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Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets

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ABSTRACT

This paper examines spillover effects among six commodity futures markets – gold, silver, West Texas Intermediate crude oil, corn, wheat, and rice – by employing the multivariate DECO-GARCH model and the spillover index. Specifically, we investigate the dynamics of return and volatility spillover indices to reveal the intensity and direction of transmission during the recent global financial and European sovereign debt crises. Our empirical results are as follows. First, we estimate a positive equicorrelation between commodity futures market returns and find that it increased sharply during the crises. This effect can persist during periods of economic and financial turmoil, diminishing the benefits of international portfolio diversification for investors. Second, we identify bidirectional return and volatility spillovers across commodity futures markets, and find more pronounced trends in their levels in the post-crisis period. This indicates the strong impact of spillovers during crisis periods. Third, both gold and silver are information transmitters to other commodity futures markets, while the remaining four commodity futures investigated were receivers of spillovers during recent periods of financial stress. Finally, we analyse the optimal portfolio weights and time-varying hedge ratios between metal and other commodities futures markets. Overall, our findings provide new insights into channels of information transmission, which may improve investment decisions and inform portfolio investors' trading strategies.

1. Introduction

From a hedging and speculation perspective, commodity futures have provided a popular investment for diversifying portfolio risk. Commodities – including energy, metals, and agriculture commodity assets – are considered profitable alternative assets, relying on low correlations, a positive comovement of commodity prices with inflation, and a tendency towards backwardation in the futures curve (Chong and Miffre, 2010). Commodity futures offer different volatilities, and returns that have lower correlations with other financial assets, especially when macroeconomic shocks tend to push returns on commodity assets and investors' portfolios in opposite directions. For these reasons, investors are interested in adding commodity futures to their portfolios, aiming to design strategies that optimize asset allocation, portfolio optimization, downside risk reduction, and hedging (Belousova and Dorfleitner, 2012; Skiadopoulos, 2012; Silvennoinen and Thorp, 2013; Andreasson et al., 2016; Karyotis and Alijani, 2016).

On the other hand, financial, economic, and geopolitical events strongly influence commodity prices, such as those for oil, precious metals, and agriculture assets. Volatile metals, oil, and agricultural commodity prices have significant impacts on supply–demand activities as well as on appropriate policy responses to associated changes in market conditions. Furthermore, a significant number of commodities across the energy, metals, and agricultural sectors have experienced harmonized boom and bust cycles during the most recent financial crises (Cheng and Xiong, 2014; Cabrera and Schulz, 2016). Finally, the financialization of commodity markets appears to have increased the degree of integration across the energy, metal, and agricultural commodity markets (Tang and Xiong, 2012; Nazlioglu et al., 2013). These changes have increased the fundamental importance for governments, speculative traders, producers, and consumers, of analysing links between shocks and volatility across these markets (Mensi et al., 2013, 2014).

The spillover phenomenon implies that one large shock increases the correlation of returns not just in the own asset (market) but also in other assets (markets). This effect may intensify during financial crises, with a further implication being that both volatility and correlation will persistently move together over time (Silvennoinen and Thorp, 2013; Sensoy et al., 2015; Ewing and Malik, 2016). The recent

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and on-going financial crises, and the attendant strength of commodity prices, have renewed interest in understanding the fundamental process of information transmission through which commodity market returns and volatility have become increasingly correlated (Chng, 2009; Chan et al., 2011). The presence of spillovers deepens the need for investors, portfolio and risk managers, manufacturers, and policymakers to better understand the dynamics of commodity futures prices (Vivian and Wohar, 2012; Sensoy, 2013). However, while the literature has focused on the linkages between stock and commodity markets (mostly oil or gold), it has paid little attention to the interrelationships among the prices of different essential commodities.[1] This latter lack of literature justifies further study.

The recent development of multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models has seen a significant use in the literature of versions of these models. For example, MGARCH models have been used to measure optimal weights and hedging ratios between commodity and other financial markets (e.g. Hammoudeh et al., 2010, 2014; Arouri et al., 2011, 2012, 2015; Mensi et al., 2013; Silvennoinen and Thorp, 2013; Thuraisamy et al., 2013; Sadorsky, 2014; Aboura and Chevallier, 2015). Yet, despite the growing global focus on commodity markets, the related empirical research remains surprisingly limited. Additionally, studies have employed the MGARCH model to provide information only about the variance–covariance matrix and correlations. Thus, their models do not capture the direction of spillovers across assets and markets (Awartani and Maghyereh, 2013; Antonakakis and Kizys, 2015). Understanding the direction of spillovers can provide useful information for designing optimal portfolio strategies, hedging practises, and risk management.

To overcome limitations associated with MGARCH models, Diebold and Yilmaz (2009, 2012) propose a new set of spillover indexes. These allow measurement of the direction of spillovers based on forecast-error-variance decompositions (FEVDs) from vector autoregressions (VARs). Several studies emphasize a number of empirical advantages of this method (Awartani and Maghyereh, 2013; Zhang and Wang, 2014; Antonakakis and Kizys, 2015). First, as it requires aggregating and offsetting invariant FEVD, this method does not depend on the Cholesky factor identification of VAR. Therefore, the results of variance decomposition do not hinge on the ordering of variables. Second, this method enables the measurement of spillovers in returns and volatilities over time and across multiple individual assets, classes of assets, and markets. Third, the dynamics of the spillover measure generated by a rolling window approach facilitates the study of both crisis and non-crisis episodes, including trends and busts in spillovers. Finally, and most importantly, this method measures spillovers from one market to any other market, as well as allowing net spillovers and their direction to be calculated. These distinctive features provide more information about dynamic directional spillovers than does measurement of the significance of a parameter estimated under a variance–covariance matrix framework, as in the MGARCH models (Zhou et al., 2012). Subsequent empirical studies have emphasized the direction of spillovers in returns and volatility across individual assets, asset portfolios, and asset markets (Awartani and Maghyereh, 2013; Zhang and Wang, 2014; Antonakakis et al., 2016; Yarovaya et al., 2016).

Our paper extends the empirical literature by accounting for the intensity and direction of spillover effects among different sections of the metal (gold and silver), crude oil (West Texas Intermediate (WTI)), and agricultural (corn, wheat, and rice) commodity futures markets, and in doing so contributions to the literature in several areas. First, we consider the potential impacts of structural breaks on commodity futures markets using the iterative cumulative sum of squares (ICSS) algorithm of Inclán and Tiao (1994). Second, we adopt the dynamic equicorrelation (DECO) model of Engle and Kelly (2012) to determine comovement across commodity futures markets. The DECO model is an extreme case of the dynamic conditional correlation (DCC) model, in which correlations are equal across all pairs but the common equicorrelation changes over time. Third, we investigate the intensity of return and volatility spillover indexes (Diebold and Yilmaz, 2009, 2012), by employing the forecast-error variance decomposition framework for a VAR model. This method measures the magnitude of return and volatility spillovers among different commodity futures markets. Understanding return and volatility spillovers among commodity futures markets assists institutional and individual investors to conduct effective risk management and undertake superior asset allocation. Fourth, we use a rolling window approach to detect the time-varying dynamics of the spillover index, insofar as recent financial crises may directly affect return and volatility structures among commodity futures markets. The dynamics of the spillover index allow this study to differentiate between the impacts of tranquil or stable periods and volatile or crisis periods, including trends and sudden movements in spillovers. Thus, the dynamics of the spillovers may provide 'early warning systems' for emergent crises and can help track the progress of possible crises. Fifth, we decompose the total spillover index into directional ('from' or 'to') spillovers to calculate the net spillover index among commodity futures markets. As the spillover effect moves in one direction then reverses direction over time, the net spillovers assist in identifying commodities futures markets that are pure 'sources' or 'recipients' of spillovers. Finally, this study further examines optimal portfolio design and hedge ratios to minimize risk in commodity futures portfolios. Our findings on optimal weights and hedge ratios indicate that investors can make appropriate capital budgeting decisions and effectively manage their exposure to commodity portfolio risks during episodes of financial turmoil.

The remainder of the study is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodology used in this study. Section 4 describes the study's data and conducts preliminary analyses. Section 5 discusses the empirical results. Finally, Section 6 provides concluding remarks.

2. Literature review

Since the 2007–2009 global financial crisis (GFC), the topic of information transmission across markets has attracted considerable attention. Such financial events significantly affect the direction of spillovers across a wide variety of asset, including commodity futures, markets. Due to the large scope of the literature on the subject, we confine the review to studies on spillovers across commodity futures markets.

Most empirical studies find that volatility transmission changes significantly following a crisis. Nazlioglu et al. (2013) employ a variance impulse response function (VIRF) to identify the structure of the volatility transmission mechanism between oil and agricultural commodities (i.e. corn, soybeans, wheat, and sugar) before and during the food crisis of 2006–2008, using causality in variance tests and impulse response functions. Their results show that while there is no risk transmission between oil and agricultural commodity markets in the pre-crisis period, oil market volatility spills into agricultural markets in the post-crisis period. Beckmann and Czudaj (2014) apply a GARCH-in-mean VAR model to investigate volatility spillovers in agricultural futures markets (i.e. corn, cotton, and wheat). They conclude that potential speculation effects on the corn futures market may be contagious for the cotton and wheat futures markets and a cause of the recent growth in interdependence of the agricultural futures markets. Lin and Li (2015) use a vector error correction (VEC) model with an MGARCH model to investigate price and volatility spillovers between the natural gas and oil markets in different regions (i.e. the US, Europe, and Japan).

[1] Many studies have researched the oil–stock nexus (e.g. Hammoudeh et al., 2004; Filis et al., 2011; Arouri et al., 2012; Sadorsky, 2012, 2014; Mensi et al., 2014; Salisu and Oloko, 2015) and the gold–stock nexus (e.g. Baur and McDermott, 2010; Hood and Malik, 2013; Arouri et al., 2015). Other researchers have investigated the commodity cross-market linkages between the oil and gold markets (e.g., Soytas et al., 2009; Reboredo, 2013; Yaya et al., 2016) and oil–agricultural relationships (e.g. Du et al., 2011; Nazlioglu et al., 2013; Mensi et al., 2014, 2015).