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Price-switching spillovers between gold, oil, and stock markets: Evidence from the USA and China during the COVID-19 pandemic

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ARTICLE INFO

JEL classification:
C58
F37
G11
G14

Keywords:
COVID-19
Chinese and US stock markets
Strategic commodity
MS-VAR model

ABSTRACT

This paper examines price-switching spillovers between the US and Chinese stock, crude oil, and gold futures markets before and during the COVID-19 pandemic. Using a Markov-switching vector autoregressive model, we show that stock markets were mainly influenced by their own shocks, with effects that were sensitive to regime shifts. Connectedness network analysis reveals that gold and stock markets were net contributors (receivers) of spillovers in the low-volatility regime (high-volatility regime), while oil was a major receiver (contributor) of spillovers in the low-volatility regime (high volatility regime). Regimes were mainly low-volatility from January 2019 to February 2020 and high-volatility from March 2020 to May 2020. We conclude that the COVID-19 pandemic intensified spillovers from commodity markets to the US and Chinese stock markets.

1. Introduction

Growing uncertainty makes portfolio risk management and asset allocation a major challenge for equity investors, traders, hedgers, and portfolio managers, as high uncertainty reduces investments (Bernanke, 1983) and increases investor fears. Furthermore, integration and interdependence between stock markets intensify in times of high uncertainty, shrinking diversification opportunities and pushing equity investors to seek alternative investments in order to manage portfolio risks.

Oil and gold are two strategic commodities for the world economy that are typically included in investors’ equity portfolios (Buyukshahin and Robe, 2014; Singleton, 2014). Oil is a highly volatile commodity (Regnier, 2007) and its price oscillations constitute valuable information in predicting commodity and financial asset prices. Gold, in contrast, is commonly viewed as a safe-haven asset during crisis periods (Baur and Lucey, 2010). Investors often switch between, or combine, oil and gold so as to diversify their equity portfolios (Soytas et al., 2009). In recent years, however, the fact that these two commodities have been marked by increasing turbulence and volatility (e.g., due to the 2006 food crisis, the summer 2008 oil price rise, and the 2014–2016 oil price crash) has complicated investment decision-making. Therefore, accurate modeling of how information is transmitted and spilled over between oil, gold, and stock markets may aid investors in their portfolio and risk management decisions.

The rapid spread of the new coronavirus disease 2019 (COVID-19) – caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) – has greatly increased uncertainty in both the financial and commodity markets (Mhalla, 2020; Zhang et al., 2020). The growing number of confirmed cases and deaths 1 has pushed governments to impose severe restrictions (e.g., lockdown countries or cities, curtail movement, impose social distancing, and suspend business operations), which have had repercussions for economies; China, for instance, recorded a slowdown of 6.8% in the first quarter of 2020, representing the biggest contraction since quarterly gross domestic product (GDP) records began. 2 Stock markets also experienced a downward trend as the number of COVID-19 cases grew exponentially, with equity and commodity investors becoming increasingly risk-averse due to the explosive

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1 WHO data indicate that, as of mid-June 2021, there have been 174 million cumulative COVID-19 cases and 3.75 million COVID-19 deaths globally since the start of the pandemic.
2 https://www.bbc.com/news/business-53399999.

https://doi.org/10.1016/j.resourpol.2021.102217
Received 23 December 2020; Received in revised form 18 June 2021; Accepted 28 June 2021
Available online 6 July 2021
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increase in cases and deaths (Ashraf, 2020; Corbet et al., 2020; Drobetz et al., 2020; Harjoto et al., 2021; He et al., 2020; Liu et al., 2020). The nexus between the stock market and the public health situation was confirmed by Salesi and Vo (2020), who found that health news enhances the accuracy of forecasted stock returns. Ichev and Marin (2018) found that information on the 2014–2016 Ebola outbreaks combined with intense media coverage was more relevant for companies geographically closer to both the origin of Ebola outbreaks and financial markets. More recently, Azimli (2020) concluded that the spread of COVID-19 has affected the dependence structure of the risk-return nexus.

It is evident that the current global health crisis – added to the damaging effects of repeated financial crises, political conflicts, Brexit, and trade wars between the USA and China in recent years – has accentuated spillovers and economic uncertainty (Sharif et al., 2020), making portfolio management more difficult than ever. Bakas and Triantafyllou (2020) confirm that the COVID-19 pandemic has had a significant impact on the real economy and financial sectors and has contributed to increasing uncertainty. As economic activity came to a halt during lockdowns in almost all industrialized economies, the value of the US reference crude oil (West Texas Intermediate) fell 37 USD per barrel by 20 April 2020 in response to a significant drop in global demand, estimated by the US International Energy Agency to be 30% for the first quarter of 2020. While oil price uncertainty tends to negatively affect world industrial production (Jo, 2014), during the 2020 pandemic, gold prices have shown a clear upward trend (Fig. 1).

Oil, gold, and stock markets are three markets that theoretically closely co-move, with information regarding commodities potentially affecting stock performance. Variability in crude oil prices affects corporate cash flows and discount rates. An oil price shock raises production costs and reduces cash flows, which, in turn, reduces share prices. Theoretically, the potential linkages between crude oil and stock markets are explained by different factors such as foreign exchange markets, corporate future cash flows, discount factors, and economic cycles. As a means of hedging positions against downward trending equity prices, the demand for gold goes up, and as a result, its price increases.

An extensive empirical literature has applied different econometric methods to address both the oil-stock market nexus (Jones and Kaul, 1996; Hassan and Malik, 2007; Joo and Park, 2017; Kilian and Park, 2009; Mensi et al., 2013, 2020; Fenech and Vosgha, 2019; Wang et al., 2013; Reboredo and Ugolini, 2016; Wang, 2020; Zhao et al., 2021) and the gold-stock market nexus, showing that gold serves as a hedge and safe-haven asset against inflation and stock market uncertainty (Baur and Lucey, 2010; Baur and McDermott, 2010; Hillier et al., 2006; Sumner et al., 2010).

The empirical literature on spillovers between commodity and stock markets during the global health crisis of 2020 is still emerging. To the best of our knowledge, ours is the first attempt to examine price-switching spillovers between strategic commodity futures (oil and gold) and the two largest stock markets in the world (US and Chinese) before and during the 2020 global health crisis. As the COVID-19 pandemic unfolds, the stock market continues to decline and equity investors are concerned about the short-term damage caused by business restrictions. We contribute to the literature on two main fronts.

First, we examine spillovers between crude oil futures, gold futures, and stock markets in China and the USA under both low- and high-volatility regimes. In addition, we explore the direction and extent of spillovers in different market scenarios, in particular, during crisis times when stock and commodity market volatility increases significantly and spillover effects are intensified across markets. Interestingly, the sign and the magnitude of spillover effects vary across market regimes. We focus on futures markets because, with some 90% of transactions traded on the Chicago Mercantile Exchange, the futures markets facilitate price discovery (Tse et al., 2006). We also focus on the world’s largest economies, first, because, in 2019, they accounted for 40.75% of global GDP in nominal and purchasing power parity (PPP) terms, and second, because the S&P500, Shanghai and Shenzhen indexes represent benchmarks for international investors. China and the USA are the world’s largest oil importers and China is an important trading partner of Organization of the Petroleum Exporting Countries (OPEC) (Lin et al., 2021). In 2019, total market capitalization for S&P500 was 26.76 trillion USD. The Shanghai index, capitalized at 6.19 trillion USD, is the second largest stock exchange in the Asia Pacific region (after the Nikkei 225 index of Japan), while the Shenzhen index is ranked fourth (after the Hong Kong stock exchange market). More importantly, the US and Chinese stock markets are especially vulnerable to external shocks because they are open to foreign investors. Oil is the leading commodity in world markets, with any change in prices affecting not only the prices of other commodities but also stock market prices. Crude oil price shocks are decisive for economic development. Changes in stock prices can be monitored by observing trends in oil and gold prices, as the spillover effects between commodity and stock markets may occur at any time, but particularly during crisis periods.

Second, we explore the direction and extent of spillovers between commodity and stock markets under low- and high-volatility regimes, using the Markov-switching vector autoregressive (MS-VAR) model and the spillover index developed by Diebold and Yilmaz (2014). The parameters of the VAR model change under different volatility regimes, with those shifts governed by a MS process. The nonlinear MS-VAR model measures how one asset reacts to shocks transmitted by another asset in different volatility regimes. It also gauges synchronization between two markets by comparing the smoothed probabilities of being in one or another regime (low-volatility or high-volatility). Specifically, the MS-VAR model determines the percentage of the forecast error variance of stock prices that can be explained by different shocks in strategic commodity markets in different volatility regimes. The MS-VAR model enhances forecast accuracy relative to the generalized VAR model without regime switching. As for the Diebold and Yilmaz (2014) spillover index, this assesses how a given asset contributes shocks to other assets, identifying whether that asset is a net contributor or net receiver of shocks to/from other markets. The spillover index captures both the transmission of volatility to/from markets and net spillovers. Our study considers spillover effects between stock and commodity markets under low- and high-volatility regimes. This is crucial to identifying both the source of contagion and the assets vulnerable to shocks. Overall, the methodology yields useful information in terms of portfolio management, as it considers shifts in investor expectations, which are not the same under low- and high-volatility regimes.

Our results show that US and Chinese stock markets were mainly influenced by their own shocks. Gold and oil price returns impacted Shanghai and Shenzhen stock index returns in the low-volatility regime. Gold price returns, but not oil price returns, affected S&P500 returns in both the low-volatility and high-volatility regimes. On the other hand, the S&P500 returns contributed positively and negatively to oil price returns in the low-volatility and high-volatility regimes, respectively. In contrast, the Shanghai and Shenzhen indexes had insignificant effects on both oil and gold returns, but effects showed greater persistence in the low-volatility regime than in the high-volatility regime. Regarding price spillovers, the main contributors were the stock markets, with impacts for gold and oil prices differing across markets; specifically, gold and oil price spillovers in Chinese stock markets were relatively weak – although tending to increase – in the low-volatility regime, even while remaining at relatively low levels. This evidence is consistent with the

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4 [http://statisticstimes.com/](http://statisticstimes.com/)
5 [https://www.statista.com/statistics/265236/domestic-market-capitalization-in-the-asia-pacific-region/](https://www.statista.com/statistics/265236/domestic-market-capitalization-in-the-asia-pacific-region/)
Fig. 1. Time series plots of daily prices.
Dickey – May 2020. JB denotes the Jarque-Bera statistic for normality; an asterisk (*) indicates rejection of the null hypothesis at the 5% level. ADF denotes the augmented Dickey-Fuller test. PP is the Phillips and Perron test, KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test. LB is the Ljung-Box statistics for serial correlation in the return (LB); ARCH-LM denotes the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) test, computed using 20 lags (p values are reported in square brackets). ρ denotes the Pearson linear correlation between the return series indicated in the subindex.

Table 1
Descriptive statistics.

|               | Shanghai index | S&P500 index | Shenzhen index | Gold | Oil |
|---------------|----------------|--------------|----------------|------|-----|
| **Panel A: Basic statistics** |                |              |                |      |     |
| Mean          | 0.030          | 0.037        | 0.064          | 0.086| –0.141|
| Standard deviation | 1.329          | 1.777        | 1.448          | 0.926| 3.800|
| Maximum       | –9.686         | –12.765      | –9.856         | –3.673| –27.976|
| Minimum       | 5.820          | 8.968        | 6.148          | 4.967| 19.077|
| Skewness      | –1.278         | –0.985       | –0.992         | 0.087| –1.578|
| Kurtosis      | 12.896         | 17.998       | 10.797         | 7.227| 21.355|
| JB            | 1558.407*      | 3413.000*    | 965.577*       | 266.945*| 5173.905*|
| Panel B: Unit root and stationarity tests |                |              |                |      |     |
| ADF           | –19.56***      | –5.94***     | –20.04***      | –17.18***| –16.62***|
| PP            | –19.55***      | –26.11***    | –20.01***      | –17.22***| –16.71***|
| KPSS          | 0.210          | 0.153        | 0.230          | 0.089| 0.204|
| Panel C: LB and ARCH-LM tests |                |              |                |      |     |
| LB            | 13.222         | 272.428      | 14.977         | 59.300| 46.126|
| LB2           | 9.643          | 578.262      | 11.619         | 256.694| 106.880|
| LM            | 8.920          | 165.654      | 11.135         | 98.347| 58.098|
| Panel D: Unconditional correlations |                |              |                |      |     |
| ρ_{stock, stock} | 0.07           | 0.04         | 0.05           |      |     |
| ρ_{stock, stock} | 0.24           | 0.36         | 0.24           |      |     |

Notes. This table reports descriptive statistics for daily price returns of Shanghai, S&P500, Shenzhen, gold and oil market returns for the period 1 January 2019 to 15 May 2020. JB denotes the Jarque-Bera statistic for normality; an asterisk (*) indicates rejection of the null hypothesis at the 5% level. ADF denotes the augmented Dickey-Fuller test, PP is the Phillips and Perron test, KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test. LB is the Ljung-Box statistics for serial correlation in the return (LB) and squared return (LB2); ARCH-LM denotes the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) test, computed using 20 lags (p values are reported in square brackets). ρ denotes the Pearson linear correlation between the return series indicated in the subindex.

Table 2
MS-VAR estimation parameters for the Shanghai index.

|               | Shanghai index | S&P500 index | Shenzhen index | Gold | Oil |
|---------------|----------------|--------------|----------------|------|-----|
| **Panel A: Basic statistics** |                |              |                |      |     |
| Mean          | 0.107*         | 0.059*       | 0.034          | –0.368*| 0.201| –0.918|
| Standard deviation | 0.060          | 0.041        | 0.020          | 0.014*| 0.323| 1.278|
| Maximum       | –0.068*        | 0.030        | 0.073          | 0.099| 0.131| 0.119|
| Minimum       | –0.114*        | 0.023        | 0.193*         | 0.099| 0.131| 0.119|
| Skewness      | –0.068*        | 0.030        | 0.073          | 0.099| 0.131| 0.119|
| Kurtosis      | –0.114*        | 0.023        | 0.193*         | 0.099| 0.131| 0.119|
| JB            | 0.171*         | 0.058*       | 0.034          | –0.297| 0.193| –0.904|
| Panel B: Shenzhen index |                |              |                |      |     |
| Mean          | 0.107*         | 0.059*       | 0.034          | –0.368*| 0.201| –0.918|
| Standard deviation | 0.060          | 0.041        | 0.020          | 0.014*| 0.323| 1.278|
| Maximum       | –0.068*        | 0.030        | 0.073          | 0.099| 0.131| 0.119|
| Minimum       | –0.114*        | 0.023        | 0.193*         | 0.099| 0.131| 0.119|
| Skewness      | –0.068*        | 0.030        | 0.073          | 0.099| 0.131| 0.119|
| Kurtosis      | –0.068*        | 0.030        | 0.073          | 0.099| 0.131| 0.119|
| JB            | 0.171*         | 0.058*       | 0.034          | –0.297| 0.193| –0.904|

Notes. This table presents estimates of the MS-VAR(1) model under two regimes for the Shanghai index, gold and oil price returns. P values are in parentheses and an asterisk (*) indicates significance of parameter estimates at the 5% level.

Table 3
MS-VAR estimation parameter for the S&P500 index.

|               | S&P500 index | Gold | Oil |
|---------------|--------------|------|-----|
| **Panel A: Basic statistics** |                |      |     |
| Mean          | 0.107*       | 0.059*| 0.031|
| Standard deviation | 0.064        | 0.181| 0.885|
| Maximum       | 0.028        | –0.035| –0.260*|
| Minimum       | 0.061        | (0.064)| (0.155)| (0.114)| (0.054)| (0.258)|
| Skewness      | 0.245        | 0.231*| 0.251*|
| Kurtosis      | 0.004        | –0.015| 0.097*|
| JB            | 0.952*       | 0.048*| (0.02)|
| Panel B: S&P500 index |                |      |     |
| Mean          | 0.107*       | 0.059*| 0.031|
| Standard deviation | 0.064        | 0.181| 0.885|
| Maximum       | 0.028        | –0.035| –0.260*|
| Minimum       | 0.061        | (0.064)| (0.155)| (0.114)| (0.054)| (0.258)|
| Skewness      | 0.245        | 0.231*| 0.251*|
| Kurtosis      | 0.004        | –0.015| 0.097*|
| JB            | 0.952*       | 0.048*| (0.02)|

Notes. This table presents estimates of the MS-VAR(1) model under two regimes for the S&P500 index, gold and oil price returns. P values are in parentheses and an asterisk (*) indicates significance of parameter estimates at the 5% level.

diversification role of gold. For the US market, the empirical evidence shows that gold spillovers tended to shrink in the low-volatility regime, while the opposite occurred for oil. Overall, our results point to low
integration between stock and gold markets, and moderate integration between oil and the US stock market. Those results have implications in terms of investor portfolio and risk management decisions when volatility is great, as has been the case in the unfolding global health crisis.

The remainder of the paper is organized as follows: Section 2 discusses the econometric framework. Section 3 describes the data and descriptive statistics. Section 4 reports and discusses the empirical results. Finally, Section 5 concludes the paper.
Notes. The table summarizes the parameter estimates for the variance-covariance matrix for the two regimes of the MS-VAR(1) model for the Shenzhen stock market, gold, and oil markets. Standard deviations are given in round brackets. An asterisk (*) indicates significance of parameter estimates at the 5% level.

Table 7
Estimation of variance-covariance for MS-VAR for the S&P500 index.

| Regime 1 (low-volatility regime) | Regime 2 (high-volatility regime) |
|---------------------------------|----------------------------------|
| S&P500                          | S&P500                           |
| Gold                            | Gold                             |
| Oil                             | Oil                              |
| 0.442*                         | 0.455*                          |
| (0.049)                        | (1.877)                         |
| -0.124*                        | 0.671*                          |
| (0.033)                        | (0.414)                         |
| 0.361*                         | 0.361*                          |
| (0.075)                        | (0.073)                         |
|                                |                                  |

Notes. The table summarizes the parameter estimates for the variance-covariance matrix for the two regimes of the MS-VAR(1) model for the S&P500 stock market, gold, and oil markets. Standard deviations are given in round brackets. An asterisk (*) indicates significance of parameter estimates at the 5% level.

2. Methodology

In this section we outline the MS-VAR model we use to identify connectedness between the stock (S&P500, Shanghai, and Shenzhen), gold, and oil markets during the first COVID-19 pandemic wave.

2.1. MS-VAR model

Let \( X_t \) be a three-dimensional vector of endogenous variables that includes information on stock, gold, and oil returns, and let \( s_t \) denotes regimes, so that \( s_t \in \{1,...,M\} \). We can thus define the MS-VAR model of order \( p \) as:

\[
X_t = \begin{cases} 
  v_1 + \sum_{j=1}^{p} A_{j1}X_{t-j} + \epsilon_t, & \text{if } s_t = 1 \\
  \vdots \\
  v_M + \sum_{j=1}^{p} A_{jM}X_{t-j} + \epsilon_t, & \text{if } s_t = M
\end{cases}
\]

where, for each state \( M \), the vector \( X_t \) is explained by its own lagged values, an intercept \( v_M \), the parameter matrix \( A_{jM} \), and a stochastic component \( \epsilon_t \), which is uncorrelated and normally distributed with zero mean and variance-covariance matrix \( \Sigma \).

Table 8
Estimation of variance-covariance for MS-VAR for the Shenzhen index.

| Regime 1 (low-volatility regime) | Regime 2 (high-volatility regime) |
|---------------------------------|----------------------------------|
| Shenzhen                        | Shenzhen                         |
| Gold                            | Gold                             |
| Oil                             | Oil                              |
| 1.256*                         | 5.255*                           |
| (0.120)                        | (1.124)                          |
| -0.053*                        | 0.629*                           |
| (0.050)                        | (0.491)                          |
| 0.356*                         | 4.791*                           |
| (0.117)                        | (2.456)                          |
|                                |                                  |

Notes. The table summarizes the parameter estimates for the variance-covariance matrix for the two regimes of the MS-VAR(1) model for the Shenzhen stock market, gold, and oil markets. Standard deviations are given in round brackets. An asterisk (*) indicates significance of parameter estimates at the 5% level.

In our empirical analysis we consider a low-volatility regime and a high-volatility regime. The dynamic behavior of a regime \( s_t \) is described by an unobservable Markov chain process, with a conditional transition probability from regime \( i \) at time \( t - 1 \) to regime \( j \) at time \( t \) given by:

\[
P(r_t = j | s_{t-1} = i) = \exp \left( -\frac{1}{2} \theta \Sigma^{-1} e_t \right)
\]

where \( \theta \) denotes the set of parameters included in the parameter matrices in Eq. (1), and where \( \Sigma \) represents the information set available at time \( t - 1 \). Hence, the conditional likelihood function at time \( t \) is:

\[
f(X_t | s_t = j, \Sigma_{t-1}; \theta) = \frac{1}{(2\pi)^{\frac{p}{2}} |\Sigma_t|^{\frac{1}{2}}} \exp \left( -\frac{1}{2} \Sigma_t^{-1} e_t \right)
\]

where \( \Sigma_t \) is the conditional probability of remaining in state \( j \) at time \( t \) given information at time \( t - 1 \), obtained recursively as:

\[
P(s_t = j | \Sigma_{t-1}; \theta) = \sum_{i=1}^{M} P(s_t = j | s_{t-1} = i, \Sigma_{t-1}; \theta) P(s_{t-1} = j | \Sigma_{t-1}; \theta)
\]

This probability is updated, from the conditional likelihood in Eq. (3), at each time \( t \) as:

\[
P(s_t = j | \Sigma_t; \theta) = \frac{f(X_t | s_t = j, \Sigma_{t-1}; \theta) P(s_t = j | \Sigma_{t-1}; \theta)}{\sum_{i=1}^{M} f(Y_t | s_t = i, \Sigma_{t-1}; \theta) P(s_t = j | \Sigma_{t-1}; \theta)}
\]

For the initial transition probability and parameter values, we can iterate Eqs. (4) and (5) for \( t = 1, ..., T \) and obtain the likelihood value as:
Estimates of the market connectedness matrix for Shanghai index.

| Regime 1 (low-volatility regime) | Regime 2 (high-volatility regime) |
|---------------------------------|----------------------------------|
| Shanghai                        | Gold | Oil | Shanghai | Gold | Oil |
| 95.42                           | 2.58 | 1.99 | 62.36     | 4.32 | 13.42 |
| (98.99, (4.08, (5.28, (16.71, 78.69, 2.82, 10.13) |
| Gold                            | 4.99 | 93.75 | 1.26 | 7.2 | 83.97 | 8.83 |
| (8.08, (98.96, (5.56, (10.29, 78.76, 4.53) |
| Oil                             | 2.53 | 18.36 | 79.11 | 11.15 | 6.19 | 82.66 |
| (4.64, (20.73, (82.06, (13.26, (8.56, (85.61, 0.42) |
| (15.99, 76.16, 9.04, 3.82, 79.71) |

Table 10

Estimates of the market connectedness matrix for the S&P500 index.

| Regime 1 (low-volatility regime) | Regime 2 (high-volatility regime) |
|---------------------------------|----------------------------------|
| S&P500                          | Gold | Oil | S&P500 | Gold | Oil |
| 77.14                           | 15.35 | 7.51 | 80.76 | 3.81 | 15.43 |
| (82.00, (20.21, (15.54, (85.62, (8.67, (18.46, 72.28, (10.49, (4.49, (75.90, (0.05, (12.41) |
| Gold                            | 12.70 | 85.98 | 1.33 | 2.96 | 92.93 | 4.12 |
| (14.59, (90.10, (5.43, (4.85, (97.05, (8.22, (10.81, (81.86, (0.02) |
| Oil                             | 10.31 | 0.14 | 89.55 | 17.26 | 81.13 | 21.81 |
| (14.02, (1.86, (93.32, (20.97, (2.93, (85.30, (6.60, (0.08, (85.78, (13.55, (0.51, (77.76) |

Table 11

Estimates of the market connectedness matrix for the Shenzhen index.

| Regime 1 (low-volatility regime) | Regime 2 (high-volatility regime) |
|---------------------------------|----------------------------------|
| Shenzhen                        | Gold | Oil | Shenzhen | Gold | Oil |
| 96.84                           | 1.62 | 1.54 | 93.77     | 2.87 | 3.36 |
| (99.87, (93.81, (3.42, (0.18, (4.43, (0.35) |
| Gold                            | 1.47 | 94.84 | 3.68 | 2.14 | 95.64 | 2.22 |
| (5.14, (0.20, (99.20, (89.48, (7.95, (0.59) |
| Oil                             | 6.85 | 9.99 | 83.16 | 4.27 | 0.29 | 95.45 |
| (9.60, (4.10, (12.38, (7.60, (85.89, (80.43) |
| (7.62, (1.52, (2.68, (2.10, (98.18, (92.72) |

Notes. The table reports estimate of the connectedness matrix computed according to normalized Eq. (8) and using a forecast horizon of \( h = 10 \) trading days. Each row accounts for the percentage fraction of the forecast error variance of the market indicated in the row that is explained by the markets indicated in columns. Values in each row sum to 100%. Each column reports the variance of the market indicated in the columns to each market indicated in the rows. Reported in round brackets are 95% confidence intervals computed using 1000 Monte Carlo simulations of the estimated MS-VAR model.
Composite and Shenzhen CSI 300 indexes (China), and futures prices for gold (GC1) and Brent crude oil (CO1). Data, sourced from Bloomberg, cover the period January 2019 to May 2020. Fig. 1 plots the dynamic price series for the sample period. Higher price oscillations were evident in the Chinese stock markets than in the US stock market. The US stock market experienced an upward trend from January 2019 to February 2020, a dramatic fall in March 2020, and a second upward trend from May 2020, and both the Shanghai and Shenzhen indexes exhibited similar patterns. Looking at commodity futures, gold showed an upward trend throughout the sample period whereas oil showed a significant decline from March 2020. Graphical evidence indicates that the pandemic contributed negatively to US and Chinese stock market performance and to the fall in oil prices. The performance of gold, in contrast, was positive, consistent with its role as a safe-haven asset during times of crisis.

Table 1 reports descriptive statistics for price returns for the S&P500, Shanghai, and Shenzhen stock indexes, and the gold and oil markets. Due to the drastically reduced demand for oil due to lockdowns imposed around the world, returns for stocks and gold were positive on average, whereas returns for oil were negative on average. Note also that oil was the most volatile market and gold was the least volatile market, and that the US stock market was more volatile than the Chinese stock markets.

The skewness values for all series, except for gold, are negative, indicating asymmetry and that the markets are inclined to generate...
losses. The kurtosis values exhibit fat tails and leptokurtic behaviors. The Jarque-Bera (JB) test corroborates the skewness and kurtosis results, strongly rejecting the null hypothesis of a normal distribution for price returns. Results for the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test indicate that all returns are stationary. Results for the Ljung-Box (LB) test statistic for residuals and squared residuals reject the null hypothesis of no serial correlation, while results for the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) test rejects the null hypothesis of no return series heteroskedasticity. Finally, the linear correlation of gold with stock returns is close to zero (0.07), while the linear correlation of oil with stock returns is positive, at 0.24 for the Chinese stock markets and 0.36 for the US stock market.

4. Results

Tables 2–4 present MS-VAR model estimates for the links between

Panel A. Low-volatility regime

Panel B. High-volatility regime

Fig. 4. Graph depicting the connectedness of the S&P500 index.
the three stock markets and the oil and gold markets, with appropriate lags selected using the Akaike information criterion (AIC). Table 2 shows the Shanghai index returns, influenced by the one-day lag price returns for Shanghai, gold, and oil price returns during the low-volatility regime – relationships that, however, become insignificant under the high-volatility regime (regimes 1 and 2, respectively). This result reveals the importance of these two strategic commodities for portfolio management during a turbulent period. Shanghai returns have no impact on commodity (gold and oil) price returns in both regimes. This finding is in line with that of Zhang et al. (2021), who demonstrate the importance of gold in portfolio diversification in Chinese stock markets. Likewise, the absence of linkages between oil and gold reveals that energy investors could include gold in their oil futures contract portfolio as a way to reduce risk during a high-volatility regime. This result is in line with Reboredo (2013) and Alkhazzâli et al. (2021), who report that combining gold and oil assets significantly reduces portfolio risk. It is also consistent with the findings of Adekoya et al. (2021), who report evidence that gold hedges against oil and stock market uncertainty during the COVID-19 crisis. Gold price returns are influenced by lagging oil price returns in the high-volatility regime. Oil is also affected by previous oil price shocks in both regimes as well as by lagging gold price returns in the low-volatility regime.

**Panel A. Low-volatility regime**

**Panel B. High-volatility regime**

Fig. 5. Graph depicting the connectedness of the Shenzhen index.
Table 3 shows that S&P500 returns are influenced only by one-day lagged gold returns under both low- and high-volatility regimes, and by its own lagged price returns in the high-volatility regime, for relationships that are positive under both volatility regimes. In addition, S&P500 returns enhance oil price returns in the low-volatility regime and reduce them in the high-volatility regime. This suggests that increased oil prices only reduce US stock price returns in a high-volatility regime, a result consistent with the findings of Li et al., (2021), who find evidence of significant spillovers from the US stock market to the oil market in the short term. Gold price returns are influenced by previous oil price shocks in the high-volatility regime, while gold positively influences oil prices in the low-volatility regime.

Table 4 reveals that the one-day lagged price returns for Shenzhen and both oil and gold affect Shenzhen index returns in the low-volatility regime, with those effects dissipating in the high-volatility regime. Gold price returns are influenced only by oil price returns in the high-volatility regime. Shenzhen index returns have positive effects only on oil prices in the low-volatility regime, while gold price returns impact oil prices in the low-volatility regime, but have an insignificant impact in the high-volatility regime. Overall, the relationships between the studied variables are stronger in high-volatility regimes, a result corroborated by Roubaud and Arouiri (2018), who report that the relationship between oil, currency, and stock markets is both regime-dependent and stronger during more volatile periods.

Table 5 presents estimates of the transition probabilities for the estimated MS-VAR(1) model. The empirical results show that the probability of transition is highest for the low-volatility regime for the three stock markets, and that the low-volatility regime is more persistent than the high-volatility regime. Likewise, for the three markets, a switch from the high-volatility regime to the low-volatility regime is more likely than a switch in the opposite direction.

Fig. 2 depicts the temporal dynamics of the smoothed probability for the low-volatility regime for the three stock markets. The low-volatility regime dominates from January 2019 to February 2020; however, with the onset of the global health crisis, the three markets move to the high-volatility regime from March 2020 to May 2020, as shown by the dynamics of the smoothed probabilities for that period. This regime can also be explained by the declaration of a national emergency by the US president on 13 March 2020 and the accusations as to China spreading and poorly handling the coronavirus.

Tables 6–8 report estimates for the variance-covariance matrices for the MS-VAR model under low- and high-volatility regimes for the three stock markets, respectively. Variance is statistically significant for all five markets, irrespective of the regime. Consistent with the descriptive evidence, variance for the oil market is highest relative to variance for the stock and gold markets. Of the three stock markets, the S&P500 exhibits the lowest variance in the low-volatility regime and the highest variance in the high-volatility regime, while the Shenzhen index is more
Panel A. Low-volatility regime

From the parameter estimates for the MS-VAR(1) model, we further quantify the spillover contribution of each commodity market to the US and Chinese stock markets and vice versa, using the forecast error variance decomposition as per Eq. (8) for a time horizon of $h = 10$ trading days. Tables 9–11 summarize the estimated parameters for market connectedness between volatility in strategic commodity returns and stock market returns. As shown in Table 9, the major spillover contributor to the Shanghai market is own shocks (95.42%) in the low-volatility regime, with gold and oil representing only 4.99% and 2.53% of shocks, respectively. The contribution of Shanghai and gold spillovers to oil is less than 2% in the low-volatility regime. This picture changes in the high-volatility regime, as the Shanghai and gold markets contribute to the forecasted error variance of oil by 13.42% and 8.83%, respectively. Likewise, gold receives the highest portion of spillovers from its own previous shocks, and more so under the low-volatility regime than under the high-volatility regime.

As for S&P500 (Table 10), empirical estimates show that the magnitude of spillovers is sensitive to the volatility regime. The US stock market is mainly influenced by its own lagged price changes (77.14% in the low-volatility regime and 80.76% in the high-volatility regime). Gold spillovers to S&P500 are lower under the high-volatility regime than under the low-volatility regime, pointing to the hedging role of gold in times of high uncertainty. In contrast, oil spillovers to S&P500 are greater during the high-volatility regime relative to the low-volatility regime by around 67.41%. Spillovers from S&P500 to gold drop during the high-volatility regime but those from oil to gold increase. Spillovers from S&P500 to oil double during the high-volatility regime (from 7.51% to 15.43%) but are still small compared to the transmission from oil to oil (above 80% for both regimes).

Table 11 presents spillover evidence for the Shenzhen index, showing that gold and oil make low contributions to Shenzhen stock returns in both volatility regimes. Likewise, gold and oil show low

volatile than the Shanghai index in both regimes. Looking at covariance between markets, we find the parameter estimates to be higher under the high-volatility regime. Specifically, covariance between the Shanghai index and gold is negative and statistically insignificant in the low-volatility regime, but is positive in the high-volatility regime. This result is also observed for the S&P500 and Shenzhen markets. The fact that gold behaves as a good diversifier against downward stock price movements in the low-volatility regime is consistent with previous literature (see Baur and Lucey, 2010; Baur and McDermott, 2010, among others); in the high-volatility regime, however, gold loses its hedging abilities. Covariance between oil and stock markets is positive and statistically significant under both regimes and rises in a scenario of increasing uncertainty. This evidence indicates that dependence between oil and stock markets increases in the high-volatility regime, leading to a reduction in diversification benefits and validating the recoupling hypothesis. As for dependence between oil and gold, this is negative in the low-volatility regime, and positive and insignificant in the high-volatility regime, confirming the hedging role of gold against exposure to oil risk, and also consistent with the findings of Selmi et al., (2018).

\[ Fig. 7. \text{Impulse response graphs for the S&P500 index.} \]
integration in terms of spillovers when markets exhibit high volatility; however, in the low-volatility regime gold has an influence on oil that is considerably greater than that of oil on gold. The impact of the Shenzhen index on oil is limited in both regimes, especially when market volatility peaks. The fact that gold decouples from Shenzhen in both regimes is consistent with the hedging capacity of gold for stock returns, also evident for oil in the high-volatility regime.

Figs. 3–5 depict the connectedness network for the studied markets in low- and high-volatility regimes, with the color of edges connecting two markets and node size indicating the size and magnitude of spillovers, respectively. The connectedness graph for the Shenzhen market under the low-volatility regime shows that gold is a net contributor of spillovers to the oil market and that gold receives spillovers from the oil market. The independence between gold and the Shenzhen index again points to the role of gold as a safe-haven asset. Oil is a net receiver of shocks from the gold and Shenzhen markets. Under the high-volatility regime, we find evidence of two-way spillovers between the Shenzhen and commodity markets. During the high-volatility regime, gold becomes a net receiver of spillovers from other markets, while the role of the Shenzhen index as a contributor of spillovers decreases. The results are similar for the S&P500 and Shanghai stock markets. Overall, the oil market increases its capacity as a shock transmitter under the high-volatility regime, while the reverse happens with the gold and stock markets. The graphical evidence reflects how connectedness between commodity and stock markets changes according to the regime, indicating the usefulness of taking regime shifts into account.

Figs. 6–8 show the outcome of the impulse response analyses based on the estimated MS-VAR models. As shown in those plots, all markets react more significantly to shocks from their own markets than from oil and gold. Furthermore, and consistent with the evidence presented in Tables 9–11, the magnitude of responsiveness is greater under the high-volatility regime than under the low-volatility regime. Shanghai stock returns respond moderately to oil shocks, independently of the regime, consistent with the fact that Chinese firms adopt effective hedging strategies to reduce the impact of adverse oil price movements. The responsiveness of the Shanghai index to gold price shocks differs according to the regime, providing evidence of an asymmetric response to gold market shocks. Considering the oil market, shocks from the Chinese stock markets have stronger effects than the commodity markets. The responsiveness of commodity market returns volatility to Shanghai stock market shocks is asymmetric, depending as it does on the regime. More importantly, the responsiveness is greater under the high-volatility regime and is greater for oil than for gold. All in all, the oil market responds significantly to shocks from both the stock and gold markets. Empirical evidence for the S&P500 and Shenzhen markets is broadly similar.

Finally, we explore how connectedness evolves over the sample period by estimating the MS-VAR models using a rolling time window of
220 trading days that is moved ahead on a day-by-day basis. Figs. 9–11 present evidence on the dynamic spillovers for Shanghai, S&P500 and Shenzhen markets in different volatility regimes. Spillover trends for the pairs differ and also depend on the volatility regime. Spillovers from gold to the Shanghai stock market are low from January to October 2019, but surge in the last quarter of 2019. The extent of spillovers is higher under the low-volatility regime than under the high-volatility regime, confirming our previous findings. As with gold, for the oil–Shanghai pair we find a significant surge in spillovers in the last quarter of 2019.

We also observe that the extent of spillovers decreased in the first half of 2020. This result may be due to the fact that the Chinese market absorbed COVID-19 pandemic information after 23 January 2020, when the central government imposed the Wuhan lockdown to control viral spread. Shenzhen market results are broadly similar to those for the Shanghai market. Before 2020, spillovers between the US stock market...
and commodities were relatively stable under the low-volatility regime. Spillovers intensified in the first quarter of 2020 and decreased between April and May 2020. This result may be attributable to the fact that many investors were taking a long-term perspective by looking ahead to the end of the pandemic. On the other hand, spillovers from gold to oil were higher than from oil to gold, and were higher during high-volatility regime, reaching a maximum between January 2020 and February 2020. These results are in line with those of Hung and Vo (2021), who report time-varying spillovers between oil, gold, and S&P500 that surged during the pandemic, in particular, at low and high frequencies.

5. Conclusion

This paper examines switching spillovers between oil futures, gold futures and US and Chinese stock markets (S&P500, Shanghai and Shenzhen indexes) using the MS-VAR model and the spillover index proposed by Diebold and Yilmaz (2014).

The results show that US and Chinese stock markets are influenced by their own shocks. Gold and oil price returns impact the Shanghai and Shenzhen stock market returns during the low-volatility regime. Gold price returns affect the S&P500 index returns, which, in turn, contribute positively to oil price returns in the low-volatility regime and negatively in the high-volatility regime. The persistence of the low-volatility regime is greater than the persistence of the high-volatility regime. The temporal dynamics of the smoothed probability for the low-volatility regime dominates over that of the high-volatility regime, particularly from January 2019 to February 2020, while from March to May 2020, the high-volatility regime dominates over the low-volatility regime.

The variance-covariance estimates for the MS-VAR model under low- and high-volatility regimes show that oil is the most volatile market. Of the three stock markets, the S&P500 exhibits the lowest variance during the low-volatility regime and the highest variance during the high-volatility regime, while the Shenzhen market is more volatile than the Shanghai market under both regimes. Own shocks are the major spillover contributor to the Shanghai market under the low-volatility regime, while gold and oil spillovers are relatively weak. The connectedness network for the Shenzhen index under the low-volatility regime shows that gold is a net contributor of spillovers to the oil market and receives spillovers from the oil market. However, we find independence between gold and the Shenzhen index, pointing to the role of gold as a safe-haven asset. Oil is a net receiver of shocks from the gold and Shenzhen markets. Under the high-volatility regime we find evidence of two-way spillovers between the Shenzhen and commodity markets, and of gold as a net receiver of spillovers from other markets. The ability of Shenzhen to contribute spillovers decreases under the high-volatility regime. These results are equally valid for the S&P500 and Shanghai stock markets.

Our results have important implications for investors and policy makers. Investors need to be aware that the relationships between commodity and equity markets vary across volatility regimes and so should seek assets that reduce their equity portfolio risk during high-volatility regimes. Moreover, knowing the transition probability from one regime to another is fundamental to optimizing decision-making processes. In fact, little time is required to transition from low-volatility to high-volatility regimes, indicating that a high-volatility regime does not persist relative to a low-volatility regime. Investors need to be aware that gold is a net receiver of shocks in high-volatility regimes and a net contributor of shocks in low-volatility regimes, while the situation is reversed for both oil and stock markets. The greatest impact of the COVID-19 pandemic on spillovers was in March 2020, which would suggest that investors should be aware of risk emanating from public health. More importantly, gold and oil futures are strongly predictive of future stock prices and protective against uncertainty. Investors should consider past stock price returns to predict future prices, especially during a high-volatility regime, in order to cut portfolio risk exposure and investment uncertainty. Chinese and US equity investors could include a large share of gold and oil futures contracts in their equity portfolios during a high-volatility regime. Portfolio managers should use regime-switching models to better reflect spillovers among markets and implement optimal hedging between commodity and stock markets. Gold’s ability to be a net spillover contributor diminishes under a high-volatility regime whereas that of oil increases. Overall, we recommend that equity investors include gold futures in their equity portfolio under a high-volatility regime and that

Fig. 11. Time-varying spillovers for the Shenzhen index, gold, and oil in the low-volatility regime (regime 1) and the high-volatility regime (regime 2).
they use oil futures as a predictive instrument.

As for implications for policy makers, our results contribute to a better understanding of spillover effects between crude oil, gold, and stock markets under different regimes. Since the world’s two largest consumers of oil are the USA and China (20.51 and 13.89 million barrels per day, accounting for 20% and 14% of total world oil consumption, respectively), governments should hold sufficient oil reserves to limit spillovers to their stock markets. Meanwhile, biofuel and renewable energies may reduce dependence on oil products. Gold continues to be a strong safe-haven asset as protection from investment risk, not only during financial and energy crises, but also during global health crises. Investors and policy makers should therefore establish gold-reserve policies that optimize equity portfolios and stabilize the financial system.

CRediT authorship contribution statement

Walid Mensi: Conceptualization, Writing – original draft, Supervision, Writing – review & editing. Juan C. Reboredo: Supervision, Visualization, Writing – review & editing. Andrea Ugolini: Data curation, Methodology, Software, Visualization.

Acknowledgement:

Juan C. Reboredo and Andrea Ugolini thank financial support received by Agencia Estatal de Investigación (Ministerio de Ciencia, Innovación y Universidades) under research project with reference RTI2018-100702-B-I00, co-funded by the European Regional Development Fund (ERDF/FEDER). Juan C. Reboredo acknowledges financial support provided by Xunta de Galicia through research project CON-SOLIDACION 2019 GRC GI-2060 Análise Económica dos Mercados e Instituciónes – AEMI (ED431C 2019/11). Andrea Ugolini acknowledges financial support provide by the Brazilian National Council for Scientific and Technological Development (CNPq).

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