Commodity Market Financialization, Herding and Signals:

An asymmetric GARCH R-vine copula approach

Abstract

Institutional investors have significantly increased their exposure to commodity futures after 2004 in the process of commodity market financialization, raising questions about the risk-sharing and price-discovery functions of the market. We identify some symptoms of financialization through examining S&P500, JPM bond index, and 18 S&P GSCI excess return indices, employing ARMA-GARCH R-vine copula approach that can flexibly model high-dimensional multivariate asymmetric tail dependence. We discover three trends: an increased resemblance between the news impact curve of stocks and those of commodities; an increased bi-variate stock-commodity tail dependence; and an increased multivariate tail-dependence across all commodities. We also explore the market structural change underlying these symptoms using an augmented news impact curve. We suggest and provide evidence that herding, in addiction to leverage effect, explains the observed symptoms. The findings have profound implications for commercial hedgers and financial traders, and for regulators who are concerned about the functionalities of commodity futures market.

Keywords: Commodity market financialization, herding, asymmetric tail dependence, risk-sharing, information friction

JEL codes: G11, G12, G13

1. Introduction, Motivation and Contribution

In the course of a few decades since the 1970s, neoliberalism ideology has shepherded the world's leading economies into a system of financialized capitalism, characterized by the development of an highly innovative, fast-moving and complex web of bank-based, market-based and network-based credit intermediation (Adrian and Shin, 2009). This fundamental structural transformation has resulted in a massive growth in debt among consumers, businesses, and governments alike (see bis.org/statistics). Unsurprisingly, financial crisis of global scale has become a frequent regular (Chang, 2019), rendering extreme investment returns far more likely than in the pre-1970s. Despite its pervasiveness, the causes, symptoms, and consequences of capitalism financialization are still being heatedly debated among scholars, practitioners, and regulators (Christophers, 2015).

In recent decades, many households have delegated the management of their savings to professional fund managers. In 2018, total world asset under management (AUM) stood at USD74.3 trillion (Heredia et al., 2019), of which USD44.1 trillion was controlled by institutional investors, such as pension funds, insurance companies, banks, and other investment companies (OECD, 2019). Consequently, the managers of these funds have become a very important political force in shaping the landscape of global finance universe (Clark, 2000, Dixon and Monk, 2009, Harmes, 1998).

The rapid influx of institutional money cannot be readily absorbed by conventional financial assets such as stocks and bonds. Furthermore, institutional investors need to diversify their AUM, in order to create stable incomes to meet their long-term liabilities (Clark, 2000, Corpataux et al., 2009). Thus fund managers were under pressure to convert into financial assets all kinds of alternative investable assets, such as private firms (Froud et al., 2006), residential or commercial mortgages (Aalbers, 2012), student loans (Montgomerie, 2009), infrastructure (O'Neill, 2013), building rights (Weber, 2015), and commodities. This process is further empowered by waves of financial liberalization, deregulation, and digitization (Clark, 2000, Corpataux et al., 2009, McCarthy et al., 2016). According to OECD (2019), the share of AUM invested by institutional investors in non-stocks and non-bonds was, in 2018, as high as 96.7% in Singapore, 51.6% in Japan, 40.6% in Germany, 39.0% in Denmark, 36.7% in South Africa, 35.6% in Canada, 35.4% in Switzerland, and 31.9% in the United Kingdom.

Among all these alternative investment assets, commodity stands out as one of the most important. Following the burst of the dot-com bubble in 2000, investors started looking for new investment opportunities. Just in time, a characteristic of commodities was discovered and widely circulated. Researchers such as Greer (2000), Gorton and Rouwenhorst (2006) and Erb and Harvey (2006) revealed that there was low or negative return correlation between commodities and equities and bonds. This discovery makes commodities an ideal instrument for portfolio managers seeking diversification. Meanwhile, great strides were made in commodity-based exchange-traded products, allowing unconventional investors to gain exposure to commodities. All these have promoted a phenomenal growth in funds pouring into commodity futures and derivatives. For example, the total open interest (long position) of Light Crude Oil at New York Mercantile Exchange rose from 615,105 contracts at the beginning of 2000 to 2,156,002 contracts by the end of 2015[i]. During the same period, the proportion of this interest held by commercial hedgers declined from 81.4% to 37.7%[ii] while that by non-commercial investors rose from 7.4% to 21.6%.[iii] A similar observation was made by Seddon (2020) who finds that, post-1970s, trading taking place at London Metal Exchange with genuine commercial interests declined from around 80% to roughly 30%, and the proportion of LME contracts settled through physical delivery has declined from nearly 20% to less than 1%.

Despite its growing importance, scholarly interests towards financialization only rose after the 2008 global financial crisis. Yet, these interests have thus far delivered sophisticated insights on, among others, the financialization of commodities (Tang and Xiong, 2012, Cheng and Xiong, 2014, Singleton, 2014, Cheng et al., 2015, Hamilton and Wu, 2015, Basak and Pavlova, 2016). While the literature has offered substantial evidence on the symptoms of financialization, for example, increased dependence between stocks and commodity market, there are unsettled important questions such as how financialization affects the functionality of commodity market. More specifically, has financialization reduced the risk-sharing function of commodity futures market? Has financialization increased information friction in commodity market? (Sec section 2 for further details of these debates). These ongoing debates offer the key motivation for the current study.

Our study makes both empirical and theoretical contributions. First, we provide evidence that the increasing participation of financial traders has increased information friction in commodity markets. By financial trader, we refer to those who treat commodities as financial assets and are not interested in taking physical deliveries (Seddon, 2020). While the stock and bond markets have been extensively studied, our collective understanding of the alternative investment markets, such as real estate and commodities, are very limited. The arrival of institutional investors in these market over the past two decades in theory should increase the information efficiency of these markets. However, if they treat these alternative investment assets just like stocks and bonds, which the literature suggests they do, then their participation will increase the information friction in these markets. Information friction refers to the cost of acquiring and processing information, which can arise due to asymmetric information and high transaction costs (Sockin and Xiong, 2015). Empirically, information friction can be measured in various ways, for example by the bid-ask spread. In the context of the current study, this information friction is reflected in the heightened volatility impact of news (see section 5.4, Table 4).

Second, we propose and provide evidence that news impact curve carries the fingerprints of commodity market financialization. It has long been recognized in the empirical literature that stock price volatilities respond more to negative than to positive news, demonstrated in their corresponding news impact curve. A popular theory explains this observation using "leverage effect," which says that the relative value of debt rises against that of equity in a company when its stock price falls, raising financial risk hence required risk premium. Given that financial traders in commodity futures use a high degree of leverage, we expect markets that attract significant numbers of financial traders to display this character. On the other hand, if the influence of financial traders is sufficiently weak, the news impact curve will either respond symmetrically to both good and bad news or respond more to positive news. This conjecture is one of our theoretical contributions to the alternative investment literature. We designed an empirical test which provide significant evidence to support this conjecture which is another contribution of this study (section 5.4).

Third, we propose herding as a complementary explanation to leverage effect. While leverage effect explains why stock price volatility is more responsive to negative news, it does not explain why the same price series displays different degree of negative asymmetry in different times. We suggest and provide evidence that negative asymmetry increases with the degree of herding which in turn increases with the number of financial traders (section 5.2 and 5.4).

Fourth, we reveal a type of news impact curve not discussed in earlier literature, namely, one that is more responsive to positive shocks. We provide theoretical explanations on why the news impact curve of certain commodity is positive asymmetric. This explanation is based on the stickiness of excess demand adjustment in the physical commodity market (section 5.3), a characteristic of the physical goods market well understood among economists.

Fifth, we apply ARMA-GARCH R-vine copula , which is rarely used in the literature of commodity market financialization, to reveal that the risk sharing function of commodity futures market has weakened with financialization, as this market has become more interdependent with stock market. But this change is non-linear and is not universal. Studies of financialization generally solely rely on pairwise correlation analysis of residuals from a structural model. Such models are more likely to be subject to misspecification compared with ARMA-GARCH model. Pairwise correlation analysis will also be insufficient in a complex investment universe where all assets and investment vehicles are related via the portfolio strategies of financial traders especially in extreme events. This difficulty is better handled by R-vine copula. Although three most recent papers which apply copula analyses to commodity markets in the context of portfolio management(Delatte and Lopez (2013), Aepli et al. (2017) and Chen et al. (2023)), all of those papers rely on pairwise copular rather than multivariate R-vine analysis. These three studies have preselected some restrictive copular structure for their data, unlike our study allowing the data to decide their copula structure from forty different copula families (Appendix A). Furthermore, their focus is either methodological as is the case in Aepli et al (2017), that discusses which copular structure is better for a given set of data; or empirical as is the case in the other two that focus on the diversification benefits of commodities. In other words, their research interests are in symptoms rather than causes. Furthermore, most earlier studies made no distinction between events of different natures, namely, good news or bad news. The current study show that these differentiations shed new lights on our understanding of the markets and can be addressed using asymmetric ARMA-GARCH model as well as news impact curve in conjunction with R-vine copula.

The remainder of the paper is organized as follows: section 2 reviews the relevant literature; section 3 describes the data and explains the GARCH-based vine copula method; section 4 displays the empirical results; section 5 discusses and explains the empirical findings; and section 6 concludes.

2. The Ongoing Debate in the Literature

Commodity futures are intrinsically different from stocks and bonds. They do not raise funds for firms to invest. Rather, they are derivative securities which allow firms to obtain insurance for the future value of their inputs or outputs. Traditionally, participants in commodity futures market are primarily composed of two classes of players: commercial hedgers and non-commercial traders. Commercial hedgers (such as farmers, producers, and consumers) regularly trade commodity futures to hedge spot-price risk inherent in their commercial activities. Non-commercial traders (such as hedge funds or other managed money vehicles) invest others' money in commodities, commodity futures, and options on futures, and they make extensive use of leverage. Non-commercial traders receive compensation for bearing the risk of short-term spot commodity price fluctuations (Gorton and Rouwenhorst, 2006).

The composition of participants in commodity futures market has changed dramatically since early 2000s, with a surging inflow of institutional investors. By 11 August 2020, their share of open interests in commodity futures had grown to 16.7%,[iv] making their combined position with non-commercial traders to be as high as 43.8%, exceeding that of commercial hedgers by 9.1%. Most of these institutional holdings are through instruments linked to broad-based commodity futures indices, such as Goldman Sachs Commodity Index (GSCI), the Dow Jones UBS Commodity Index (DJ-UBS) or the S&P Commodity Index (SPCI). Institutional investors of this kind are thus also called commodity index traders. Commodity index traders, unlike the conventional non-commercial traders, treat commodity futures as a financial asset class just like stocks and bonds. They often establish commodity positions by acquiring index swap contracts from financial swap dealers or purchasing exchange traded funds (ETFs) and exchange-traded notes (ETNs) from fund companies, rather than directly taking long positions in individual commodity futures. These financial swap dealers and funds then hedge themselves by taking long positions in individual commodity futures. Consequently, index traders tend to trade in and out of all commodities in a given index simultaneously (Barberis and Shleifer, 2003). Given the different weight on the constituent commodities in these popular indices, we expect the process of commodity market financialization to impose divergent impacts on different commodities, hence alters the fundamental structure of the market. This is confirmed by our empirical findings.

In the asset management literature, commodity financialization is often understood as the apolitical outgrowth of sweeping technological change, and of advancements in risk-management techniques. Seddon (2020) argues that the sources of financialization are gradual and political. Seddon challenges theories that present financialization as a deterministic and undifferentiated process and suggests that the financialization debate should go beyond the superficial symptoms (commodity price spikes, volatility increases, etc.) to reveal their roots, namely, market-structural change. Through examining the evaluation of the 150-year-old London Metal Exchange (LME), Seddon argues that the LME's evolving market structure can only be understood through its historical institutional heritage (once designed to support the global trade of metals), its new purpose (now reinvented for the benefit of financial investors), and the continued ground-level politics between traditional metal merchants and financial speculators. Seddon thus defines financialization as an ongoing contentious process through which banks and financial firms challenge merchant incumbents that gives rise to market-structural changes.

In line with his own definition, Seddon classifies commodity markets into four types, with type I being the least and type IV the most financialized market structure. Spot markets, type I, are execution platforms, supporting physical transactions for immediate or near-immediate delivery. Active forward markets, type II, enable industrial users to hedge trading commitments and engage in speculation. The key constituents of futures markets, type III, are financial institutions. These constituents are not interested in taking physical deliveries, rather, they treat futures as financial investments. Synthetic markets, type IV, are execution-only platforms that provide a meeting place for the transfer of contracts, often developed by third parties. The key constituents of synthetic markets are algorithmic financial traders who often infer prices without reference to underlying contracts. Our empirical study reveals that even within the type III futures market, the process of financialization is extremely uneven.

Against this background and in line with Seddon (2020) and Sockin and Xiong (2015) , we define commodity market financialization as a process associated with growing influence of financial traders.

By financial trader, we refer to the combined force of commodity index traders, conventional non-commercial traders, and others who have no interests in the delivery of the physical commodity.

With substantial growth in the net commodity exposure of financial traders after 2004, researchers observe that the price volatilities of many commodities have grown (Cheng and Xiong, 2014, Tang and Xiong, 2012). This new development has led to increasing concerns in the policy circles as to whether it has distorted commodity prices, and whether more government regulation is warranted (Cheng and Xiong, 2014, Brown and Sarkozy, 2009, Masters, 2008, Kennedy, 2012, Krugman, 2008, Stoll and Whaley, 2010, Irwin et al., 2009, Irwin and Sanders, 2012, Fattouh et al., 2013). This change has also attracted rising interests among the scholars. One central point of debate is whether financialization has affected commodity markets through the mechanisms that underpin the functioning of these markets, such as risk-sharing, information discovery and storage (see (Rouwenhorst and Tang, 2012) and (Cheng and Xiong, 2014) for recent surveys).

First, financialization can affect risk sharing through the dual roles of financial traders: as providers of liquidity to commercial hedgers when trading to accommodate hedging needs and as consumers of liquidity from hedgers when trading for their own liquidity needs (Cheng et al., 2015, Acharya et al., 2013). Commodity futures market has had a long history of assisting commodity producers to hedge price risks. Hedgers are typically on the short side of futures market and need to offer positive risk premia to attract financial traders to take the long side (Hicks, 1939, Hirshleifer, 1988, Keynes, 1923, Blau, 1944-45). Financialization mitigates this hedging pressure and improves risk sharing among hedgers and investors. However, the latter has a time-varying risk appetite. For example, portfolio investors may have to reduce risk by unwinding their long commodity positions if a sudden price drop in stock market occurs. Consequently, they transmit outside risks to commodity futures market (Tang and Xiong, 2012).

Many empirical studies related to this strand of literature focus on detecting changes in the average correlation as measured by Pearson's ρ among commodity futures. For example, Cheng and Xiong (2014) indicate that, after 2000, there is a marked increase in the correlation of non-energy commodity GSCI indices with the GSCI Energy index. They also demonstrate a significant increase in the correlation between commodity futures and other asset classes during the same period. (See also (Silvennoinen and Thorp, 2013) and (Büyükşahin and Robe, 2014)).

However, the method used by most earlier studies experiences shortcomings of undifferentiated treatment towards usual and extreme events. Gorton and Rouwenhorst (2006) show that commodity returns display high kurtosis, which suggest that extreme events occur more frequently in commodity markets than one would expect under normal distribution. Furthermore, random variables that appear to exhibit no correlation can show strong tail dependence in extreme deviations. It is a stylized fact that stock returns commonly exhibit tail dependence (Fortin and Kuzmics, 2002, Beine et al., 2010). Further understanding is need on how tail dependence affects the risk-sharing function of commodity futures market. This study thus proposes to contribute to this knowledge front using R-vine copula analysis.

Second, financialization can affect information discovery in commodity markets through information frictions. According to Grossman and Stiglitz (1980) and Hellwig (1980), centralized futures markets play a supplement role to the commonly decentralized spot markets in information discovery. In the presence of informational frictions, heterogeneous expectations among financial traders can lead to drift in commodity futures prices. Final-goods producers cannot easily differentiate whether a futures price move is due to noisy financial traders' trading or due to changes in global economic fundamentals. Thus, noises brought about by the trading activities of financial traders in the futures market can be passed through to the spot markets hence distorting the production of primary product (Singleton, 2014, Sockin and Xiong, 2015).

Cheng and Xiong (2014) point out that Information frictions help to explain the price increases of many commodities in early 2008. Hamilton (2009) and Kilian (2009) on the other hand argue that a key factor in explaining the commodity price boom in that time is strong commodity demand from China and other emerging economies, coupled with a stagnant commodity supply. Cheng and Xiong (2014) counter-argue that this factor fails to explain the large oil price increases in the first half of 2008, unless final-goods producers increased their oil demand after temporarily mistaking the price increase in oil futures as a signal of robust economic growth when it may have been induced by noise in futures market trading. The current study contributes to this line of debate based on some characteristics of news impact curve.

Some scholars argue that inventory must have risen if speculation distorted futures prices upward (Kilian and Murphy, 2014, Juvenal and Petrella, 2014, Knittel and Pindyck, 2016). These studies find that the price boom of crude oil in 2007-2008 was not accompanied by an inventory spike and are hence evidence supporting the business-as-usual view. Cheng and Xiong (2014) explain this observation differently. They argue that futures market speculation may distort price discovery and induce a temporary price boom accompanied by a demand response that mistakes the futures price increase as a signal of strong future fundamentals and unaccompanied by an inventory response. This is because traders may not be able to distinguish between a rise in prices induced by speculation and a rise in prices induced by changes in economic fundamentals in the face of informational frictions in spot markets. The current study does not examine inventory stock, but our investigation of information friction is relevant to this line of debate.

3. Data and Methodology

3.1. Data

Our sample includes daily S&P 500 index, JP Morgan U.S. government bond index, and 18 S&P GSCI excess return indices. All data are directly sourced from DataStream. The S&P GSCI is calculated primarily on a world production-weighted basis and comprises the principal physical commodities that are the subject of active, liquid futures markets. A Contract included in a S&P GSCI index must be on a physical commodity and may not be on a financial commodity and must be denominated in U.S. dollars and traded on or through a trading facility that has its principal place of business or operations in a country that is a member of the Organization for Economic Cooperation and Development (OECD).

Our sample spans from 2000 through 2015. Variable descriptions and mnemonics are given in Table 1 and their daily returns summary statistics are listed in Table 2. As shown in Table 2, stocks, crude oil, coffee and nearly all metals have fat tails; all but a few commodities exhibit negative skewness. To capture the dynamics of the commodity market financialization process, we divide the sample into four equal subsample periods (2000-03, 2004-07, 2008-11, and 2012-15, respectively denoted as p1, p2, p3, and p4). The subsample-split decision is informed by the literature and major events. For instance, the first subsample ends at the end of 2003 as Tang and Xiong (2012) suggest that the financialization of commodity market started in 2004. The second subsample ends at the end of 2007, informed by the 2008 financial crisis. The third subsample covers the period containing both the subprime mortgage crisis and the Eurozone debt crisis. The final subsample covers the post crisis period.

3.2. Methodology

This study attempts to utilises a stepwise ARMA-GARCH based R-vine copula procedure to capture the commodity market financialization process, through detailed analyses of the tail dependences among 20 assets in four consecutive subsample periods. Copula is a tool often used by traders and analysts to exploit statistical arbitrage opportunity between two assets. Copula itself is not limited to just 2 dimensions. It can be expanded to arbitrarily large dimensions. However when it goes to higher dimensions, restrictive structural assumptions are often imposed for practicality reasons. A lot of useful details are lost because of such rigidity. Vine copula is invented to address this high dimensional probabilistic modelling problem. ARMA-GARCH R-vine copula not only has the advantage of extending to higher dimensions easily, but also provides a more flexible approach to capture asymmetric tail risk dependence among assets.

When return series exhibit autocorrelation in mean and volatility, ARMA-GARCH is a good model approximating such return behaviour — ARMA models the conditional mean while GARCH the conditional variance. On the other hand, information concerning tail dependence among different assets may still reside in the independent and identically distributed (i.i.d.) residuals. When data display dependence among extreme values, the rich characteristics of such dependence may be captured and described by a member of the copula family. There exists a variety of copula families. Gaussian copula is one of them. However, multivariate Gaussian copula is unsuitable as it does not have tail dependence. Multivariate t copula can be used in a situation where reflection symmetry can be assumed. When it is necessary to have reflection asymmetry and flexible lower/upper tail dependence, vine copulas may be the best choice (Joe et al., 2010).

In this application of R-vine copula, each sub-sample is treated following a three-step procedure. First, the log-returns of each asset are filtered by a univariate ARMA-GARCH model to obtain its i.i.d residuals. Second, the residuals of each pair of assets are modelled by the most suitable bi-variate copula family to procure their tail dependence types. Finally, an R-vine copula is constructed based on the bi-variate copulas established in the second step. The mathematical details of these steps are given below.

3.2.1. Step 1: News impact curve

We extract news impact curves using two types of ARMA-GARCH filters, standard ARMA-GARCH and ARMA-GJR-GARCH. The optimal model is selected based on information criteria. A standard ARMA-GARCH model captures the symmetric response of a return series to both positive and negative shocks. ARMA-GJR-GARCH, on the other hand, represents a return series that reacts asymmetrically — the response to a negative shock is either greater or weaker than that to a positive shock of the same magnitudes. All models are estimated with skewed t distributed innovations, with reference to the distribution of the raw data (Table 2).

The standard ARMA(P,Q)-GARCH(p,q) filter has the following general form:

$$R_{t,j} = \mu_j + \sum_{i=1}^{P} \phi_{i,j} R_{t-i,j} + \sum_{i=1}^{Q} \theta_{i,j} \epsilon_{t-i,j} + \epsilon_{t,j} \tag{1}$$

$$\epsilon_{t,j} = z_{t,j}\sigma_{t,j} \tag{2}$$

$$\sigma_{t,j}^2 = \alpha_{0,j} + \sum_{i=1}^{q} \alpha_{i,j} \epsilon_{t-i,j}^2 + \sum_{i=1}^{p} \beta_{i,j} \sigma_{t-i,j}^2 \tag{3}$$

where $R_{t,j}$ is the log daily return of commodity or asset j at time t, and $j = 1,...,d$, $t = 1,...,T$, $z_t \sim T(0,1,\nu)$. The conditions on coefficients which guarantee positive and finite conditional volatility are $\alpha_i > 0$, $\beta_i > 0$ and $\sum \alpha_i + \sum \beta_i < 1$.

The effect of news on volatility can be represented by the news impact curve described as follows (Engle and Ng, 1993b):

$$\sigma_{t,j}^2 = A + \alpha_j \epsilon_{t-1,j}^2 \tag{4}$$

where $A = \omega + \beta\bar{\sigma}^2$, $\bar{\sigma}$ is unconditional standard deviation of R, and ω a constant.

An ARMA(P,Q)-GJR-GARCH(p,q) filter differs from the above only in the asymmetric nature of the GARCH process:

$$R_{t,j} = \mu_j + \sum_{i=1}^{P} \phi_{i,j} R_{t-i,j} + \sum_{i=1}^{Q} \theta_{i,j} \epsilon_{t-i,j} + \epsilon_{t,j} \tag{5}$$

$$\epsilon_{t,j} = z_{t,j}\sigma_{t,j} \tag{6}$$

$$\sigma_{t,j}^2 = \alpha_{0,j} + \sum_{i=1}^{q} \alpha_{i,j}\epsilon_{t-i,j}^2 + \sum_{i=1}^{q} \gamma_{i,j}\epsilon_{t-i,j}^2 I_{t-i,j} + \sum_{i=1}^{p} \beta_{i,j}\sigma_{t-i,j}^2 , \qquad 7$$

where

$$j = 1, \ldots, d,\ t = 1, \ldots, T,\ z_t \sim T(0, 1, \nu).\ \ I_{t-i} = 1 \text{ if } \epsilon_{t-i} < 0;\ I_{t-i} = 0 \text{ if } \epsilon_{t-i} \geq 0.$$

The news impact curve (NIC) for GJR-GARCH is as follows (Engle and Ng, 1993b):

$$\sigma_{t,j}^2 = \begin{cases} A + \alpha_j \epsilon_{t-1,j}^2,\ \forall\ \epsilon_{t-1} > 0 \\ A + (\alpha_j + \gamma_j)\epsilon_{t-1,j}^2,\ \forall\ \epsilon_{t-1} < 0 \end{cases} \qquad 8$$

where $A = \omega + \beta\overline{\sigma}^2$, $\overline{\sigma}$ is unconditional standard deviation of R, and ω a constant.

Akaike information criterion (AIC) (Akaike, 1974) is used to select the optimal model. AIC is calculated as follows:

$$AIC = 2k - 2lnL, \qquad 9$$

where k is the number of estimated parameters and L the likelihood.

The standardized residuals are subject to weighted Ljung-Box test (Wooldridge, 1991) and Weighted Li-Mak test (Li and Mak, 1994), which respectively look for extra ARMA and GARCH orders. Passing both tests indicates that there is no higher order autoregression in both the first and second moments, and the residuals are independent and identically distributed (i.i.d). The chosen test methods overcome the potential arbitrage results from traditional Ljung-Box and ARCH LM tests.

3.2.2. Step 2: Bi-variate copula

To be modelled by a copula family, the estimated residuals from step 1 need first to go through a Probability Integral Transformation (PIT). The transformed residuals become uniformly distributed. The essence of the copula approach is that the joint distribution of multivariate random variables can be expressed as a function of the marginal distributions of individual variables. According to Sklar (1959), given a joint cumulative distribution function $F(x_1,x_2)$ for random variables X_1,X_2 with marginal cumulative distribution functions (CDFs) $F_1(x_1)$, $F_2(x_2)$, F can be written as a function of its marginals:

$$F(x_1,x_2) = C(F_1(x_1),F_2(x_2)) \qquad 10$$

where $C(F_1(x_1),F_2(x_2))$ is a bi-variate joint distribution function with uniform marginals.

The twenty assets in our sample would imply 190 bi-variate pairings. We would report in this paper only a restricted set of results related to pairings of commodities with stocks or bonds, given the objective of this study. For each such pairing, thirty-nine different copula families are fitted and the best one of these is selected according to AIC criterion. Each copula family reveals a unique form and property of tail dependence. For instance, tail independence is the property of Frank copula while symmetric upper and lower tail dependence is that of Student-t copula. On the other hand, Gumbel copula represents the existence of upper tail dependence only, while Clayton copula expresses the lower tail dependence feature of the series. Furthermore, a series with asymmetric upper and lower tail dependence can be modelled by some BB families (see Appendix A for details).

3.2.3. Step 3: R-vine copula

R-vine copula is a multivariate copula constructed hierarchically with bi-variate copula as building blocks. It is a graphical tool, developed and based on traditional canonical vine (C-vine) and drawable vine (D-vine) copula, for analysing high-dimensional probability distributions. It not only allows for a wider range of dependence structures but also outperforms the traditional vine copulas (Zhang et al., 2018, Dißmann et al., 2013). An example of a seven-dimensional R-vine can be viewed in Figure 1 (Dißmann et al., 2013). On the first level of the tree, pairs (1,2), (2,3), (3,4), (2,5), (3,6) and (6,7) are estimated; while on the second, pairs (1,3|2), (2,4|3), (2,6|3), (3,5|2), and (3,7|6) are estimated and so on. The choice of a copula family on the lower level will influence the conditional copula on a higher level. The vine structure is determined by the 'edge' matrix estimated using maximum likelihood function. In this analysis, the first tree level will be used to analyse the surface structure of the assets.

According to Dißmann et al. (2013),

$$f(x) = \prod_{k=1}^{d} f_x(x_k) \times \prod_{i=1}^{d-1} \prod_{e \in E_i} c_{C_{e,a},C_{e,b}|D_e}\left(F_{C_{e,a}|D_e}(x_{C_{e,a}}|x_{D_e}), F_{C_{e,b}|D_e}(x_{C_{e,b}}|x_{D_e})\right) \qquad 11$$

where e = a,b, x_{De} is variable from D_e, i.e. $x_{De} = x_i|i \in D_e$.

The log-likelihood function of a R-vine copula with parameter θ_{RV} and $E_1, E_2, ..., E_{d-1}$ is as follows:

$$\ell_{RV}(\theta_{RV}|u) = \sum_{k=1}^{N} \sum_{i=1}^{d-1} \sum_{e \in E_t} log\left[c_{j(e),k(e),D(e)}\left(F(u_{i,j(e)}|u_{i,D(e)})|\theta_{j(e),k(e),D(e)}\right)\right] \qquad 12$$

where $u_i = (u_{i,1}, \dots, u_{i,d})' \in [0,1]^d, i = 1, \dots, N$. $c_{j(e),k(e),D(e)}$ is the bi-variate copula density with edge e and parameter $\theta_{j(e),k(e),D(e)}$.

4. Description of Empirical Findings

4.1. New impact curve

News impact curve (NIC) shows how an asset's return volatility (σ^2) reacts to a shock in the previous period (ε^2) (ENGLE and NG, 1993). Throughout the four sub-sample periods (p1, p2, p3, and p4), the NICs indicate that the volatilities of S&P 500 (SPS) were more responsive to negative shocks. We will refer to this kind of news impact curve as A-NIC-Neg, with "A" and "Neg" being the abbreviations of "asymmetric" and "negative" respectively. On the other hand, the NICs of JP Morgan U.S. government bond index (JPB) suggest that its volatilities respond symmetrically to shocks of either nature. We will refer to this latter type as S-NIC, with "S" standing for "symmetric". To capture the characteristics of commodity futures in one quick glance, we have constructed an index, COM, based on the equal weighted average of the eighteen commodity excess returns. The NICs of COM were symmetric in p1, p2 and p4, like JPB, and only displayed the SPS-style A-NIC-Neg in p3.

Examinations of individual commodities however reveal something unexpected. While the NICs of some commodity futures were A-NIC-Neg (like those of SPS) or S-NIC (resembling those of JPB), there is yet a third type of NICs which is observed in neither SPS nor JPB. Nor was it discussed in earlier literature to the best of our knowledge. This third type displays more responsiveness of volatilities to positive shocks. We will refer to it as A-NIC-Pos, with "Pos" standing for "positive".

In p1, except for LCT and LHG which exhibited A-NIC-Neg, commodity volatilities were either more responsive to positive shocks or responded symmetrically to both positive and negative shocks, with the number of S-NIC (nine) slightly dominates that of A-NIC-Pos (seven). Thus, A-NIC-Neg was rare among commodities before 2004. In the following three sub-samples, only NKL and CTN maintained their S-NIC throughout, while WTI decidedly turned into A-NIC-Neg. The rest of commodities wavered among the three types of NICs. During p2, commodity futures either continued exhibiting S-NIC (six of them) or turned into A-NIC-Pos (ten of them), apart from WTI and SLV whose NICs turned into A-NIC-Neg. Meanwhile, the NICs of LTC and LHG turned into S-NIC and A-NIC-Pos, respectively. Therefore, up until the end of 2007, there were little resemblance between stocks and commodity futures in this regard.

Moving to p3, nine out of the eighteen commodities exhibited stock-like A-NIC-Neg, while eight exhibited bond-like S-NIC. Only CCW kept its A-NIC-Pos inherited from p1 and p2. During p4. WTI, CPR, LED and LTC inherited their A-NIC-Neg from p3, while GLD and ALM switched from S-NIC in p3 to A-NIC-Neg. Nine out of the eighteen commodities kept or turned into S-NIC, and only SGA, SBN and CFE exhibited A-NIC-Pos in the final sample.

4.2. Bi-variate copula

There are different types of copula families, each reveals a different kind of tail dependence among paired assets. An upper tail dependence indicates correlation in positive extreme events, a lower tail dependence suggests correlation in negative extreme event, while a symmetric tail dependence stipulates correlation in both. For each of the four sub-sample periods, the best fit copula family is selected from 39 different copula families for every pair of assets, based on the highest likelihood index. Our discussion below will focus on the bi-variate copula results concerting commodities respectively paired with SPS and JPB (see Table 3).

4.2.1. Stock-commodity

During p1 and p2, SPS and commodity futures were mostly tail independent of each other. Changes swept across all SPS.commodity pairs in p3 and p4, except for SPS.SGA and SPS.LHG. In p1 and p2, most of stock-commodity pairs can be represented by three copula families with independent tails: independence copula, Gaussian copula, and Frank copula (Figure 4a, 4b & 4c). In p1, only SPS.CPR displayed student t copula property, with symmetric upper and lower tail dependence. SPS.NKL was best modelled by a 180°rotated Clayton copula, suggesting upper tail dependence only; while SPS.LED appeared to be Clayton copula, indicating lower tail dependence (Figure 4e and 4f). However, the corresponding measures of dependence are very close to zero for the above three pairs (see panels headed by 'lower tails dep.' or 'upper tail dep.' in Table 3). There was therefore in general no tail dependence between commodity futures and SPS during 2000-03. Tail dependence was still not common between commodity futures and stocks during 2004-7. Among the few pairs displayed tail dependence, SPS.CPR was best modelled by BB1 copula while SPS.ALM by BB7 copula, suggesting asymmetric upper and lower tail dependences, with the upper tail dependence ($\tau_u = 0.03$) higher than the lower tail dependence ($\tau_l = 0.00$) in both cases. SPS.CRN appeared to be rotated Gumbel copula with a mild lower tail dependence ($\tau_u = 0.06$) (Figure 4g).

Visible changes occurred in p3, when either or both upper and lower tail dependences grew strong among most SPS.commodity pairs, but their pattern of dependence varied. The pairings involving CCA, CTN, ZNC, SLV were best modelled by 180°rotated BB8 copula, indicating asymmetric two-tail dependence (Figure 4h); but their degree of dependence measured by τ_u and τ_l were near zero. Among those having tail-dependences with SPS and τ_u and/or $\tau_l \neq 0$, WTI, CCW, LED and GLD had symmetric two-tail dependence with SPS, and CRN, SBN, CFE, CPR, had asymmetric dependence with SPS with stronger upper tail dependence, while ALM, and NKL had asymmetric tail dependence with stronger lower tail dependence. Among the remaining pairs, SPS.LCT revealed lower tail dependence, while SPS.NTG showed upper tail dependence only.

In p4, the degree of SPS.commodity tail dependences, τ_u and τ_l, fell in general, and their pattern of dependence also changed here or there. However, when compared to p1 and p2, τ_u and τ_l were still strong, with some exceptions. For example, the tail dependence of SPS.CPR and SPS.SLV turned symmetric (both with $\tau_u = \tau_l = 0.06$). SPS.ALM and SPS.LED also showed symmetric tail dependence, but the levels of dependence were very low ($\tau_l = \tau_u = 0.01$). SPS.NKL and SPS.ZNC exhibit asymmetric upper and lower tail dependences, with the upper much stronger than the lower. SPS.WTI maintained strong lower tail dependence (τ_l=0.14) and upper tail dependence (τ_u=0.12), albeit weaker than in p3.

To see the general trend at one glance, we also estimated the bi-variate copula of SPS and COM, with the latter being a simple equal weighted index for the eighteen commodities. The results confirm the above observations: SPS and COM were correlated at positive extreme event during p1 but became tail independent during p2. They turned asymmetric two tail-dependent in both p3 and p4, with stronger dependence in negative extreme event.

4.2.2. Bond-commodity

The evolution paths of JPB.commodity bi-variate copulas from p1 to p4 looked like those of SPS.commodity (Table 3). During p1 and p2, most JPB.commodity pairs were tail independent. Although JPB.ALM, JPB.CPR and JPB.NKL displayed symmetric tail dependence during p1, their τ_u and τ_l were zero in value. Only GLD and SLV showed strong lower tail dependence with JPB in p1, providing evidence for their widely recognized safe-haven status. In the following sub-sample period, all commodities remained tail independence from JPB, except for NTG, CTN and GLD. The copula structure of JPB.NTG appeared to be 180°rotated BB8 copula, and that of JPB.CTN 270° rotated Gumbel copula (see Figure 4h and 4k). In both cases, the commodity returns moved in the opposite direction of JPB returns in extreme market fluctuations, but their τ_u and τ_l were all zero in value. The tail-dependence of JPB.GLD also became symmetric and weak.

In p3, nearly all JPB.commodity pairs exhibit tail dependence. Strangely, GLD became tail independent of JPB. With reference to the symmetric two-tail dependence of SPS and GLD in p3, we infer that gold had lost its safe-haven status in one of the most turbulent financial storms of the recent history. (This status was restored in p4.) JPB.ZNC is best represented by student t copula, displaying a symmetric upper and lower tail dependence. The rest pairs fell into six different copula families (90°rotated Clayton copula, 90° rotated BB1 copula, 90°rotated BB7 copula, 270°rotated Gumbel copula, 270°rotated Joe copula, and 270°rotated BB8 copula), indicating that the concerned commodities moved in the opposite direction of JBP in tail events (Figure 4). This suggests that most commodities exhibited negative co-dependence with bonds during the 2008 financial crisis when surprising shocks reached the market, however their τ_u and τ_l were all zero in value. Moving into p4, the majority of JPB.commodity pairs became tail-independent again. Only JPB and GLD were significantly tail dependent, with much stronger lower-tail dependence, like in p1.

The nuance of the above observations was lost in the estimated bi-variate copula between JPB and COM. JPB and COM were negatively tail co-dependent in p1 (if JPB return dropped, COM return rose, but the reverse is not necessarily true) and p3 (If JPB return dropped, COM return rose, and vice versa) with zero τ_u and τ_l., independent in p2 and weakly asymmetric tail-dependent in p4.

4.3. R-vine copula structure

Figures 5a - 5d display the estimated R-vine structures of the 20 assets across the four subsample periods, along with Kendall's τ. Kendall's τ is a measure of rank correlation which differs from the τ in the previous section that measures dependence between two variables at extreme values only. Intuitively, Kendall correlation between two variables will be high when observations have a similar rank (or identical rank for a correlation of 1), and low when observations have a dissimilar rank (or fully different rank for a correlation of -1).

In p1, with a few exceptions, commodity futures were very neatly clustered by categories: energy (WTI, NTG), softs (SGA, CFE, CCA), grains (CCW, CRN, SBN), livestock (LCT, LHG), and metals (LED, ZNC, NKL, ALM, CPR), with only the exception of CTN which was clustered with grains rather than softs. The precious metals, SLV and GLD, were then quite separate from the industrial metals. Each category was connected to the stock market in a different way - the precious metal through GLD with a Kendall's $\tau = -0.13$; industrial metals through CPR with tau = 0.13. The rests were distantly related to SPS via GLD or CPR. On a closer examination, we can divide this investment universe into two parts: the GLD sub-universe and the SPS sub-universe. The former includes the softs, livestock, energy, and precious metals, the latter the industrial metals, grains, and the financial markets. The two were linked through the GLD-SPS connection when gold acted its role as hedge and safe-haven for the stock market.

In p2, the pivotal role of SPS as a linkage between the separate commodity categories dissolved. Instead, all commodities became one directly connected universe, via metals. JPB also became separated from SPS, and peripherally associated with GLD. The precious and industrial metals merged into one cluster. The tie between metals and SPS was now offered by an obscure ZNC, which also replaced SLV as the direct link between metals and livestock. Among the softs, CFE, which was affixed to GLD via CCA, became directly attached to SLV like CCA itself. The branch of the grains connected to CPR in p1 now became attached to SLV in p2. Energy, which was quite separate from other commodities in p1 apart from GLD, remained so in p2. However, the strength of this link as measured by Kendall's τ leapt up from 0.07 to 0.22.

During p3, the crisis period, WTI took over the centre stage, became the very commodity which linked all categories under examination except for livestock. It linked to grains via SBN, to metals via CPR, to softs via CFE, and to the financial markets via SPS. The strengths of category-to-category links were also noticeably stronger. Through their strengthened attachment to WTI, all commodities became closely connected to the financial markets, except for the very remotely located livestock.

Post crisis in p4, the strength of connections among all commodities weakened somewhat but remained sturdy. Metals via their robust association with WTI, continued to be solidly linked to the financial market. There was still a high degree of integration among commodities of different categories, compared to the pre-crisis period. CPR took over the pivotal role from WTI to connect the rest of commodities. The increased connection between all commodities with stock and bond markets through WTI/CPR suggests commodities' declined diversification benefit after 2008.

The above messages were consistently picked up by COM, which only became directly linked to SPS on the R-vine from p2 onwards. The strength of this connection as measured by Kendall's τ also rose significantly during p3 but faded slightly in p4.

5. Discussion

5.1. Leverage effect leads to A-NIC-Neg in stock volatility

It has long been recognized that stock volatility responds asymmetrically towards good and bad news. Earlier writers suggested that this feature was the result of leverage effect. Black (1976) was the first to discover this effect, which was later cross-examined, among others, by French et al. (1987), Schwert (2015), Nelson (1991), Aït-Sahalia et al. (2013), and Christie (1982). The concept of news impact was introduced by ENGLE and NG (1993) to measures how price volatility reacts to new information. All the NICs depicted in their study were A-NIC-Negs, showing that stock volatilities were more sensitive to negative shocks. The theory goes that, when share price declines, the associated company becomes mechanically more leveraged since the value of its debt rises relative to that of its equity. This would raise the company's financial risk, its investors' required risk premium, and its price must therefore drop more than an unleveraged company facing the same situation. The reverse is true when the stock price rises. Consequently, volatility reacts more to a negative shock than to positive one, thus the presence of A-NIC-Neg in stock volatility.

Despite its popularity in the finance literature, it is not yet clear that leverage effect accounts fully for the asymmetric properties of stock price volatility (ENGLE and NG, 1993). The risk premium argument is nevertheless very appealing. By this argument, the fundamental determinant of the shape of NIC is the required risk premium from market participants. The factors which drive the perceived risk will however vary from market to market. We will discuss in turn these different factors in stock, bond and commodity futures, and why certain factor may spread their influence from stock to commodity futures market.

5.2. Herding increases the asymmetry of A-NIC-Neg in stock volatility

While leverage effect to a large extent explains the presence of A-NIC-Negs in stock prices, it fails to throw light on why there is a difference in the degree of asymmetry in the case of, say, SPS, across different subsamples (Figure 2a). In this paper, we propose herding as a complementary explanation. The idea of herding has a long history in philosophy and crowd psychology, which is sometimes referred to as information cascades in politics, science, and popular culture (Bikhchandani et al., 1992). This concept has only recently been acknowledged by the mainstream financial economists. For example, Banerjee (1992) discussed herding in the context of collective investor irrationality. Recent studies reveal evidence of persistent herding behaviour during both bull and bear markets (Chiang and Zheng, 2010, Hwang and Salmon, 2004).

Uncertainty, researchers suggest, is a key factor driving herding (Lin, 2018). For any stock, there is a wedge between the stock (a financial product) and the underlying company (a real entity) it represents. This wedge is created by complicated accounting, legal and financial processes. It brings in uncertainty regarding the true worth of the company, hence herding. However, investors are heterogeneous. Most investors are trend-followers in the sense their views are strongly influenced by their networks of families, friends, colleagues, and influential analysts. Trend-following may also be strong among decision makers with a shared identity, such as institutional investors (Berger et al., 2018). There are nevertheless always a minority of investors who are trend-setters, who judge the situation largely based on their own idiosyncratic acumen (Xiao, 2010). Thus, we expect the return assessments among investors to have a bell-shaped distribution (Figure 3).

It is reasonable to expect that herding increases with the proportion of amateur investors – by amateur, we mean that their stock buying and selling decisions are not based on sufficient understanding of the underlying company. A booming stock market buoyant with optimism usually attracts a lot of amateur investors who are mostly trend-followers. There are therefore more unanimities in the market (Figure 3b) and trend-followers will have a dominant influence on the price swings. A positive shock would further strengthen such unanimity of optimism, lowering the average required risk premium, hence the return response to a positive shock would be relatively gentle. The opposite would be true with a negative price shock, which raises the perceived risk and required risk premium among the large number of trend-followers, causing the price to sink deeper, and hence the presence of A-NIC-Neg. The higher the proportion of trend-followers in the market, the greater the degree of NIC asymmetry. This would explain the subtle difference of SPS's NIC in p1, p2, p3 and p4, which are all asymmetric, yet some are more asymmetric than others.

Chiang and Zheng (2010) provide evidence that crisis triggers herding activity. Hwang and Salmon (2004) on the contrary find that crises appear to stimulate a return to efficiency rather than an increased level of herding - during market stress, investors turn to fundamentals rather than overall market movements. This empirical controversy is understandable. During market crises, on the one hand, uncertainty increases which raises herding; on the other, many amateur investors drop out which reduces herding. Thus, there is a theoretical ambiguity whether crises raise herding. This ambiguity can only be settled empirically.

Economou et al. (2018) suggest that fear is another key driver of herding. Fear heightens during crisis thus herding should intensify. This is partly supported by our findings that in p3 more commodities' NICs behaved like stocks, a financial asset known in the literature to be subject to the strong forces of herding.

Herding would also at least partly explain the symmetry of JPB's NIC (Figure 2b). The values of bonds are relatively stable compared to those of stocks hence involves less uncertainty. Furthermore, amateur investors rarely enter this market, which makes it far less likely to be overwhelmed by mass psychology.

5.3. Volatile excess demand generates A-NIC-Pos in commodity futures

Our analysis of the commodity futures revealed a new type of news impact curve (A-NIC-Pos) which is not discussed in earlier literature. Commodity futures were traditionally used as an insurance for producers of primary products whose prices are subject to significant fluctuations. Such fluctuations are caused by volatile shifts in demand and supply in the real sector. A positive return shock to a commodity future occurs when an unexpected shortage befalls its corresponding physical commodity market. In theory, the positive excess demand can be satisfied with increased output. Raising output is not always simple straight forward. In some cases, the producer may not respond to a shortage if they perceive it to be temporary. In others, for example oil, it may take time for the major producers to agree on their collective output. Even agreement is reached without delay, it may take time for its implementation. In short, since the adjustment process in a real goods market is far stickier than in a financial market, a positive excess demand creates significant uncertainties about future boom and bust cycles, raising perceived risks, and required risk premium. The price must therefore rise further hence the increased volatility in the presence of a positive return shock.

Conversely, a negative return shock to a commodity future reflects a negative excess demand in its corresponding physical commodity market, which can happen either there is a glut on the supply side or a drop on the demand side. A negative excess demand in the primary goods market may or may not be easier to get rid of than a positive excess demand. For example, in the case of live cattle and lean hogs, producers may simply destroy the excess inventory to maintain a profitable price. In the case of oil, reducing output can be equally difficult as raising output.

Theoretically, the NICs of commodity futures can take any shape: A-NIC-Neg, S-NIC, or A-NIC-Pos. If a negative excess demand creates less uncertainty than a positive excess demand, it will render a lower perceived risk hence a lower required risk premium than the latter. Thus, for a return shock of the same scale, the required price drop in the face of a negative surprise will be less than the required price rise in the event of a positive surprise. This case corresponds to commodity futures with A-NIC-Pos. Conversely, an A-NIC-Neg will be observed. On the other hand, if negative and positive excess demands of the same scale create an equal level of uncertainty, there will be an equal amount risk premium required under both kinds of surprises. This case corresponds to commodity futures with S-NIC. Thus, although both S-NIC and A-NIC-Neg are possible among commodity futures, if they remain insurance products rather than financial assets, the economic force behind them is different from those driving the NICs of stocks and bonds.

Empirically, however, this study finds that A-NIC-Neg was rare among commodity futures before 2004 – only two out of the eighteen commodity futures exhibited this pattern. It was nevertheless the most common pattern observed in 2008-11. This change corresponds to a paradigm shift in the constituents of players in this market since 2004 (see discussion in section 1), with the arrival of institutional investors.

5.4. Institutional investors and commodity market financialization

Recall that we define commodity market financialization as a process associated growing influence of financial traders who have no interests in the physical commodity market. Earlier studies such as Tang and Xiong (2012) and Erb and Harvey (2006) show that, after the 2000 equity market collapse, fund managers began to pay attention to the unfamiliar commodity market, which then promised a low or negative correlation with the stock market. Starting from 2004, billions of investment funds were poured into commodities from a wide set of financial traders (hedge funds, pension funds, insurance companies and retail investors, etc.) with no physical interests and little experience in commodity futures. Unlike commercial hedgers and non-commercial traders, these newcomers simply treat commodity futures as another financial asset class. They are thus analogous to the amateur investors of the stock market. As the relative activities of these financial traders rise, we expect herding increases in the commodity futures, making the market swing more with the capricious changes in investors' expectations, moods, and preferences, and rendering the fundamental (excess demand) less relevant as a market driver. In other words, financialization has increased information friction in the market. Consequently, A-NIC-Neg becomes more common.

Earlier studies used increased commodity-stock correlation as an indication of commodity market financialization. Following the discussions in section 5.1-5.3, we suggest that commodity market financialization is reflected by the news impact curve. More specifically, we test the relationship between the news impact cure (NIC) and the share of commercial hedgers, C, with C calculated by the authors as the open interest held by commercial hedgers divided by the total open interest associated with a commodity. We use series C in this test because the relevant data for other types of traders, for example swap dealers and managed money, are available mostly only after 13 June 2006 which is not surprising given that their interests in this market began mostly after 2004. We extracted the raw data from Eikon. Only fourteen series have data available for our purpose (i.e. WTI, NTG, CCW, CRN, SBN, CFE, SGA, CCA, CTN, CRP, GLD, SLV, LHG, LCT). The hypothesis we test is the following:

H0: Falling relative commercial hedging increases herding in commodity futures market.

To implement the test, we augment the news impact curve by C as follows:

$$\sigma_{t,j}^2 = \begin{cases} \alpha_{0,j} + \alpha_{1,j}\varepsilon_{t-1,j}^2 + \alpha_2 C_t + \alpha_3 C_t \varepsilon_{t-1,j}^2, \forall \varepsilon_{t-1} > 0 \\ , \alpha_{0,j} + (\alpha_{1,j} + \gamma_{1,j})\varepsilon_{t-1,j}^2 + \alpha_2 C_t + \alpha_3 C_t \varepsilon_{t-1,j}^2, \forall \varepsilon_{t-1} < 0 \end{cases} \quad 13$$

where α_1 measures the volatility response to news, α_2 the marginal impact of C on price volatility, and α_3 the noisy interaction between news and commercial hedging.

In a market where trading is based on fundamentals, trading increases market efficiency and the information content of the price. Hence news is less likely to induce market overreaction. On the other hand, if trading is a result of herding, trading increases the noisiness of the price and hence the price volatility. Thus, a priori, we expect α_3 to be negative as a falling C is associated with less trading by commercial hedgers who know the fundamentals of the physical market. A falling C is also associated with an increased activity by financial traders. These traders, who have no specialist knowledge of the underlying market, are more likely to trade for their portfolio balance needs than for fundamental reasons. Consequently, the commodity futures market is subject to the spillover of fads from stocks and bonds markets.

Table 4 lists the estimated values of α_3 and their corresponding p-values for the fourteen commodity futures with available data. Out of the fifty-six estimates only five (WTI in p1 and p2; CRN in p3; and CPR and LCT in p4) have insignificant α_3, and seven (SGA and CCA in p4; CRP, GLD, SLV, LHG, LCT in p3) have the wrong sign. The remaining forty-four estimates are all highly significant with the expected sign. Thus, there is substantial evidence supporting the null hypothesis.

5.5. Herding strengthens bi-variate copula and R-vine copula

Evidence from bi-variate copula estimation indicates that the involvement of the financial traders and herding have changed not only the nature of commodities' NIC but also the tail-dependence characteristics between stocks and commodities, especially during crisis when uncertainty was great, and fear prevailed. Like in the case of NIC, this change is not universal and more lasting among energy, metal, and live cattle (e.g. WTI, ALM, CPR, NKL, LED, and LCT) than in others.

The significant levels of tail dependence between stocks and commodities during p3 (2008-11) not only support the evidence of financialization provided by NIC but also suggest that the diversification benefit of many commodities with respect to stocks has eroded away. This is consistent with some previous literature which found decreased diversification benefit between 2004-8. In these studies, in general, correlation analysis was applied to residuals from some structural model (see for example Tang and Xiong (2012), as opposed to ARMA-GARCH model. These structural models could have been mis-specified, and the residuals may contain information rather than those arising from financialization. Their studies made no distinction between normal markets and markets in extreme movements; nor do they differentiate between events of different natures, namely, good news or bad news. The current study show that these differentiations do tell richer stories.

Our findings regarding JPB.commodity corroborate that of Jensen and Mercer (2011) which shows significant negative correlations of S&P GSCI with US T-bond and T-bills. Our study also complements Fattouh et al. (2013), who state that commodities perform counter-cyclically against bonds and offer attractive diversification potential when added to a portfolio with a heavy fixed-income allocation. Our evidence further suggests that caution must be exercised with respect to different phases of a market cycle, when exploiting the co-movement and tail-dependence features between commodity and bond.

While bi-variate copula analyses help us to understand the relationship between individually paired assets, their relationship must not be viewed in isolation. In a complex investment universe where all assets and investment vehicles are related via the portfolio strategies of investors, their returns are intimately interconnected in a multilateral way and explicable only by referencing to their multivariate dependence structure. R-vine copula is therefore, in this regard, a valuable tool aiding our holistic apprehension of this investment universe. As a visual tool, R-vine also conveys information more directly. From Figure 5, we deduce that the fingerprints of herding show up not only in the NICs of individual commodities, their bi-variate copula with stocks and bonds, but also in their multi-variate dependence with stocks, bonds and among themselves. Given all these are dynamically evolving, observing their change in the future and understanding their wide-reaching impact would be beneficial to all concerned parties. Furthermore, R-vine structure can assist the decision-making process of portfolio allocation. For example, by including assets located at the end of the vine branches, fund managers will have a more diversified portfolio with minimum tail dependences. Assets located at interconnected nodes, however, offer reduced diversification benefits for one another.

6. Summary and Conclusions

Financialization in the major economies has led to increasing concern about the proper function of the commodity futures market. In this study we explore the causes, symptoms, and consequences of commodity market financialization both empirically and theoretically. Seddon (2020) argues that the course of financialization has rendered structural change in the commodity market – once designed to support global trading of commodities but now the battling ground between commercial hedgers and financial traders. Seddon classifies commodity markets into four types, with type I being the least and type IV the most financialized market structure. Seddon gives commodity futures market a type III status. Our study reveals that even within the type III futures market, the process of financialization is extremely uneven. As argued by earlier literature, the process of financialization is characterized by the influx of commodity index traders who trade in and out of certain commodity indices rather than trading commodity future contracts directly; and as different weights are given to the constituent commodities in the popular indices, we expect that the process of financialization varies from one commodity futures market to another. Our evidence suggests that the market for crude oil is more financialized than those for others, consistent with the fact that crude oil carries more weight than most other commodities in the major indices. Our evidence also suggests that this process was non-linear, which intensified during 2008-11, but toned down in 2012-15. Consequently, the structure of each commodity market must be examined individually and timely.

Consistent messages were delivered by the three types of analytical tools employed in this study. For example, WTI was not close to SPS on the R-vine during p1 and p2 but became directly linked to SPS with strong Kendall's τ during p3 and p4; WTI was tail-independent of SPS during p1 and p2 but became strongly tail-dependent of SPS during p3 and p4. The signal was picked up by the NIC of WTI, which started to resemble that of SPS as early as p2. These observations were in line with the steady decline of commercial hedging activities associated with WTI. Recall that the rising influence of the financial traders, who have no specialist knowledge of the underlying market, is by definition financialization of the commodity market. Lacking knowledge of the fundamentals encourages herding. Herding, we show in section 5.4, drives up the price volatility impact of shocks in all commodities, therefore increasing their riskiness simultaneously.

In conclusion, our study indicates that the process of commodity market financialization has resulted in a fundamental shift in the functions of commodity futures market, especially those involving crude oil. Shocks in the stock market are now easily transmitted to the commodity futures market, reducing its risk-sharing power, and increasing its information friction. This shift has implications for both commercial hedgers, who use the market to guide their production plans, and for the financial traders, who use the market as a diversification tool. It is also worth the attention of the financial regulators, as commodities are important factors of production and fundamental to wellbeing of the real economy.

Table 1 Variable descriptions. Data are directly sourced from DataStream

Category	Mnemonic	Series title	Source code
Stocks	SPS	S&P 500 composite price index	S&PCOMP
Bonds	JPB	JPM United States government bond US$ price index	JPMUSU$
Index	COM	Equal-weighted average of the18 commodity excess returns listed below	Self-calculation
Energy	WTI	S&P GSCI crude oil excess return	GSCLEXR
	NTG	S&P GSCI natural gas excess return	GSNGEXR
Agriculture	CCW	S&P GSCI wheat (CBOT) excess return	GSWHEXR
	CRN	S&P GSCI corn excess return	GSCNEXR
	SBN	S&P GSCI soybeans excess return	GSSOEXR
	CFE	S&P GSCI coffee excess return	GSKCEXR
	SGA	S&P GSCI sugar excess return	GSSBEXR
	CCA	S&P GSCI cocoa Index excess return	GSCCEXR
	CTN	S&P GSCI cotton excess return	GSCTEXR
Metal	ALM	S&P GSCI aluminium excess return	GSIAEXR
	CPR	S&P GSCI copper excess return	GSICEXR
	NKL	S&P GSCI nickel excess return	GSIKEXR
	LED	S&P GSCI lead excess return	GSILEXR
	ZNC	S&P GSCI zinc excess return	GSIZEXR
	GLD	S&P GSCI gold excess return	GSGCEXR
	SLV	S&P GSCI silver excess return	GSSIEXR
Livestock	LHG	S&P GSCI lean hogs excess return	GSLHEXR
	LCT	S&P GSCI live cattle excess return	GSLCEXR

Table 2 Summary statistics of daily returns (04/01/2000 – 31/12/2015).

	SPS	JPB	WTI	NTG	CCW	CRN	SBN	CFE	SGA	CCA	CTN	ALM	CPR	NKL	LED	ZNC	GLD	SLV	LHG	LCT
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standard Error	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mode	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standard Deviation	0.01	0.00	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.01
Sample Variance	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kurtosis	8.42	2.16	3.41	2.32	2.02	2.27	2.21	3.73	2.10	2.82	1.35	2.55	4.57	3.75	3.78	3.27	5.84	7.85	0.97	2.01
Skewness	-0.19	-0.19	-0.29	0.06	0.08	0.07	-0.20	0.18	-0.27	-0.23	-0.05	-0.25	-0.11	-0.13	-0.21	-0.14	-0.24	-0.93	-0.08	-0.17
Range	0.20	0.04	0.30	0.35	0.19	0.17	0.14	0.30	0.21	0.19	0.14	0.14	0.22	0.31	0.26	0.21	0.18	0.32	0.12	0.10
Minimum	-0.09	-0.02	-0.17	-0.17	-0.10	-0.08	-0.07	-0.13	-0.12	-0.10	-0.07	-0.08	-0.10	-0.18	-0.13	-0.11	-0.10	-0.19	-0.06	-0.06
Maximum	0.11	0.02	0.13	0.19	0.09	0.09	0.06	0.16	0.08	0.09	0.07	0.06	0.12	0.13	0.13	0.10	0.09	0.12	0.06	0.04
Sum	0.34	0.20	-0.67	-5.09	-1.75	-1.38	1.04	-2.26	0.10	0.73	-1.36	-0.87	1.06	0.29	1.05	-0.46	0.93	0.52	-1.98	-0.30
Count	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173	4173
Largest(1)	0.11	0.02	0.13	0.19	0.09	0.09	0.06	0.16	0.08	0.09	0.07	0.06	0.12	0.13	0.13	0.10	0.09	0.12	0.06	0.04
Smallest(1)	-0.09	-0.02	-0.17	-0.17	-0.10	-0.08	-0.07	-0.13	-0.12	-0.10	-0.07	-0.08	-0.10	-0.18	-0.13	-0.11	-0.10	-0.19	-0.06	-0.06

Table 3 paired copula estimation of commodities with stocks and bonds.

Asset pair	family				lower tail dep.				upper tail dep.			
	p1	p2	p3	p4	p1	p2	p3	p4	p1	p2	p3	p4
SPS.JPB	39	2	37	2	-	0.03	-	0.01	-	0.03	-	0.01
SPS.COM	104	1	7	17	-	-	0.22	0.14	0.05	-	0.18	0.01
JPB.COM	26	0	29	2	-	-	-	0.01	-	-	-	0.01
SPS.WTI	0	0	2	7	-	-	0.21	0.14	-	-	0.21	0.12
SPS.NTG	0	0	104	0	-	-	-	-	-	-	0.07	-
SPS.CCW	0	0	2	0	-	-	0.04	-	-	-	0.04	-
SPS.CRN	0	14	7	0	-	0.06	0.01	-	-	-	0.09	-
SPS.SBN	0	0	9	5	-	-	0.06	-	-	-	0.11	-
SPS.CFE	0	1	7	0	-	-	0.06	-	-	-	0.11	-
SPS.SGA	0	0	1	1	-	-	-	-	-	-	-	-
SPS.CCA	0	0	20	3	-	-	-	0.00	-	-	-	-
SPS.CTN	0	0	20	1	-	-	-	-	-	-	-	-
SPS.ALM	1	9	7	2	-	0.00	0.17	0.01	-	0.03	0.13	0.01
SPS.CPR	2	7	7	2	0.01	0.00	0.18	0.06	0.01	0.03	0.19	0.06
SPS.NKL	13	1	7	7	-	-	0.14	0.04	0.00	-	0.10	0.07
SPS.ZNC	1	1	20	7	-	-	-	0.02	-	-	-	0.08
SPS.LED	3	1	2	2	0.00	-	0.03	0.01	-	-	0.03	0.01
SPS.GLD	5	1	2	0	-	-	0.04	-	-	-	0.04	-
SPS.SLV	23	204	20	2	-	-	-	0.06	-	0.10	-	0.06
SPS.LHG	0	0	5	0	-	-	-	-	-	-	-	-
SPS.LCT	5	0	3	14	-	-	0.07	0.08	-	-	-	-
JPB.WTI	0	0	34	2	-	-	-	0.01	-	-	-	0.01
JPB.NTG	0	20	34	0	-	-	-	-	-	-	-	-
JPB.CCW	0	0	34	0	-	-	-	-	-	-	-	-
JPB.CRN	0	0	34	0	-	-	-	-	-	-	-	-
JPB.SBN	0	0	29	1	-	-	-	-	-	-	-	-
JPB.CFE	0	0	27	0	-	-	-	-	-	-	-	-
JPB.SGA	0	0	40	0	-	-	-	-	-	-	-	-
JPB.CCA	0	0	34	34	-	-	-	-	-	-	-	-
JPB.CTN	0	34	23	224	-	-	-	-	-	-	-	-
JPB.ALM	2	0	34	224	0.00	-	-	-	0.00	-	-	-
JPB.CPR	2	0	27	2	0.00	-	-	0.00	0.00	-	-	0.00
JPB.NKL	2	0	34	2	0.00	-	-	0.00	0.00	-	-	0.00
JPB.ZNC	5	0	2	29	-	-	0.01	-	-	-	0.01	-
JPB.LED	5	0	40	2	-	-	-	0.00	-	-	-	0.00
JPB.GLD	14	2	0	19	0.15	0.01	-	0.11	-	0.01	-	0.01
JPB.SLV	14	0	36	0	0.07	-	-	-	-	-	-	-
JPB.LHG	0	5	5	0	-	-	-	-	-	-	-	-
JPB.LCT	5	0	34	0	-	-	-	-	-	-	-	-

Note: (i) p1=2000-03, p2=2004-07, p3=2008-11, p4=2012-15; (ii) the number in the table indicates the best fit copula family selected from all the copula families given in Appendix A.

Table 4 The moderating effect of commercial hedging on the volatility impact of news. A negative parameter estimates, when significant, is in line with the hypothesis that falling commercial hedging increases herding in commodity futures market.

	p1		**p2**		**p3**		**p4**	
	Est.	p.	Est.	p.	Est.	p.	Est.	p.
WTI	-0.00004	0.33	0.00006	0.12	-0.00091	0.01	-0.00048	0.00
NTG	-0.00040	0.01	-0.00078	0.00	-0.00163	0.00	-0.00043	0.00
CCW	-0.00028	0.00	-0.00045	0.00	-0.00078	0.00	-0.00021	0.00
CRN	-0.00025	0.00	-0.00028	0.00	-0.00009	0.37	-0.00026	0.00
SBN	-0.00015	0.00	-0.00016	0.00	-0.00024	0.02	-0.00020	0.00
CFE	-0.00032	0.00	-0.00025	0.00	-0.00013	0.00	-0.00125	0.00
SGA	-0.00014	0.00	-0.00012	0.00	-0.00030	0.00	0.00002	0.09
CCA	-0.00016	0.00	-0.00002	0.04	-0.00016	0.00	0.00008	0.00
CTN	-0.00018	0.00	-0.00006	0.03	-0.00033	0.01	-0.00005	0.01
CRP	-0.00006	0.00	-0.00001	0.70	0.00077	0.00	0.00000	0.92
GLD	-0.00002	0.00	-0.00011	0.00	0.00015	0.00	0.00	0.00
SLV	-0.00013	0.00	-0.00023	0.00	0.00068	0.00	-0.00013	0.00
LHG	-0.00003	0.10	-0.00015	0.00	0.00010	0.00	-0.00019	0.00
LCT	-0.00005	0.00	-0.00010	0.00	0.00003	0.00	0.00001	0.61

Figure 1 Example of 7-dimensional R copula. Source: (Dißmann et al., 2013)

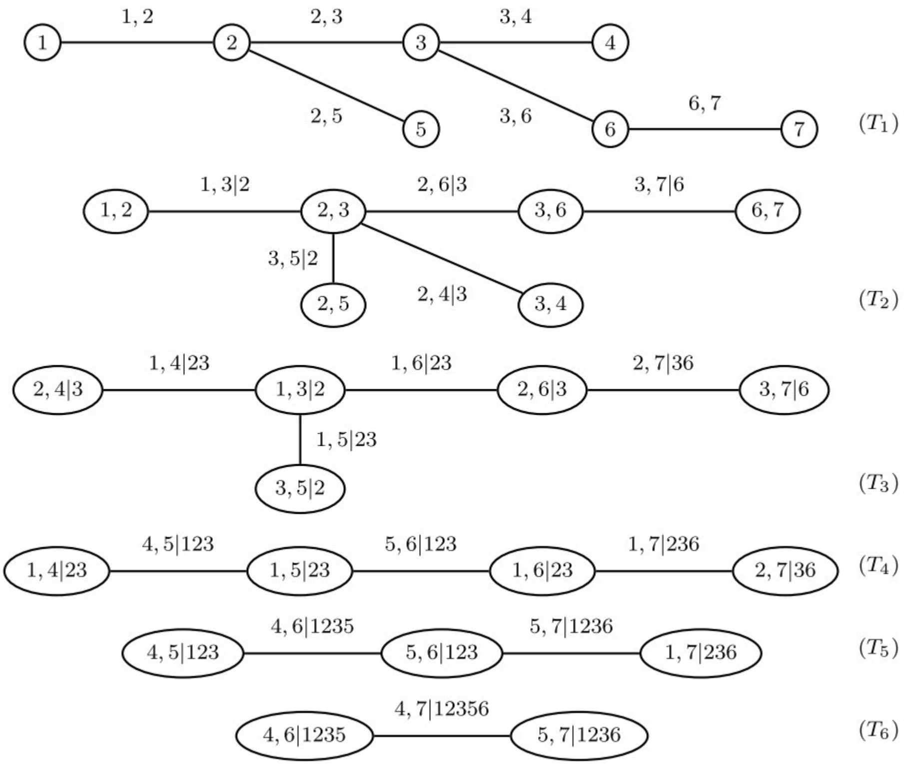
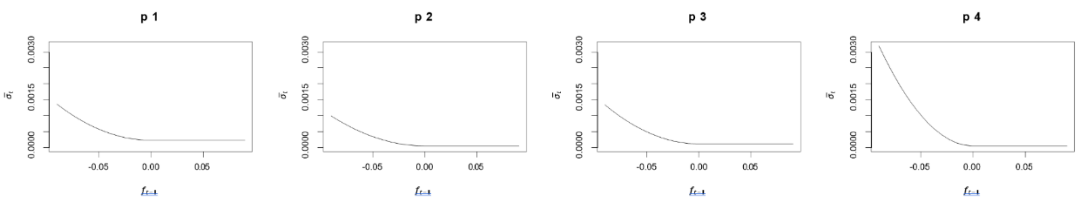


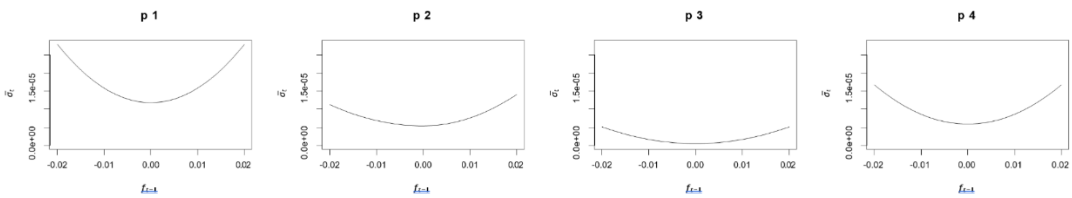
Figure 2 Selected news impact curves. The complete set of NIC is displayed in Appendix B.

p1 = 2000-03; p2 = 2004-07; p3 = 2008-11; and p4 = 2012-15.

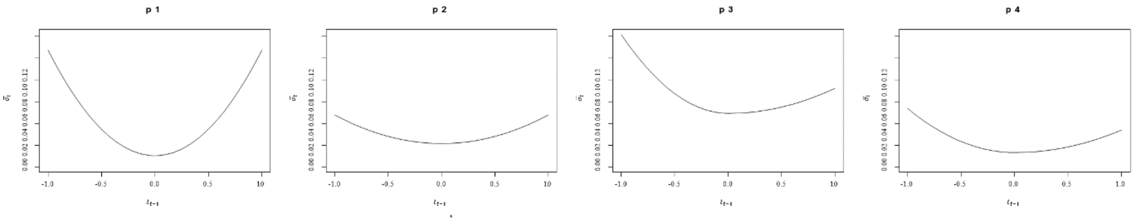
(a) SPS



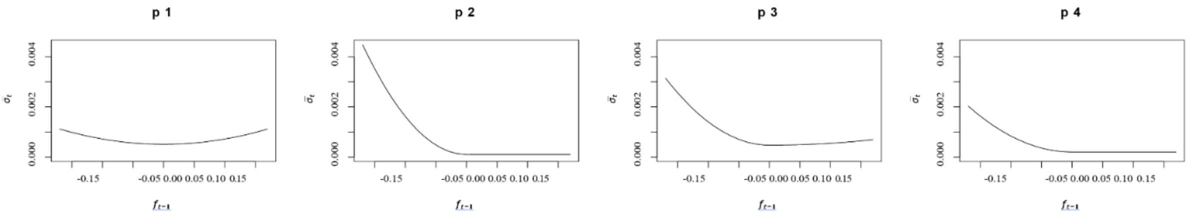
(b) JPB



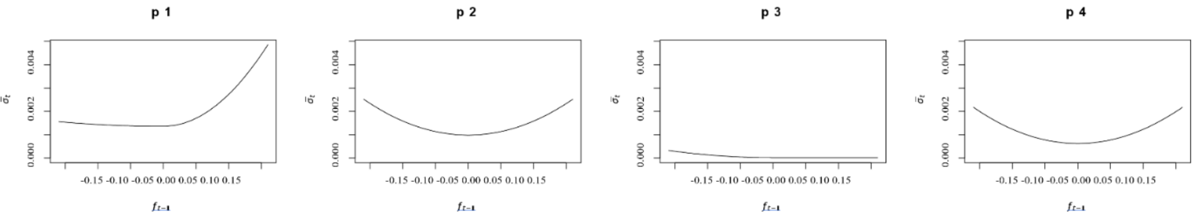
(c) COM



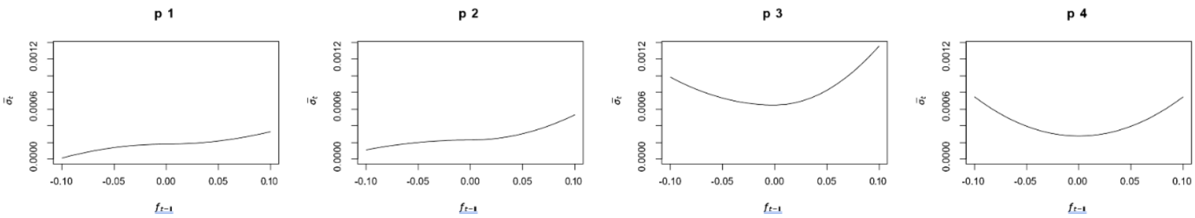
(d) WTI



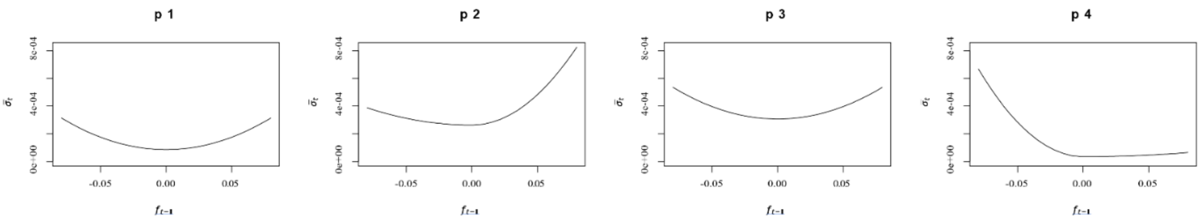
(e) NTG



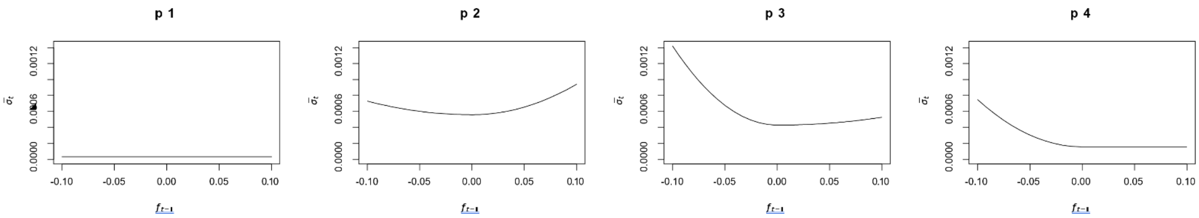
(f) CCW



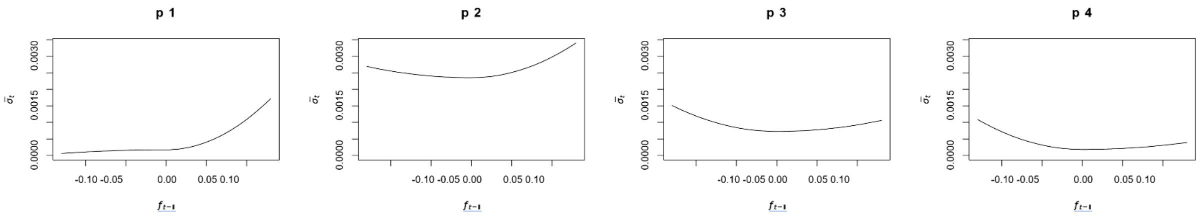
(g) ALM



(h) CPR



(i) LED



(j) GLD

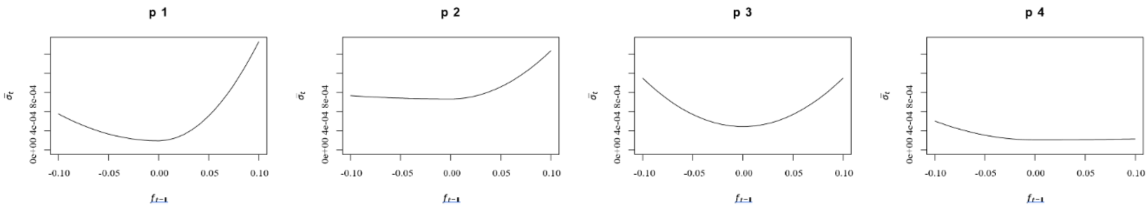


Figure 3 Uncertainty and herding

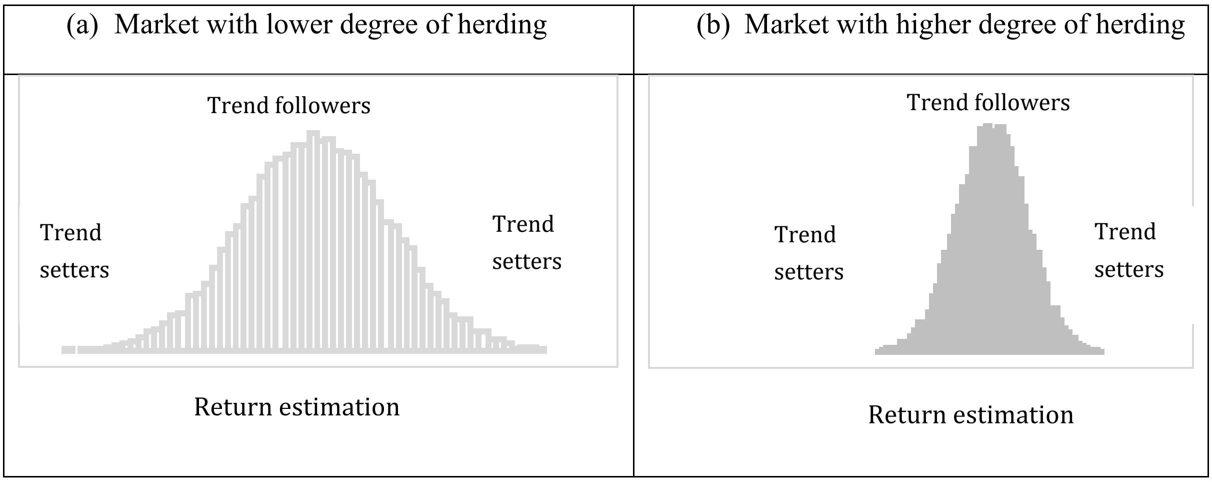


Figure 4 Density plot of bi-variate copula family samples

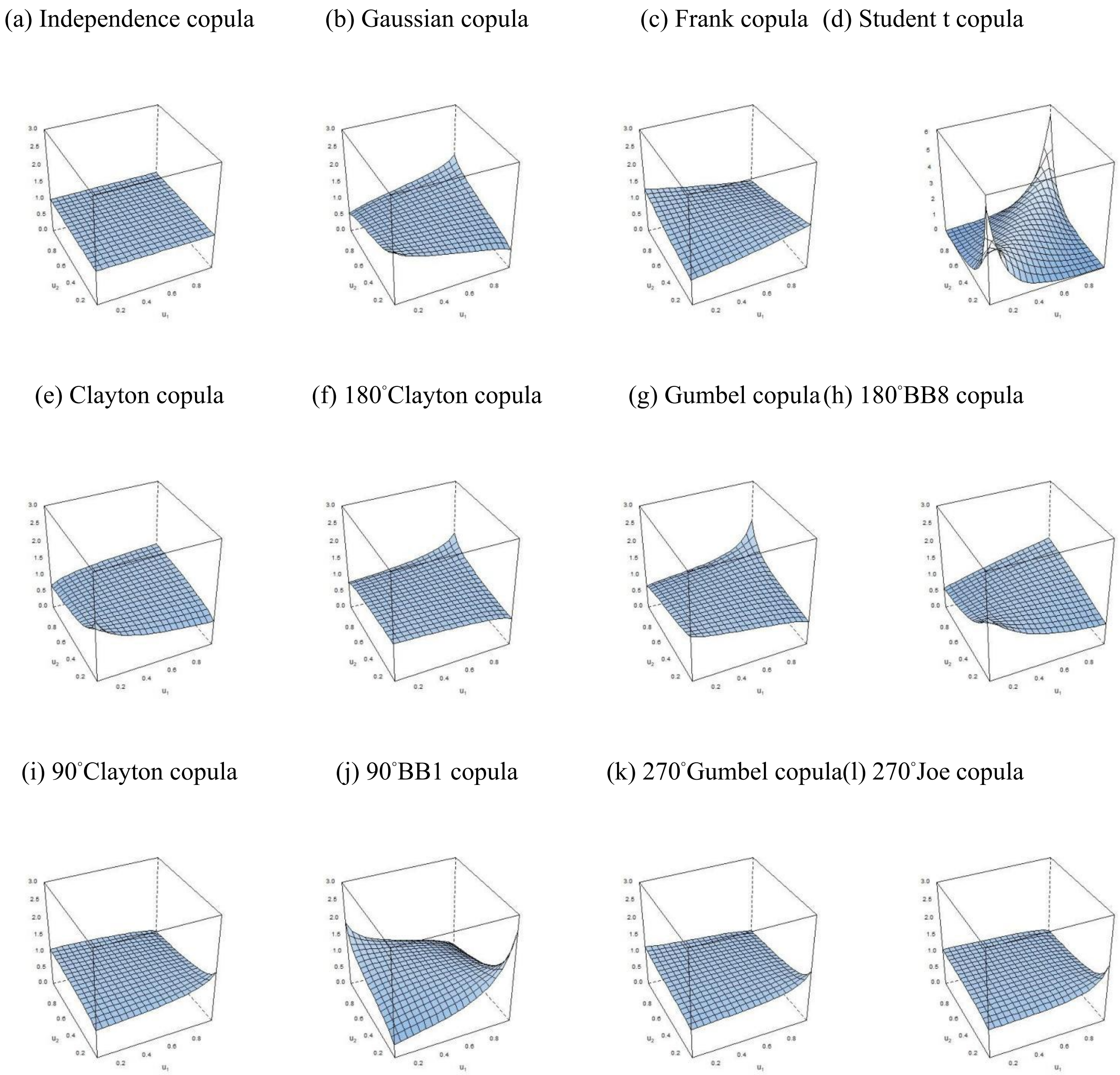
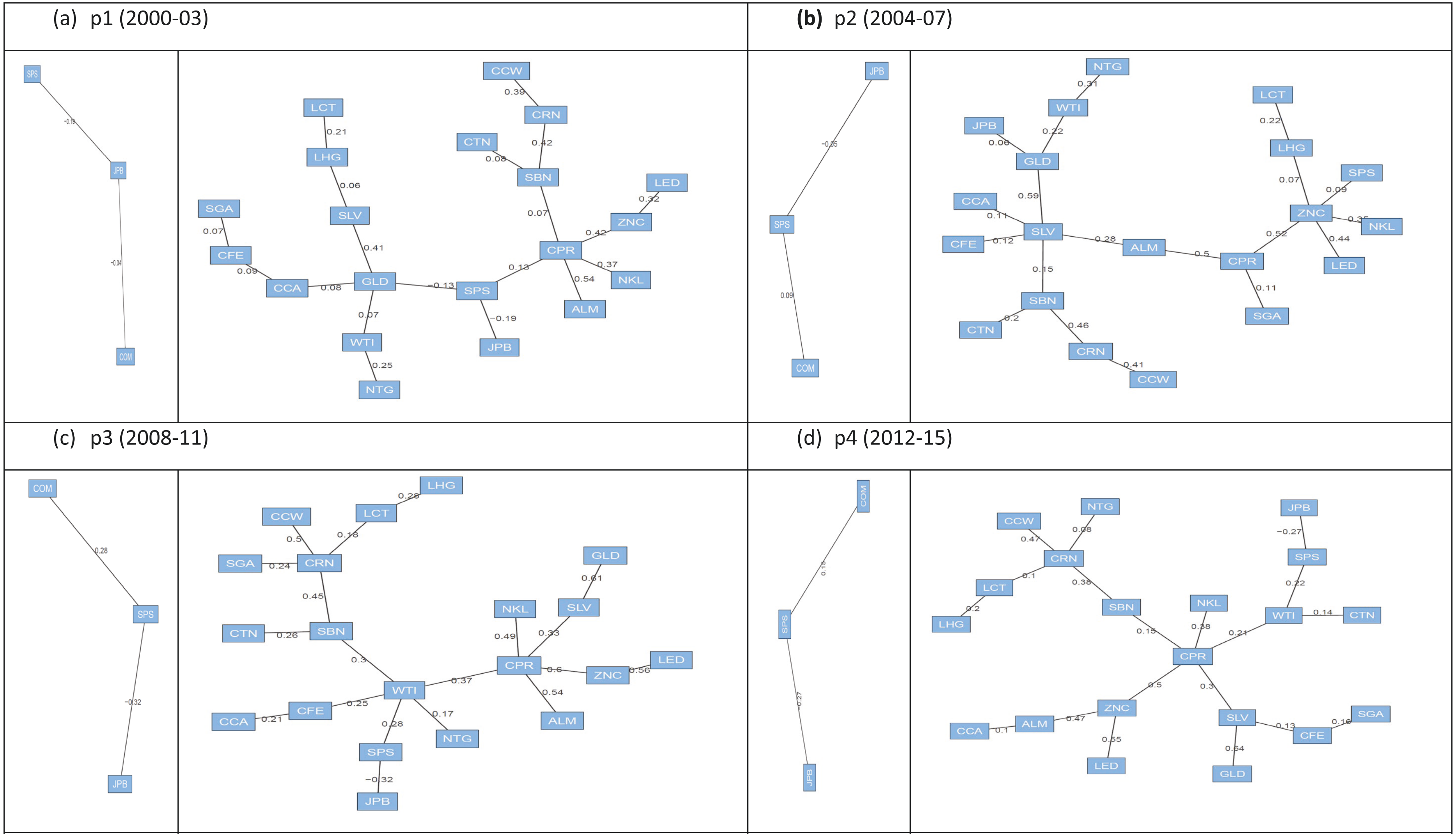


Figure 5 R-Vine tree – level one



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[i] DataStream series code NCLTRLC.

[ii] DataStream series NCLCMLC divided by series NCLTRLC.

[iii] DataStream series NCLNCLC divided by series NCLTRLC.

[iv] DataStream series NCLMMLC divided by series NCLTRLC.