*continued on next page*)

Table A.1 (*continued*).

Panel D: EPU index as global factor	Global financial crisis				European sovereign crisis				COVID pandemic			
	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val	No global factor	Global factor	Diff.	Cont. p-val
Brazil	12.3	10.4	−1.8	0.8	35.7	29.7	−6.0	1.0	24.6	22.9	−1.7	0.9
Canada	21.7	19.1	−2.6	0.9	33.4	26.7	−6.7	1.0	38.3	35.4	−2.9	1.0
Chile	5.1	4.5	−0.6	1.0	8.7	7.0	−1.7	0.9	8.4	7.3	−1.1	0.9
Colombia	4.9	3.6	−1.3	1.0	12.1	7.2	−4.9	1.0	31.7	29.1	−2.6	1.0
Mexico	5.8	4.9	−1.0	0.8	14.7	11.5	−3.2	1.0	20.7	19.2	−1.5	0.9
Norway	20.3	17.5	−2.9	0.8	34.0	27.2	−6.8	1.0	32.7	30.1	−2.7	1.0
Peru	21.5	19.4	−2.1	0.9	28.3	25.5	−2.8	1.0	23.0	21.6	−1.4	0.9
Russia	16.0	13.6	−2.4	0.9	32.0	26.6	−5.4	1.0	25.3	23.5	−1.8	0.8
S. Africa	8.9	8.7	−0.2	0.6	7.3	6.6	−0.7	0.9	5.2	3.8	−1.4	1.0

Column 'No global factor' ('Global factor') corresponds to the average spillover, expressed as a percentage, from domestic stock returns to country-specific commodity returns during the selected crisis episodes computed using the Diebold–Yilmaz methodology excluding (including) the global factor in the model specification Stock return spillovers correspond to the percentage of the forecast error variance of country-specific commodity returns explained by orthogonal shocks of stock returns Panel A, B, C, and D depict the estimation results using the VIX index, the Put-Call Ratio (PCR), the St. Louis Fed Financial Stress (SLFFE) index, and the Economic Policy Uncertainty (EPU) index, respectively, as a proxy of the global factor Column 'Diff.' corresponds to the difference between the columns 'Global factor' and 'No Global factor' Column 'Cont. p-val' corresponds to the *p*-value of the contagion test of Section 3.4, where H_0: No contagion, and H_a: Contagion Global financial Crisis dates: 17 July 2007 to 31 August 2009. European Sovereign Default Crisis dates: 2 October 2009 to 26 July 2012. Covid pandemic dates: 2 January 2020 to 31 May 2021. (*), (**), (***) indicates statistical significance at 10, 5, and 1% level, respectively.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jcomm.2023.100369.

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