The Determinants of Dynamic Dependence:
An Analysis of Commodity Futures and Equity Markets

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ABSTRACT

This paper investigates the determinants of the dynamic equity-commodity return correlations between five commodity futures sub-sectors (i.e. energy, foods and fibers, grains and oilseeds, livestock, and precious metals) and two equity market indices (i.e. S&P 500 and Russell 3000). We employ the DCC model, as well as three time-varying copulas: (i) the normal copula, (ii) the student's t copula, and (iii) the rotated-gumbel copula as dependence measures. We then explore the determinants of these various dependence measures by analyzing several macroeconomic, financial, and speculation variables over several sample periods. Our results indicate that the dynamic equity-commodity correlations for the energy, grains and oilseeds, precious metals, and to a lesser extent the foods and fibers, sub-sectors have become increasingly explainable by broad macroeconomic and financial market indicators, particularly after May 2003. Furthermore, these variables exhibit heterogeneous effects in terms of both magnitude and sign on each sub-sectors' equity-commodity correlation structure. We also find the effects of increased financial market speculation to be varied among the dynamic correlations of the five sub-sectors.

Keywords: Dynamic Dependence, Commodity Futures, DCC, Copulas

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1. INTRODUCTION

Numerous strands of literature have emerged over the last decade which have touted commodity futures as useful additions to investor portfolios for diversification, inflation hedging, and risk management purposes (see Gorton and Rouwenhorst, 2006; Buyuksahin et al., 2010; Conover et al., 2010; Jensen et al., 2000). Moreover, as documented by Erb and Harvey (2006), investment in commodity futures can provide "equity like" returns through a tactical rebalancing strategy. These attractive investment benefits stem from the theoretical motives that commodities, and in turn commodity futures, form an alternative asset class to that of the more traditional equity and bond markets. Thus, the financially transformed fungible raw materials, in theory, are expected to exhibit little (or even negative) correlation with the more traditional asset classes. The reason for this low correlation is that the underlying factors which drive the commodity futures prices, such as weather, supply and demand constraints, geopolitical conditions, and event risk, are very different, if not completely segmented, from those factors which drive the value of the equity and bond markets (see Symeonidis et al., 2012).

Investors of the 21st century clearly found the benefits of commodity-related investment appealing and fruitful, as the influx of money allocated toward the distinctive asset class by market participants exploded over the last ten years. Such rapid growth in commodity-related exposure has primarily come through the futures market, which has made direct exposure to the commodities market much easier in terms of accessibility and costs. According to the Commodity Futures Trading Commission (CFTC), the total value of different commodity index-related instruments purchased by institutional investors, including pension funds, endowments, trusts, and banks, increased from $10 billion in 2000 to a staggering $256 billion by mid-2011. However, despite the documented advantages of adding commodity futures to an investment portfolio, there has been recent mounting evidence that the commodity futures market has become increasingly integrated with (the previously segmented) equity markets, hence reducing the benefits that commodity-related investments can potentially provide. An ever-growing strand of literature posits that the financialization—the process whereby the raw materials (i.e. commodities) have been transformed from mere goods into widely (popular) tradable financial instruments—of the commodity markets is a first-order determinant of this increased integration with more traditional asset classes (see Buyuksahin et al., 2009; Daskalaki and Skiadopoulos, 2011; Tang and Xiong, 2012; Silvennoinen and Thorp, 2013) and that this financialization is largely a result of increased investor participation over the last decade (see Buyuksahin and Robe, 2013). In other words, increased investor interest in commodity futures, particularly by speculators, which is motivated by the belief that the unique asset class offers steadfast diversification and hedging opportunities in market downturns, as well as "equity-like" returns, has weakened, or otherwise eroded, the potential advantages of commodity futures as the shocks from the conventional asset markets enter the commodity futures price dynamics through the increased integration (or dependence) of the return structure.

However, not all commodities, and hence commodity futures, are created equal—some commodities are storable goods while other are not, and what is more, some commodities serve as intermediate goods while others are merely input goods. Hence, due to these fundamental differences, the factors which drive the dependence between commodity futures and the other asset classes may likely be heterogeneous. This observation motivates our choice to examine the issue of time-varying dependence and its determinants between the commodity futures market and the equity markets at the sub-sector level. Recent studies on the determinants of the equity-commodity returns correlation generally utilize a single commodity index composed of futures returns from numerous different sub-sectors (see Buyuksahin and Robe, 2013; Bhardwaj and Dunsby, 2013; Delatte and Lopez, 2013). Moreover, these indices, such as the well-known Goldman Sachs Commodity Index (SP-GSCI) and the Dow Jones UBS Commodity Index (DJ-UBS), tend to put more weight on certain commodity futures (such as energy or agriculture) and less weight on other particular futures, hence shifting (and effectively decreasing) the importance of other sub-sectors of the commodity futures market. While studies which implement such broad commodity futures indices in their analysis have uncovered both interesting and valuable contributions to the literature sect on commodities as investments, we feel that the heterogeneous nature of commodities, in general, gives sufficient motivation to further investigate the futures at a more disaggregated level in an effort to reveal the distinct characteristics of the dynamic equity-commodity correlations for the five futures sub-sectors. For instance, the factors which effect the equity-commodity returns correlation for the energy sub-sector may be completely different than the factors which effect the equity-commodity returns correlation for say, livestock. A commodity futures index makes it virtually impossible to detect and disentangle such effects, but an analysis of the various sub-sectors highlights such relevant information, providing active traders in the commodity futures market, particularly those who do not merely invest in index-related products, invaluable information regarding the futures return behavior and the potential for portfolio diversification benefits.

However, determining the factors which affect the dependence of the equity-commodity returns correlation for the various sub-sectors is further complicated by the issue of determining the appropriate nature of dependence among the two asset classes. It is well-documented that asset classes are not normally distributed (see Longin and Solnik, 2001), thus simple correlation coefficients are not sufficient to properly measure the true relationship between returns. Further, many empirical studies tend to impose the, somewhat unrealistic, assumption of time-stability on asset relationships. Accounting for these problematic issues, a recent study by Buyuksahin and Robe (2013) implement the popular time-varying dynamic conditional correlation (DCC) dependence measure (see Engle, 2002), the likes of which they use to show that the correlation between rates of return on broad market investible commodity and equity indices have increased as a result of greater participation by speculative hedge funds. However, the DCC model imposes the assumption of common dynamics among all assets used (see Billio et al., 2006). This particular restriction may or may not be true, but the imposition that the correlations of commodity futures are identical to US equity indices seems somewhat impractical. In order to overcome these previously ascribed pitfalls and assumptions associated with estimating asset correlations we appeal to the alternative copula approach which provides a dynamic measure of financial market comovements. This approach disentangles the unique characteristics of each return series from the dependence structure which links them together, and allows for a range of models which capture different forms of dependence between variables. The dependence structure estimated via copula is more robust in the sense that the approach separates the dependence structure from the choice of marginal distributions. Moreover, the copula approach does not require elliptically distributed returns and is invariant with respect to increasing and continuous transformations of the marginals.

In this paper, we calculate the dynamic dependence structure between the returns of five different commodity futures sub-sectors (i.e. energy, foods and fibers, grains and oilseeds, livestock, and precious metals) and two different well-known equity market indices (i.e. S&P

500 and Russell 3000).[1] We employ the DCC model, as in Buyuksahin and Robe (2013), as a baseline approach to our investigation of the determinants of equity-commodity correlations, as well as three time-varying copulas. In particular, we analyze (i) the normal copula—a symmetrical and frequent dependence structure which has no tail dependence, (ii) the student's t copula—a symmetrical but non-zero tail dependence structure which nests the normal copula, and (iii) the rotated-gumbel copula—a left tail, non-linear, asymmetrical dependence structure, which is mostly present during extreme negative events. Practically speaking, these copulas represent the most relevant shapes for finance and are frequently used in empirical papers (see Embrechts et al., 2002; Patton, 2004; Rosenberg and Schuermann, 2006; Patton, 2009; Chollete et al., 2011; Aloui et al., 2011; Delatte and Lopez, 2013). We then explore the causes (or determinants) of these various dependence measures by analyzing several comprehensive macroeconomic, financial market, and speculation variables over several sample periods.

Our examination finds that while copulas offer a more robust measure of time-varying dependence there are numerous similarities between the DCC model and the copula dependence measures. We document that the dynamic equity-commodity correlations for the energy, grains and oilseeds, and precious metals sub-sectors have become increasingly explainable by broad macroeconomic and financial market indicators, particularly after the period May 2003. This evolution of predictive variables largely seems to be a byproduct of the financialization of the commodities market, whereby the behavior of commodity futures prices, and hence returns, seemingly behave in a manner associated with more traditional asset classes. The foods and fibers and livestock sub-sectors' equity-commodity correlations seem to be much less integrated with the overall economy (as proxied by our explanatory variables), as their dynamics are not as

[1] Both the S&P 500 and the Russell 3000 reveal very similar univariate statistics and regression results; therefore, we only discuss and present the equity-commodity results regarding the S&P 500. Statistics and results pertaining to the Russell 3000 will be provided upon request.

readily explainable with our model. Additionally, we find that increased participation by financial market speculators is not a primary determinant for all sub-sectors' dynamic correlations, as posited by other papers. Though sensitive to the dependence measure, the energy, foods and fibers, and grains and oilseeds sub-sectors, generally, register a statistically significant speculation coefficient. However, as with the macroeconomic and financial variables, the magnitude and sign of the speculation coefficients are heterogeneous across sub-sectors.

The rest of this paper is organized as follows. Section 2 provides a pertinent review of the literature on the commodity-equity dependence relationship, as well as our contribution. Section 3 focuses on the methodology, models considered, and dataset. Section 4 describes our empirical regression analysis and provides the results over all sample periods. Section 5 offers concluding remarks.

2. LITERATURE REVIEW

Given the numerous strands of literature which have emerged on the dynamic return and diversification benefits that commodity futures can offer investors, several important empirical questions arise: what is the nature of the relationship between commodity futures and traditional assets, in particular equities, (i.e. is it symmetrical or asymmetrical)? How has the relationship evolved over time? What kinds of factors drive, or effect, the relationship? How have those factors evolved over time?

In a flight-to-quality argument, Chong and Miffre (2010) document that over the period 1981-2006, the correlations between equities and individual commodity futures tend to fall both over time, in general, and tempestuous financial market periods. Buyuksahin et al. (2010) document a similar result over the early 1990's to mid-2000's while investigating structural shift in correlation dynamics over both calm and tumultuous financial market periods. In particular, they find a lack of "greater return co-movement across equities and commodities [which] suggests that commodities should retain their role as a portfolio diversification tool."

However, much more recent research finds contradictory conclusions regarding the movement of these correlations. For instance, Silvennoinen and Thorp (2013) find that conditional volatility and correlation dynamics for returns to commodity futures, stocks, and bonds have become increasingly integrated over the period 1990-2009. Furthermore, they note a structural break in conditional correlations occurring in the late 1990's. Buyuksahin and Robe (2011) document significant changes in the make-up of the open interest between 2000 and 2010 and show that these changes impact asset pricing for the energy futures market. Specifically, they find that the dynamic conditional correlations between the rates of return on energy and stock market indices increase significantly from greater activity by speculators and hedge funds.

Interestingly, there is a growing strand of literary evidence that links the growth of index funds and other investment vehicles in the commodity futures market as the means of integration between the commodity market and the stock and bond markets; this integration has effectively reduced or diminished the sought after benefits of commodities. Recent work by Tang and Xiong (2012) finds that since the early 2000's the futures prices of non-energy commodities in the US have become significantly more correlated with oil futures prices. They argue that this increased integration, or comovement, is largely a reflection of the financialization of commodity markets. Furthermore, they show that this trend is more pronounced for commodities in the popular SP-GSCI and DJ-UBS commodity indices, which they attribute to the growing prominence of index trading. Buyuksahin and Harris (2011) look at the impact of financialization and speculation in the crude oil futures market; however, their analysis finds little evidence that hedge funds or other non-commercial speculators position changes cause price changes. They conclude that fundamentals and not speculation were most likely behind the 2004-2008, boom-bust commodity price cycle. Numerous other recent studies exist which investigate and attribute financial speculation as a primary determinant of commodity spot price correlation, but these papers are largely confined to the investigation of the crude oil markets (see Hamilton, 2009; Fattouh et al., 2013; Kilian and Murphy, 2014) or industrial metals markets (see Korniotis, 2009). In recent work, Buyuksahin and Robe (2013) implement a unique non-public dataset of trader positions in US commodity futures which focuses on the trading activity of speculators. They document that "excess speculation" by investor participants, especially by hedge funds, is positively related to the commodity returns' (index) increased correlation with equity markets. Furthermore, they find that the strength of the commodity-equity linkages has fluctuated substantially over the last 20 years, but that the activities of speculators, helps to predict observed long-run fluctuations in the dynamic commodity-equity correlation.

Given that both theory and empirical work predict no common factors which drive equity and commodity market returns, and empirical work finds no common risk factor structure in the cross-section of commodity futures risk premiums (see Daskalaki et al., 2014) we demonstrate that an analysis of commodity futures within their respective sub-sectors provides a much more meaningful analysis. Furthermore, Delatte and Lopez (2013) posit that a lack of consensus regarding the correlation structure between commodity futures and traditional asset market returns is due to the different dependence measures considered. Thus, in this paper, we contribute to dual strands of literature. First, we explore several potential broad macroeconomic, financial, and speculation variables as determinants of the time-varying commodity-equity correlations. However, in contrast to prior work, we analyze each of the commodity futures sub-sectors individually as we believe these effects to be heterogeneous. Second, given the pronounced increase in participation of financial traders in the commodity futures market in the early 2000's, we analyze the evolution of these factors across different sub-sample periods, for the five commodity futures sub-sectors, to see how they have changed. Third, and finally, we investigate each of the dependence measures of the commodity-equity relationship in a regression setting, which includes both the DCC as a baseline approach, and three popular copulas in the field of finance. This approach allows us the advantage of viewing our determinants against different forms of dependence structures and seeing how the determinants of the dynamic commodity-equity correlation change with the implementation of different dependent variables. Knowledge of the factors which drive the dependence between commodity futures and equity markets, how they have evolved over time, and the sensitivity of these factors to different forms of dependence will provide investors, particularly those involved in the commodity futures market a more detailed level of understanding of the commodity futures market. Additionally, our analysis may help to highlight potential investment benefits for non-index futures investors.

3. METHODOLOGY AND DATASET

3.1 Measures of Dependence

The DCC framework, of Engle (2002), has become a largely popular approach to measuring the dependence structure between different financial assets. Notably, this dependence measure relies on the marginal distributions of returns. Hence, some empirical studies have taken a different approach to estimating the dependence structure using a copula methodology which, in contrast to the DCC approach, separates the dependence structure from the choice of marginal distributions creating a more robust approach to measuring dependence. Though the copula methodology is widely known and has been around for quite some time, its application to financial markets has become increasingly momentous in finance and risk management valuation within the last decade (see Patton, 2006; Kole et al., 2007; Chollete et al., 2010; Aloui et al., 2011) as copulas provide an important way to appropriately define a correlation structure, which may be non-linear, between different variables. We employ the commonly implemented DCC dependence measure as a baseline approach to our investigation, as well as three time-varying copulas popular in the field of finance, specifically—the normal copula, the student's t copula, and the rotated-gumbel copula.[2]

3.1.1 DCC Model

The multivariate GARCH model with DCC, a process whereby correlations are driven by the cross product of the lagged standardized residuals and an autoregressive term, was initially proposed by Engle (2002) and has since become a mainstream econometric methodology in finance and related applications. Briefly, the model is specified as:

$$\mathrm{H_t} = \mathrm{D_t R_t D_t} \tag{1}$$

where, $\mathrm{D_t} = \mathrm{diag}\{\sqrt{\mathrm{h_{i,t}}}\}$, $\mathrm{R_t}$ is a time-varying correlation matrix containing conditional correlations, and the expressions for h, the conditional standard deviations, are generally thought of as univariate GARCH models, but can include functions of other variables in the system as either pre-determined or exogenous. The estimation procedure bears some similarities to that of copula models. First, an ARMA model is fit to the specified return series and used to estimate the GARCH parameters for the individual series. Second, the parameters driving the correlation

[2] We disregard the constant dependence structure and focus solely on time-varying relationships as copious amounts of prior work have found the dependence relation among financial assets to indicate that it is anything but constant (see Erb et al., 1994; Longin and Solnik, 1995; Engle, 2002).

dynamics are estimated using the standardized residuals from the first step estimation.[3] We outline the details of our estimation procedure for the DCC model in Section 3.2.1.

3.1.2 Copula Functions

Copulas provide a convenient way to join or "couple" the marginal distributions of random variables into a joint distribution. Conversely, they can also allow one to separate a joint distribution into two contributions: the marginal distribution of each variable and the copula which combines these into a joint distribution (see Sklar, 1959). Copulas generally have a convenient parametric form and provide a large degree of flexibility in the specification of the marginal distributions and their dependence structure. Further, the choice of copula provides a great deal of control over what parts of the distribution the variables are most strongly associated; this convenience is particularly intriguing to market practitioners who are concerned with strong left tail dependence (i.e. the comovement of asset prices/returns during market crises).

The theorem of Sklar (1959) illuminates the role copulas play in the relationship between multivariate distribution functions and their univariate marginals. Formally, in the bivariate case, if $F(X_{1t}, X_{2t})$ is a joint distribution function with marginal distribution functions $F_1(X_{1t})$ and $F_2(X_{2t})$, for random variables X_{1t} and X_{2t}, then there exists a copula, $C(u, v)$, mapping the marginal distributions of X_{1t} and X_{2t} to their joint distribution:

$$F(X_{1t}, X_{2t}) = C\big(F_1(X_{1t}), F_2(X_{2t})\big) \tag{2}$$

If $F_1(X_{1t})$ and $F_2(X_{2t})$ are continuous, then the copula is unique, otherwise, the copula will not necessarily be unique.[4] Thus, in the bivariate case, that means:

[3] Given the popularity of the DCC model we refer the interested reader to Engle (2002) for additional details regarding the technical notes of the model and estimation procedure.

$$C(u,v) = \Pr[U \le u, V \le v] \tag{3}$$

where, U and V are uniformly distributed on [0,1].[5] Equation (2) explicitly highlights the practicality of copulas, in that one can simplify the analysis of dependence for a particular joint (return) distribution, $F(X_{1t}, X_{2t})$, by merely studying the copula. Conversely, if $C(u,v)$ is a copula, and F_1 and F_2 are univariate distribution functions, then $F(X_{1t}, X_{2t})$ is a joint distribution function with $F_1(X_{1t})$ and $F_2(X_{2t})$. Assuming that each marginal distribution is continuous and strictly increasing, we can write the copula as:

$$C(u,v) = F(F_{1^{-1}}(u), F_{2^{-1}}(v)) \tag{4}$$

where, $u = F_1(X_{1t}) \Leftrightarrow X_{1t} = F_{1^{-1}}(u)$ and $v = F_2(X_{2t}) \Leftrightarrow X_{2t} = F_{2^{-1}}(v)$ holds. Furthermore, assuming the marginals can be modeled parametrically, the probability integral transformation of equation (2) is given as:

$$U_{it} = F_i(X_{it}; \phi_i) \tag{5}$$

where, ϕ_i is the vector of parameters. The function $F_i(X_{it}; \phi_i)$ can be a conditional distribution (as it is in our analysis), where X_{it} is modeled by an ARMA-GARCH model, whose residuals are treated as independent and identically distributed (i.i.d.) random variables.[6] Following Manner and Reznikova (2012), it is also assumed that each variable only depends on its own past, but not on the past of the other variable, and that there is only instantaneous causality between the variables. This supposition implies that the parameters of the copula are separate from the parameters of the marginal distributions.

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[4] In such situations, the work of Deheuvels (1979) aids in refining the types of admissible copulas.
[5] While copulas also work in the multivariate context, we give our primary attention to the bivariate case.
[6] It is also assumed that the copula belongs to a parametric family $C_\theta, \theta \epsilon \Theta \subset \mathbb{R}^K$.

Given, once again, that the copula function and the marginals are continuous, the following equation for the join probability density function (PDF) holds:

$$f(X_{1t}, X_{2t}) = c(U_{1t}, U_{2t}; \theta) \prod_{i=1}^{2} f_i(X_{it}; \phi_i) \tag{6}$$

where, $c(\cdot,\ \cdot)$ is the copula density. Further, assuming a sample for X_{1t} and X_{2t} where, $t = 1, \dots, T$, then the log-likelihood function is given as:

$$L(\theta, \phi) = \sum_{t=1}^{T} \{\log c(U_{1t}, U_{2t}; \theta) + \log f_1(X_{1t}; \phi_1) + \log f_2(X_{2t}; \phi_2)\} \tag{7}$$

This statement is equivalent to:

$$L(\theta, \phi) = L_C(\theta, \phi) + L_{X_1}(\phi_1) + L_{X_2}(\phi_2) \tag{8}$$

where, $\phi = (\phi_1', \phi_2')'$. Hence, the full log-likelihood function $L(\theta, \phi)$ can be split into two parts, the copula likelihood $L_C(\theta, \phi)$ and the likelihood of the marginals $L_{X_1}(\phi_1)$ and $L_{X_2}(\phi_2)$. The parameters θ and ϕ are estimated via a two-step process proposed by Genest et al. (1995). First, since the marginal models are unknown, the marginal distributions are estimated with the empirical CDF, based on the i.i.d. of the residuals, via the following form:

$$u = \widehat{F_1}(X_{1t}) = \frac{1}{n+1} \sum_{j=1}^{n} 1_{\{X_{1,t-j} \leq x_{1t}\}} \text{ and } v = \widehat{F_2}(X_{2t}) = \frac{1}{n+1} \sum_{j=1}^{n} 1_{\{X_{2,t-j} \leq x_{2t}\}} \tag{9}$$

Second, the copula parameters are estimated based on the ranks of the data by maximizing the corresponding copula likelihood function given the results from the first step. This method proves useful in that it is robust to misspecification of the marginals, which can cause biased estimates of the copula parameter.[7]

Patton (2006) proposes an extension of the copula model where the time-varying dependence parameter of a copula is a function of an autoregressive term, which captures persistence in the dependence term, and a forcing variable, which captures any variation in dependence. We follow Patton's extension to facilitate our analysis. For the normal and student's t copula, the evolution equation for the dependence parameter, ρ_t, is given as:

$$\rho_t = \bar{\Lambda}\left(\omega_\rho + \beta_\rho(\rho_{t-1}) + \alpha \frac{1}{n}\sum_{j=1}^{n} \phi^{-1}\big(F_1(X_{1,t-j})\big)\phi^{-1}\big(F_2(X_{2,t-j})\big)\right) \tag{10}$$

where, $\bar{\Lambda}(x) = \frac{(1-e^{-x})}{(1+e^{-x})}$ is a modified logistic transformation, designed to keep the correlation parameter ρ_t between (-1,1) at all times, and n is an arbitrary window length.[8] The average of the product of the last n observations of the transformed variables is the forcing variable. For the rotated-gumbel copula, the evolution equation for the dependence parameter, φ_t, is given as:

$$\varphi_t = \bar{\Lambda}\left(\omega_\rho + \beta_\rho(\rho_{t-1}) + \alpha \frac{1}{n}\sum_{j=1}^{n} |\big(F_1(X_{1,t-j}\big) - \big(F_2(X_{2,t-j}\big)|\right) \tag{11}$$

where, $\bar{\Lambda}(x)$ is a modified logistic transformation to ensure the parameter always remains in its domain, for the rotated-gumbel copula ($\varphi_t = \delta_t$) it's $1 + e^{-x}$. In this instance, the mean absolute difference of the transformed variables over the previous n periods is the forcing variable.[9]

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[7] The theoretical properties of this estimator in a time series are derived by Chen and Fan (2006).

[8] We follow the dynamic framework methodology proposed by Creal et al. (2013) for the estimation procedure of the student's t copula. The authors derive a Generalized Autoregressive Score (GAS) specification for the time-varying correlation parameter, ρ_t, using the density of the Gaussian (normal) copula, following Patton (2006).

[9] See Manner and Reznikova (2012) for additional details.

The merits and importance of the copula methodology in our analysis comes from the convenience (and ability) to impose a particular distributional dependence structure between our two variables of interest (i.e. commodity futures returns and equity returns). For instance, we can observe both symmetrical dynamics and asymmetrical dynamics. Consequently, we can also measure the strength of the relation with appropriate density function; however, our primary objective is to measure the time-varying relation between our two choice variables and determine the factors which drive the particular dependency relationship, as well as examine the evolution of these factors over time.[10] While prior research has focused on a number of different parametric copula specifications, we focus on three types in our investigation of the determinants between commodity futures sub-sectors and equity returns: the normal, the student's t, and the rotated-gumbel copulas. The normal copula specification, with zero tail dependence, is a common distributional assumption in finance and provides a reasonable benchmark for our analysis. Further, it provides a practical basis in which to compare the results from the baseline approach using the DCC dependence measure. The student's t copula is a useful measure as it has symmetric but non-zero tail dependence, consequently, it nests inside the normal copula. Finally, the rotated-gumbel copula is appealing because it provides the ability to measure the potential for the joint occurrence of left-tail extreme events, or lower tail dependence; that is, it captures the comovement of the return series jointly taking extremely low values. The rotated-gumbel has non-linear dependence as well as asymmetric tail dependence present during extreme negative events (i.e. the mass in the left tail is far larger than the mass in the right tail) and is a member of the extreme value copula family. Longin and Solnik (2001) find evidence of both extreme and asymmetrical forces at work in asset markets, thus, it seems reasonable to

[10] Tabel A6 in Appendix A provides the best fit measure for all the copula functions for each sub-sector and sample period based on the log-likelihood criteria.

investigate the presence and determinants of these effects in equity-commodity correlations. In particular, investors are very much interested in how different markets commove together especially during severe downturns or crisis situations, as strong market comovements indicate a lack of diversification benefits, and weak comovement indicates the contrary. As noted in Chollete et al. (2011), practically speaking, these copulas are the most important shapes for finance as they represent a large subset of those implemented in empirical work. The corresponding copula functions and their dependence parameters are outlined in Table 1.

[Insert Table 1 Here]

3.2 Estimation Procedure and Dataset

Our primary interest is the determinants of the dynamic equity-commodity return correlations for the five commodity futures sub-sectors, both over the entire sample period and two sub-sample periods so as to gauge the evolution of the determinants. Given this, we employ two conditional-based methodologies in order to obtain dynamically correct estimates of the intensity of the equity-commodity return comovements. First, we implement the well-known DCC methodology, which Buyuksahin and Robe (2013) use in a similar vein of research. Second, we implement the copula methodology and utilize three relevant copulas in the field of finance which yield a more robust approach to measuring dependence and allow us to evaluate the factors which drive the equity-commodity correlations over different portions of the return distribution.

In order to facilitate both types of analyses we have to calculate the return series for both the futures and equity indices. We extract daily price data, over the period October 1992 to October 2013, for each of the individual commodity futures we consider from the Commodity

Research Bureau (CRB) database.[11] Each individual commodity future (along with its CRB symbol) is listed in Panel A of Table 2, along with the respective sub-sector to which it belongs. The inclusion of the specific commodity futures listed for this study are based on two criteria. First, each commodity future must have a continuous price series over the entire sample period considered. Second, the commodity futures must also have corresponding speculation data which can be extracted from the US Commodity Futures Trading Commission (CFTC)—described in section 3.3. These daily price series are then averaged on a (Tuesday-Tuesday) weekly basis to obtain an individual weekly price series. The same process is repeated for our two equity indices to get our weekly equity price series; we extract our daily equity price data from Bloomberg. Panel B of Table 2 lists the two equity indices as well as their respective ticker symbols.

[Insert Table 2 Here]

We calculate the return series for all financial assets using the common log transformation on two consecutive weeks, formally, this sequence is given as:

$$X_{it} = \log P_{it} - \log P_{it-1} \tag{12}$$

where, X_{it} represents the log return series for each individual commodity future or equity index based on the price series, P_{it}. The weekly return series for each of the five commodity futures sub-sectors (energy, foods and fibers, grains and oilseeds, livestock, and precious metals) are calculated by taking an equally-weighted average of all futures returns, X_{it}, which comprise that particular sub-sector. For instance, the energy sub-sector is composed of an equally-weighted index of returns from Brent crude oil, heating oil #2, unleaded gasoline, and natural gas. Table 3 provides the summary statistics for the weekly rates of return. Specifically, Panel A summarizes

[11] In constructing the futures price series we follow the typical methodology, for each commodity future, of rolling over the futures prices to the next-nearby contract when the current futures contract is one month from expiration.

the statistics for the weekly returns of the equity indices, while Panel B encapsulates the weekly return statistics for the five commodity futures sub-sectors. The excess skewness and kurtosis that the equity and commodity futures returns exhibit confirm the non-normality assumption; hence, reaffirming the need to use alternative measures of correlation structure to those based on simple linear assumptions. In general, we see that the returns of the energy and precious metals sub-sectors seem to most closely mimic those of the equity indices in terms of average return, skewness, and kurtosis. However, the standard deviation of returns for the equity indices is markedly lower than that of all commodity sub-sectors, except livestock (0.007169). Further, livestock, interestingly is the only sub-sector (or composite index if we include equities as well) which exhibits positive skewness (0.030680) over the sample period. Overall, one can observe that the return properties of the five sub-sectors appear to decidedly differ, giving rise to the notion that their determinants may likely be heterogeneous.

[Insert Table 3 Here]

3.2.1 DCC Estimation

The DCC model is in effect a two-step process to estimate the time-varying correlations between two different financial series. The first step involves estimating the time-varying variances, from the specified mean equation, using a GARCH(p, q) model. In the second step, the time-varying correlation matrix is estimated.

High frequency asset returns have a tendency to display fat-tails, along with conditional heteroskedasticity and autoregressive characteristics; hence, we select a mean equation, for each equity index and commodity sub-sector return series, via an AR(k) model based on the Bayesian Information Criterion (BIC)criterion—which in our estimation provides the most parsimonious model. We then implement the GARCH(p, q) model, and following Buyuksahin and Robe

(2013) use the commonly applied $p = q = 1$ for our sample. Thus, the model for each sub-sector and equity index log return series, X_t, is described via the following set of equations:

$$\left.\begin{aligned} X_t &= \mu + \sum_{j=1}^{k} \theta_j X_{t-j} + \varepsilon_t \\ \varepsilon_t &= \sigma_t \xi_t, \quad \text{where } \xi_t \sim \mathrm{i.i.d.}(t_v) \\ \sigma_t^2 &= \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 \end{aligned}\right\} \tag{13}$$

The residual series from (13) are standardized and used to estimate the time-varying correlation matrix between each of our five commodity futures sub-sectors and the equity indices, respectively, via maximum likelihood. Panel A of Table 4 presents the summary statistics for the DCC correlations between the S&P 500 and each of the commodity futures sub-sectors. The highest mean correlations occur between precious metals (0.153452) and grains and oilseeds (0.147074), while the greatest variation belongs to the energy sub-sector which has a standard deviation of 0.210793, far surpassing that of any other sub-sector. Most importantly, all sub-sector correlations, which are bounded between above (+1) and below (-1), are stationary, thus permitting our use of it as a reliable dependent variable in our regression analysis in Section 4.

[Insert Figure 1 Here]

The most interesting aspect of the DCC model comes from an inspection of Figure 1 which plots the time-varying correlations between the S&P 500 and the five sub-sectors. Two things become readily apparent from the figure. First, the correlations between the equity markets and the commodity sub-sectors differ tremendously over the sample period, for example, the foods and fibers sub-sector shows much less variation in its correlation with the equity markets than does the energy sub-sector. Second, starting around mid-2003 the correlations between the commodity sub-sectors and the equity market seems to experience a slight upward trend, which becomes readily apparent in the post-2006 period. This rise in correlations corresponds to Buyuksahin et al. (2010) who note that this particular period (i.e. post-May 2003) is characterized by increasing participation of financial traders in the commodity futures market.

3.2.2 Copula Estimation

The initial steps of the copula estimation procedure are similar to those of the DCC described above. We again select a mean equation, for each equity index and commodity sub-sector return series, via an AR(k) model (based on the BIC) to compensate for autocorrelation, and then apply the GARCH(p, q) model, where we again use $p = q = 1$, to compensate for heteroskedasticity, as in equation (13). The residuals from each series are standardized and used to estimate the empirical CDF of each filtered return series. Following the work of Patton (2006), we use these values to estimate the copula parameters (of the normal, student's t, and rotated-gumbel) outlined in Table 1 using maximum likelihood. Panels B, C, and D of Table 4 present the summary statistics for the normal, student's t, and rotated-gumbel copula correlations between the S&P 500 and each of the commodity futures sub-sectors, respectively. The correlations for the normal and student's t copula closely resemble those of the DCC model in terms of mean, maximum, and minimum correlation values. However, there are a few distributional changes regarding the correlation measures; in particular, the normal copula tends to exhibit greater kurtosis over that of the DCC specification. In addition, the skewness measures for both copulas differ (both positively and negatively) from the DCC case. These distributional differences in univariate statistics underlie the fundamental differences in how copulas disentangle the unique characteristics of each return series from the dependence structure which links them together in order to estimate its dependence series. As in the DCC model, all sub-sector correlations are bounded above (+1) and below (-1) for the normal and student's t copulas, thus intuitively permitting our use of the correlation measures as dependent variables in our regression analysis due to their stationarity. Alternatively, in Panel D of Table 4, the rotated-gumbel offers another view of the equity-commodity dynamic correlations. The measure itself captures the lower left tail dependence and is unbounded above (∞), but bounded below (+1). The mean correlation measures, for all sub-sectors, range from 1.03 to 1.13, and have, in general, skewness and kurtosis distributional measures which are much greater than those in the DCC (baseline) case or the other two copulas for that matter.[12] Since this particular copula measures the comovement of the different financial assets in an extreme sense, these distributional differences are not too surprising. Furthermore, examination of the properties of the rotated-gumbel correlations also reveals that they are, in fact, stationary and permissible as a dependent variable in a regression setting.

[Insert Figures 2A, 2B, 2C Here]

Figures 2A, 2B, and 2C highlight the various correlation time paths between the S&P 500 and the five different commodity futures sub-sectors for the normal, student's t, and rotated-gumbel copulas, respectively. While all three copulas highlight the heterogeneity between the dynamic equity-commodity correlations, the student's t copula, and to a lesser extent the normal copula, clearly illustrate the increase in correlations that occurred in mid-2003 for many of the sub-sectors, which many have attributed to an increase in market participants and in particular speculators. Interestingly, over the latter part of the sample period, we also witness a spike in the

[12] Even though the rotated-gumbel copula is unbounded above, we perform Monte Carlo simulations of the copula and find that, in the bivariate case, financial asset return series would have to comove very, very strongly to achieve a dependence parameter greater than two.

lower tail dependence for several equity-commodity pairings, in particular, energy, precious metals, and grains and oilseeds.

[Insert Table 4 Here]

3.3 Explanatory Variables

We employ a series of macroeconomic and financial market variables, along with a measure which captures the aggregate market speculation for each commodity sub-sector, in order to determine what factors determine the dynamic correlations for each equity-commodity sub-sector pairing. We follow the suggestions of prior literature in our choice and implementation of these variables.

3.3.1 Macroeconomic Fundamentals

It is well-known that business cycle factors have an impact on commodity returns (see Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). Given this observation, we use an aggregate measure of US macroeconomic conditions called the Aruoba-Diebold-Scotti Index (ADSI), which tracks real business conditions at a high frequency (see Aruoba et al., 2009; Buyuksahin and Robe, 2013). The ADSI variable is a composite of several underlying seasonally adjusted (high- and low-frequency) economic indicators, which include: weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP. The average value of the ADSI variable is zero. Progressively larger positive values indicate better-than-average business conditions, whereas progressively more negative values indicate worse-than-average business conditions. Using historical statistics dating back to 1960, Bhardwaj and Dunsby (2013) find that the equity-commodity correlation business cycle component increases during period of economic weakness, and that the link between the equity-commodity correlation and business cycle is stronger for industrial commodities than agricultural commodities. However, Buyuksahin and Robe (2013) find that business conditions impart a positive, though not consistently significant, impact on dynamic equity-commodity correlations.

While US macroeconomic conditions are of substantial importance to the prices of financial assets, worldwide economic activity also plays a central role, particularly for commodities. Thus, we implement a measure of real global economic activity called the Baltic Dry Shipping Index (BDSI). The BDSI is an indicator of transportation costs for raw materials shipped by sea. It's based on a daily quote, published by the Baltic Exchange in London, for booking vessels of various sizes and across multiple maritime routes. Specifically, the BDSI is calculated as a weighted-average of the Baltic Exchange's indices for the shipping costs of the four largest dry-vessel classes. Our interest in this measure is based on the idea that the supply structure of the shipping industry is generally predictable and that changes in shipping costs are largely due to changes in the worldwide demand for raw materials. Kilian (2009) uses a similar type of freight measure and finds that increases in the shipping rates of freight can be used as indicators of both demand and supply shifts in global commodity markets. This link to global demand has prompted some interest in the BDSI as a leading indicator of global economic activity. Withstanding recent work by Bakshi et al. (2011), who investigate the BDSI as a predictor for global stock and commodity returns, not many studies have used the variable for any type of analysis beyond that of economic growth.

Panel A of Table 5 provides the summary statistics of these macroeconomic variables. Most importantly diagnostic tests reveal that the variables are both stationary in the level form, thus permitting them as usable variables in our regression. Additionally, it is apparent that the magnitude of the mean of the BDSI variable (2356.17) is much greater than the mean of the ADSI (-0.149949), or any of our dependent variables, so we use the natural logarithm of the BDSI to remedy the issue in our regression analysis in Section 4.

3.3.2 Financial Market Indicators

Recent work by Silvennoinen and Thorp (2013) documents that for certain commodity futures higher than expected US stock volatility can help to predict higher volatility in those markets. Alternatively, for a small sample of other commodity futures they note the opposite effect. Overall, they conclude that an increase in stock market volatility, as proxied by the VIX index, can be linked to an increase in correlations across markets. Based on this finding we include the VIX index, a measure of implied volatility of S&P 500 index options, or better regarded as a gauge of investor sentiment (or "fear" index), as a regressor in our analysis. A general interpretation of the index is as follows, higher values of the VIX correspond to greater investor uncertainty about the equity markets.

While equity market volatility is well captured using the VIX index, broad market financial stress may not be so easily encapsulated. The finance literature has acknowledged that an increase in cross-market correlations in crisis periods occurs due to arguments such as spill-over effects and flight-to-quality (see Danielsson et al., 2011; Pavlova and Rigobon, 2008; Kyle and Xiong, 2001). Therefore, following the work of Hong and Yogo (2012), who investigate the predictability of commodity futures as well as other asset returns, we proxy for aggregate financial market stress using a slight variation of the yield spread (YS). Here, YS is defined as the difference between Moody's Aaa corporate bond yield and Baa corporate bond yield.

Panel B of Table 5 provides the summary statistics of the financial market variables. As in the case of BDSI, we use the log of VIX to facilitate our regression analysis given that its mean value (20.39216) is substantially larger than the mean value of all other independent and dependent variables. Additionally, both financial indicators are stationary in their level permitting reasonable inferences from the regression in Section 4.

[Insert Table 5 Here]

3.3.3 Excess Speculation

Recent literature on the financialization of commodity markets recognizes the idea that "who trades matters," and that the presence of increased market participation may in fact propagate the linkage between cross-market (price) correlation dynamics (see Etula, 2009; Tang and Xiong, 2012; Buyuksahin and Robe, 2013). We address this issue by acknowledging that speculators and index investors perform very different economic roles in the commodity futures market, and that these differences should have dissimilar influences on commodity prices. A survey by Greely and Currie (2008) highlights that speculators bring information to the commodity futures markets on future supply and demand fundamentals, while index investors merely earn a passive return as payment for bearing the risk of price fluctuations. We postulate that the role of speculators may be unique among the different sub-sectors of commodity futures given the inimitability of the commodities themselves, as well as their individual trading volume.[13]

In order to create an index which accounts for market speculation we appeal to the Commitment of Traders (COT) reports which aggregate the positions of "major players" in the US commodity futures markets each week. It is exclusively devoted to the domain of open interest with no price or volume data. Traders are divided into commercials traders, non-commercial traders, and small traders. Commercial traders (or hedgers) participate in order to hedge their inherent commodity price risk exposure, whereas non-commercial traders (or

[13] See volume statistics at www.futuresindustry.org.

speculators) participate in order to profit from the anticipation of future price movements. We utilize the US Commodity Futures Trading Commission's (CFTCs) sub-classification of open interest data to measure speculation in the market. Prior studies analyzing the role of speculation have utilized Working's "T" index, defined as the ratio of positions held by speculators to that of hedgers (see Buyuksahin and Robe, 2013). Working's "T" measures the extent to which speculation is in "excess" of the level required to satisfy hedgers' net demand for hedging at the market clearing price. It is common to interpret a high index or high volatility of the index as indicative of excess speculation. For each of our 23 commodity futures $(\mathrm{i} = 1,2, \ldots, 23)$, we calculate Working's "T" on a weekly basis (Tuesday-Tuesday), as that is when COT publically publishes their trading data.

Formally, for the i^{th} commodity market in week t we calculate the speculation index as follows:

$$\mathrm{T_{it}} = \begin{cases} \dfrac{\mathrm{SS_i}}{\mathrm{HL_{it}} + \mathrm{HS_{it}}} \text{ if } \mathrm{HS_{it}} \geq \mathrm{HL_{it}} \\ \dfrac{\mathrm{SL_i}}{\mathrm{HL_{it}} + \mathrm{HS_{it}}} \text{ if } \mathrm{HS_{it}} < \mathrm{HL_{it}} \end{cases} \quad (\text{for } \mathrm{i} = 1, \ldots, 23) \tag{14}$$

where, $\mathrm{SS_i} \geq 0$ and represents the "Speculator Short" positions held in aggregate by all non-commercial traders, $\mathrm{SL_i} \geq 0$ and represents the "Speculator Long" positions held in aggregate by all non-commercial traders, $\mathrm{HS_{it}} \geq 0$ and represents all commercial "Hedge Short" positions, and $\mathrm{HL_{it}} \geq 0$ and represents all commercial "Hedge Long" positions. After calculating excess speculation in each individual market, we aggregate the measure for each sub-sector as follows:

$$\mathrm{SI_{nt}} = \sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{T_{it,n}} \quad (\text{for } \mathrm{n} = 1, \ldots, 5) \tag{15}$$

where, SI_{nt} is the "Speculation Index" for each of the five sub-sectors, n, composed of the individual commodity futures which belong to it.

Panel C of Table 5 summarizes the speculation measures for each of the five sub-sectors investigated in this paper. The univariate statistics differ quiet drastically between markets, with livestock reporting the highest mean measure of excess speculation (1.289389) and energy reporting the lowest (0.333579). Further, tests of non-stationarity reveal that all speculation indices are, in fact, stationary in their level form and hence usable variables in our regression analysis.

4. REGRESSION RESULTS

Given the unique characteristics among the different types of commodities, the correlations and the factors which determine the time-varying comovement among the various sub-sectors with other asset markets, in particular equities, should also be unique. In order to explore this hypothesis we utilize the following regression model:

$$y_{nt} = \alpha w_t + \beta x_t + \gamma z_{nt} + \varepsilon_t \qquad (16)$$

where, y_{nt} is a $t \times 1$ vector of the dynamic correlations from either the DCC model or one of the copula specifications for a given sub-sector (n), x is a $t \times k$ vector of regressors consisting of macroeconomic and financial market variables, z_{nt} is $t \times 1$ vector of Working's "T" excess speculation for a given sub-sector (n), and w is a $t \times 1$ vector of one's. We estimate the model parameters using ordinary least squares (OLS) and report Newey-West t-statistics which correct for both autocorrelation and heteroskedasticity. The results from this regression analysis will provide a more detailed level of understanding of the commodity futures market and its dependence with the equity markets. Furthermore, accurate and current knowledge on the determinants of the dynamic equity-commodity correlations at the sub-sector level has implications for non-index commodity futures investors and portfolio managers alike in terms of potential benefits.

4.1 Equity-Commodity Correlation Determinants for the S&P 500

In order to evaluate the evolution of the determinants of the dynamic correlations we decompose our overall sample (October 1992 to October 2013) into two sub-samples: sub-sample A (October 1992 to May 2003) and sub-sample B (May 2003 to October 2013). The justification for splitting the sample around mid-2003 stems from Buyuksahin et al. (2010) who note that the latter sub-period is characterized by increasing participation of financial traders in the commodity futures market. This observation and the emerging literature which argues that the increased financialization of commodities has contributed to the increase in dynamic correlations with more traditional assets, makes the break in the overall sample period a natural choice.

4.1.1 The DCC Model

Table 6 presents our baseline approach using the DCC between the S&P 500 and the five futures sub-sectors as our dependent variable. Panel A presents the results for the energy sub-sector. For the full sample period, we find that the variables ADSI, YS, and SPE_ENERGY are all positive and highly statistically significant. Hence, a 1% increase in ADSI, YS, and SPE_ENERGY, ceteris paribus, results in a 0.0838%, 0.1492%, and 0.4429% increase in the dynamic equity-commodity correlations, respectively. These findings are largely consistent with those of Buyuksahin and Robe (2013), which is not too surprising since they examine the DCC between the SP-GSCI (which is heavily weighted in energy futures) and the S&P 500. Conversely, we find that coefficient on BDSI is negative, but highly statistically significant. Its economic influence seems to be substantially less than the other factors however, as only a 1% decrease in

BDSI results in a 0.003531% increase in the equity-commodity correlations. Since aggregate worldwide demand is approximated using BDSI, this result confirms the intuition that cross-market correlations increase in poor global economic conditions. Interestingly, when we decompose these results into the two sub-periods, we find that in the latter sub-period, B, all of the explanatory variables become highly significant, whereas in the former sub-period, A, only two of the variables (BDSI and VIX) are statistically significant at conventional levels. Thus, in the period characterized by increased market participation, we find that the equity-commodity correlations for the energy sub-sector are strongly determined by our macroeconomic, financial, and speculation indicators. Prior to this period, however, the determinants of the dynamic correlations are less linked to overall macroeconomic and global market conditions.

Panel B presents the results for the foods and fibers sub-sector. Only three of the explanatory variables are significant for the full sample period (VIX, YS, SPE_FOODFIB). Interestingly, the coefficient on VIX is significantly negative; however, given the findings of Silvennoinen and Thorp (2013) we would expect the sign to be positive. The overall economic significance of this change seems rather small however, as a 1% decrease in the VIX results in a mere increase of 0.001178% in the equity-commodity correlations. Furthermore, a quick comparison across the energy sub-sector shows that the coefficients on YS and SPE_FOODFIB seem to be markedly smaller, implying a much smaller overall effect on the return correlations by the regressors. Furthermore, within the two sub-periods the significance of the results dissipates. Yet, the speculation measure for the sub-sector remains significant in the latter sub-period, though it’s economic impact is decidedly smaller, a 1% increase in speculation leads to a 0.002% increase in the equity-commodity correlations. Nonetheless, this result lends some credence to the argument that increased market participation, by market speculators, is in fact a prime contributor to the increased comovement between commodity futures and equities, hence deteriorating the long-run benefits of commodity futures.

Panel C, which shows the grains and oilseeds sub-sector, displays some interesting results regarding the evolution of the determinants of the commodity-equity correlations. In the full sample period, the only coefficients which are not rendered insignificant are ADSI and YS. However, an examination of sub-period A shows that none of the factors surveyed help to explain the dynamic correlations. Yet, sub-period B reveals that all of the factors are now highly significant at conventional levels. The latter sub-period results are similar to those found in Panel A, except the coefficients are comparably smaller and the sign on the speculative variable (SPE_GRAINS) is negative, which according to prior studies using commodity indices is generally positive (as increased speculator participation increases correlations). Nonetheless, for the grains and oilseeds market a 1% decrease in speculative activity results in a 0.1289% increase in dynamic correlations between the equity and commodity futures market. This result highlights the point that outside of a commodity index setting the factors which affect the dynamic correlations between commodity futures and traditional assets are not homogenous across all futures markets.

[Insert Table 6 Here]

Panel D highlights the regression results for the livestock sub-sector. A quick inspection of the results reveals that over all sample periods only a few of the explanatory variables generally aid in explaining the dynamic equity-commodity correlations. Over the full sample period, yield spread (YS) is highly significant and positive, which is observed in all the other commodity sub-sectors examined up to this point as well. As in Panel C, the regression model does a poor job of explaining the equity-commodity correlations in sub-period A. At first glance, the explanatory variables in sub-period B also seem to do a rather inadequate job of explaining the dynamic correlations as well, as only ADSI and VIX are significant at standard confidence intervals. It is worth pointing out that the coefficient on ADSI is negative in this instance (for sub-period B), which contrasts with Buyuksahin and Robe (2013), but is more in line with the conclusions drawn by Bhardwaj and Dunsby (2013). Further inspection of the regression in Panel D shows an R-squared for the sub-period B that is over 40% (comparably, sub-period A only has an R-squared of 1.6%). Thus, while only two factors show any statistical prominence in the period characterized by increased investor participation, the two variables for the livestock sub-sector seemingly carry a lot of weight.

Finally, the results panel E, which contains the precious metals sub-sector, tells a strikingly similar story to that of the grains and oilseeds sub-sector (in Panel C). Sub-period A shows that the regression model is again quite poor in predicting the factors which determine the equity-commodity correlations, yet sub-period B shows considerable improvement. As in all sub-sectors, the coefficient on YS is positive and significant for the full sample period. However, in sub-period B, YS is statistically insignificant. Furthermore, as in Panel C, the speculation variable (SPE_PMETALS) is negative and statistically significant in the latter sub-period. This means that a 1% decrease in speculative activity actually increases the equity-commodity correlations for the sub-sector by 0.0627%. This interesting result once again highlights the heterogeneous effects of not only speculation, but also all of the determinants considered across the various sub-sectors.

Implementing the DCC model as the dependent variable reveals some very interesting results across the different commodity futures sub-sectors. In general, we see that in moving from sub-period A to sub-period B the dynamic equity-commodity return correlations are increasingly explained by our series of macroeconomic and financial market indicators. Furthermore, the effect of increased investor speculation in the market is heterogeneous across the various commodity futures sub-sectors. For both the energy and foods and fibers sub-sectors the speculation variable is positive and significant for their respective equity-commodity return correlations, in both the full and sub-sample B periods. Contrastingly, for the grains and oilseeds and precious metals sub-sectors we find the speculation variable is insignificant for the full sample period and takes a negative and significant sign in sub-period B. In the livestock sub-sector the speculation variable is insignificant in all regressions. Additionally, for the full sample period the proxy for financial stress (YS) is positive and significant for all sub-sectors. Overall, a 1% increase in the yield spread results in a 0.06%-0.15% increase in dynamic equity-commodity return correlations.

4.1.2 The Normal Copula

Table 7 presents our regression results using the normal copula correlations between the S&P 500 and the five futures sub-sectors as our dependent variable. The normal copula is a symmetrical dependence structure which allows for no tail dependence and provides in many senses a more robust measure of the return comovement. Panel A summarizes our findings for the energy sub-sector. In general, we find a similar pattern the normal copula and the DCC results for the sub-sector. The significance of the results do not vary much, although we do note that the ADSI variable becomes (marginally) insignificant for the full sample and SPE_ENERGY becomes significant, although negative, in sub-period A. The magnitude of the relevant coefficients seem to decrease for both the full sample and sub-sample B in comparison to the results in Table 6, Panel A. Overall results here illuminate the unique fact that the returns of the energy sub-sector and equity market both seem to be highly intertwined and determined via broad market macroeconomic and financial market indicators, in addition to speculative activity.

Interestingly, the regression results of Panel B differ quite a bit from those of the DCC (baseline) model. In the normal copula case, only YS is significant (and positive) for the full sample period. However, the most prominent changes come in evaluating the results in sub-period B. The variables ADSI, VIX, and YS all become highly significantly positive for the normal copula, though the magnitudes of the coefficients seem economically small in comparison to other sub-sectors. Furthermore, the normal copula distribution provides a much higher R-squared in sub-sample B. The normal copula based findings paint an overall picture of increased integration among the factors which drive the equity-commodity return correlations.

The results of Panels C and D, which summarize the grains and oilseeds and livestock sub-sectors, respectively, do not dramatically differ from those found in Table 6, both the magnitude and sign of the coefficients are relatively unchanged. The only major difference is that the YS coefficient becomes significantly positive in sub-period A of the livestock sub-sector. Regarding grains and oilseeds, the speculation variable, interestingly, remains significantly negative, indicating that a 1% decrease in speculative activity results in a 0.1031% increase in the equity-commodity return correlations. Results based on the dynamic copula correlations for the two sub-sectors also highlight the heterogeneous effects of the broad market indicators. Furthermore, they also detail a story of increased integration among the deterministic return factors between the equity and commodity futures market, though the copula based results tend to be less acute.

The results for Panel E, the precious metals sub-sector, are markedly different from the DCC baseline case, as in the foods and fibers sub-sector (Panel B). The entire set of coefficients are rendered insignificant for the full sample period. Yet, in sub-sample A, we find that three of our choice variables (ADSI, BDSI, and YS) all become statistically significant, however, two of them are of the opposite than expected sign (ADSI and YS). We document that a 1% decrease ADSI, BDSI, and YS results in an increase of 0.0268%, 0.00870%, and 0.0643%, respectively, in equity-commodity return correlations. Sub-period B displays similar results to our baseline case, though the coefficients seem to be of a slightly smaller magnitude, and our speculation variable is now rendered insignificant. Panel E provides an interesting point for analysis, the fact that ADSI and YS are of the negative sign in sub-period A, but of the positive sign in sub-period B, highlights an evolution of the determinants in the particular sub-sector. This is particularly intriguing given that it has been well-documented that equity-commodity return correlations have been increasing over time, and as a result many have posited that commodity futures may no longer preserve their once sought after benefits. Panel E brings to light some interesting points to this debate. For example, the macroeconomic conditions variable (ADSI) shows that during the period October 1992 to May 2003 a 1% decrease in the macroeconomic conditions results in an increase of 0.0268% in commodity-equity return correlations, and vice versa. However, over the period June 2003 to October 2013, the effect is the opposite, a 1% increase in macroeconomic conditions increases the commodity-equity return correlations by 0.0304%, and vice versa. Given that equity markets tend to prosper during economic booms, sub-period A underlies the fact that when equity returns were increasing, returns in the precious metals sub-sector were not commoving with them. Alternatively, when economic times were poor and equity markets were retrogressing, the commodity futures returns were moving in the opposite direction. Hence, the sub-sector returns were acting as a type of diversifying tool. A similar story can be made for YS, though it turns out to be insignificant in sub-period B. In sub-period A this effect has disappeared, coinciding with the literature which posits that the recent financialization and increased participation has otherwise diminished the benefits of commodity futures.

[Insert Table 7 Here]

Overall, the results using the normal copula correlations as the dependent variable reveal some similarities and interesting differences from the DCC baseline case. It is clear that the broad market macroeconomic and financial indicator variables, which are generally associated with traditional asset (equity) market return fluctuations, have become similar type determinants of commodity returns over time, hence providing a measure of increasing return comovement. These findings support the financialization of commodity futures argument and show that over the last decade or so, these broad market indicator variables now help to explain the sub-sectors comovement with the traditional equity market. Additionally, the results also point out that the equity-commodity return correlations tend to increase in times of market distress (as proxied by YS), a downfall in global economic conditions (as proxied by BDSI), and periods of domestic market uncertainty (proxied by VIX), particularly over the full and sub-sample B periods. These findings seemingly imply that commodity futures returns act less like a hedge or diversifying tool than the used too. However, our analysis also reveals that the magnitude and significance of these effects is, again, heterogeneous across sub-sectors.

4.1.3 The Student's t Copula

Table 8 presents our regression results using the student's t copula correlations between the S&P 500 and the futures sub-sectors as our dependent variable. The student's t copula is a symmetrical but non-zero tail dependence structure which nests the normal copula. Panel A summarizes our findings for the energy sub-sector. Overall, regression results closely mirror that of the DCC baseline approach. Noticeably, however, the coefficient for the speculation factor (SPE_ENERGY) is quite larger under the student's t copula correlations, implying a greater role for speculation regarding the equity-commodity correlations. The results also reveal a larger R-squared for both the full sample and sub-period B. The overall consistency of the findings for the energy sub-sector across all correlation measures solidify our findings that its returns with the equity market are strongly determined by all of our broad macroeconomic and financial indicators, as well as excess speculative activity. Furthermore, there is an evolution of the deterministic factors as seen by the change in significance and sign of the coefficients across the two sub-periods. This observation also gives credence to the financialization of commodities argument, in which large capital inflows to the energy sub-sector have integrated its prices with the overall financial markets, hence distorting their behavior.

Contrastingly, Panel B results, for the foods and fibers sub-sector, resemble a blend of both the DCC and normal copula findings. Allowing for symmetrical tail dependence gives the highest R-squared (approximately 38%) for the full sample period out of all dependence measures considered. We also see that all explanatory variables are highly significant in explaining the dynamic equity-commodity return correlations, whereas in the case of the normal copula only the variable YS is significant at conventional levels. The results of sub-period A are equivalent to those of the normal copula in Table 7, but in sub-period B we observe that ADSI, VIX, and SPE_FOODFIB have lost their explanatory power (when compared to the normal copula correlations), yet YS and ADSI remain significant and the coefficient magnitudes remain largely the same. The regression results using the student's t copula correlations for the foods and fibers sub-sector in some sense lend themselves to the idea that the sub-sectors' return properties are still somewhat segmented from the equity market return determinants given the relatively weak results in sub-period B. However, in another sense, the correlations show that the macroeconomic and financial indicator variables are relatively important deterministic factors for the entire sample period. The results of the sub-sector appear to be particularly sensitive to the measure of dependence. Nonetheless, taking the results of both the normal and student's t copulas together tells a story, to some degree, of increasing integration between the deterministic factors for the two asset markets.

Panels C and D, of the grains and oilseeds and livestock sub-sectors, strongly resemble those found in both Tables 6 and 7. Results indicate that regardless of the dependence measure used, the deterministic factors of the equity-commodity return correlations largely remain unchanged. Interestingly, the negative coefficient for the speculation variable in Panel C is still significant using yet another correlation measure, hence providing a sense of robustness for this incongruous result. Overall findings provide considerable credence to the observation that while the determinants of the grains and oilseeds sub-sector have become more integrated with those of the equity markets, as seen by the considerable change in its return dependence factors, the determinants of the livestock sub-sector seem to remain, in part, more segmented from those of the equity markets.

[Insert Table 8 Here]

Panel E, the precious metals sub-sector, presents results which are more similar to those in Table 6 than in Table 7. It is clear once again, for this particular sub-sector, that the equity-commodity return correlations between the period October 1992 and May 2003 are largely unexplained by any macroeconomic or financial market variables. However, the post-May 2003 period is much more strongly associated with the macroeconomic conditions, and to a lesser extent, financial market indicators. As seen in Table 7, the speculation factor (which was negative and significant in Table 6) is again rendered insignificant in this regression setting.

Given the findings from Table 8, as well as those in Tables 6 and 7, it can be concluded that the factors which explain the equity-commodity return correlations for the energy, grains and oilseeds, precious metals, and to a lesser degree the foods and fibers sub-sector, have significantly changed over the last decade. The return correlations between the two different asset classes have become increasingly explained by both macroeconomic and financial market variables. However, the inferences regarding the foods and fibers sub-sector seems to be sensitive to the dependence measure used. The livestock sub-sector appears to display a somewhat different dynamic correlations pattern with the equity market in that their return dependence is not explained by the broad macroeconomic, financial, or speculation variables. Overall, the determinants of the sub-sectors equity-commodity correlations display the slightest overall trend toward increasing market integration. Moreover, the sign and significance of the regression coefficients in Table 8 supplement the conclusions of Tables 6 and 7, in that the variables which relate to local market distress (YS), uncertainty (VIX), and global financial market destabilization (BDSI) imply that commodity futures returns act less like a hedge as equity-commodity returns increase in such instances. Yet, again, the magnitude and significance of these effects is heterogeneous across sub-sectors.

4.1.4 The Rotated-Gumbel Copula

Table 9 presents our regression results using the rotated-gumbel copula correlations between the S&P 500 and the futures sub-sectors as our dependent variable. The rotated-gumbel copula is a left tail, non-linear, asymmetrical dependence structure, which is mostly present during extreme negative events. Panel A summarizes our findings for the energy sub-sector. In general, the findings reveal a similar pattern to the DCC model, normal copula, and student's t copula in the prior tables. This is interpreted to mean that the factors which drive the equity-commodity return dependence relationship under the previous dependence structures examined are very similar to those which drive the time-varying relationship in left-tail crises situations. However, the overall explanatory power of the model does decrease for both the full sample period and sub-period B. The foods and fibers sub-sector, in Panel B, consistently shows that the VIX and yield spread (YS) are important determinants of the left-tail dynamic dependence structure for both the full and sub-sample periods. Fascinatingly, the coefficients in the two sub-periods change sign. Regardless, the small R-squared for all sample periods suggests that these explanatory variables matter much little when only left tail dependence is analyzed.

Focusing on sub-period B, of the grains and oilseeds sub-sector, in Panel C, it can be seen that the magnitude of the coefficients is markedly smaller than those found in the prior tables, though significance levels remain largely unchanged. In addition, the R-squared of the model is considerably lower than what was found in the prior tables. Similar to the interpretation of the overall results in Panel B, this means that while these factors do help to explain the dynamic equity-commodity correlations when analyzing the lower tail dependence, they do not have the substantial impact found under more general or symmetric dependence models.

[Insert Table 9 Here]

The results of Panel D, the livestock sub-sector, show a substantial increase in the significance of the variables which explain the dynamic correlations structure, though similar to the other panels in that the R-squared remains low and the magnitude of the coefficients are smaller. Overall, we see that BDSI and VIX are highly negatively significant, and the YS variable is positive and significant for the full sample period. However, in sub-period B we see that only BDSI remains significant (in addition to ADSI which takes a negative value). The precious metals sub-sector, in Panel E, seems to moderatey resemble the findings from the DCC model.

Overall, regression results pertaining to the rotated-gumbel dependence structure seem to indicate that across the full sample and two sub-periods macroeconomic and financial market variables are important in determining the equity-commodity dynamic correlations in crisis situations. However, the overall explanatory power of the relevant variables seems to be substantially reduced. Most importantly, these results, similar to our prior findings, reflect the fact that the impact of the explanatory variables across the different sub-sectors is heterogeneous both in terms of magnitude and sign.

5. CONCLUDING REMARKS

In this paper, we calculate the dynamic dependence structure between the returns of five commodity futures sub-sectors—energy, foods and fibers, grains and oilseeds, livestock, and precious metals—and two different well-known equity market indices—S&P 500 and Russell 3000. We then investigate the determinants of these dynamic dependence structures via regression analysis using several comprehensive macroeconomic, financial market, and speculation variables over several sample periods. We employ the well-known DCC model as a baseline approach to our investigation of the determinants of the equity-commodity correlations, as well as three time-varying copulas. We analyze (i) the normal copula—a symmetrical and frequent dependence structure which has no tail dependence, (ii) the student's t copula—a symmetrical but non-zero tail dependence structure which nests the normal copula, and (iii) the rotated-gumbel copula—a left tail, non-linear, asymmetrical dependence structure. Practically speaking, these copulas represent the most relevant shapes for finance and are frequently used in empirical papers.

Prior empirical literature, which examines periods leading up to 2008, conclude that conditional dynamic correlations between equity and commodity futures are not significantly different from zero, have shown a tendency to decrease over time, or are lower during periods of high financial stress (see Chong and Miffre, 2010; Buyuksahin et al., 2010). Furthermore, they find no significant evidence of financialization of commodity futures markets with more traditional asset markets, suggesting the highly touted diversification and investment benefits of commodity futures are still intact. Our results substantially differ from these conclusions and find merit within the work of Buyuksahin and Robe (2011), Silvennoinen and Thorp (2013), and Buyiksahin and Robe (2013) who document an increase in equity-commodity markets.

We find that while copulas offer a more robust measure of time-varying dependence, there are several similarities between the DCC model and the copula dependence measures. We document that the equity-commodity correlations for the energy, grains and oilseeds, precious metals, and to a lesser extent the foods and fibers sub-sectors have become increasingly explainable by macroeconomic and financial market indicators, particularly after the period May 2003. We largely attribute the change in predictive variables to the financialization of the commodity futures market. The determinants of the livestock sub-sector seem to exhibit the least increase in integration with the equity market determinants. Additionally, we document that increased participation by financial market speculators is not a primary determinant for all sub-sectors' dynamic equity-commodity correlations. Furthermore, the macroeconomic, financial, and speculation variables exhibit heterogeneous effects in terms of significance, magnitude, and sign. We also document that the macroeconomic and financial market variables play a much broader role in determining the dynamic correlations structure for the lower tail dependence of the equity-commodity return correlations, though the magnitude and explanatory power is seemingly much smaller than under the other copula distributions.

Recent research has documented an increase in equity-commodity correlations over the last decade. Further, we show a noticeable change in the determinants of the equity-commodity correlations, in which broad macroeconomic and financial market variables become highly relevant in predicting the dynamic correlations. Moreover we find that, in general, the sign and significance of the coefficients for the variables which relate to local equity market distress (YS), equity market uncertainty (VIX), and global financial market depressions (BDSI), particularly in more recent years, signal that equity-commodity return correlations increase during these instances, suggesting that commodity futures act less like a hedge or diversification tool. However, the magnitude (and occasionally significance) of these effects is heterogeneous across sub-sectors. This has interesting implications for non-index commodity futures investors. Given that not all sub-sectors are equally affected by the broad macroeconomic, financial market, and speculation variables, which generally play a strong role in traditional equity market pricing, we posit that for certain sub-sectors, such as livestock (or to a lesser degree foods and fibers), the potential benefits which commodity futures offer portfolio investors may be stronger.

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Table 1

Copula Distributions

	Copula	Parameter Range
Normal		
	$C_N(u, v; \rho) = \Phi_\rho\left(\Phi^{-1}\left(F_1(X_{1t})\right), \Phi^{-1}\left(F_2(X_{2t})\right)\right)$	$\rho \,\epsilon(-1{,}1)$
Student's t		
	$C_t(u, v; \rho, d) = t_{d,\rho}\left(t_d^{-1}\left(F_1(X_{1t})\right), t_d^{-1}\left(F_2(X_{2t})\right)\right)$	$\rho \,\epsilon(-1{,}1)$
Rotated-Gumbel		
	$C_{RG}(u, v; \delta) = F_1(X_{1t}) + F_2(X_{2t}) - 1 + \ e^{\left\{-\left[\left(-\ln\left(F_1(X_{1t})\right)\right)^{\delta} + \left(-\ln\left(F_2(X_{2t})\right)\right)^{\delta}\right]^{\frac{1}{\delta}}\right\}}$	$\delta \,\epsilon[1, \infty)$

Note. This table provides the various distributions for the copulas examined. For the normal copula, Φ^{-1} is the inverse of the cumulative distribution function (CDF) of a standard normal distribution, and the dependence parameter ρ is the Pearson's correlation coefficient, where the value 1 or -1 indicates complete dependence and 0 indicates complete independence. For the student's t copula, if the dependence parameter, ρ, takes the value 1 or -1 it indicates complete dependence, and 0 indicates complete independence. Both the left (lower) tail and right (upper) tail dependence measures take the form $2t_{d+1}\left(-\sqrt{\frac{(d+1)(1-\rho)}{1+\rho}}\right)$. For the rotated-gumbel copula, the dependence parameter, δ, takes the value of 1 for the case of independence and does not allow for negative dependence. The left (lower) tail dependence measure takes the form $2 - 2^{\frac{1}{\delta}}$.

Table 2

Commodity Futures Groupings and Equity Indices

Panel A: Commodity Sub-sectors	
Commodity Futures	CRB Symbol
Energy	
Crude Oil, Brent	CB
Heating Oil #2	HO
Unleaded Gasoline	HU/RB
Natural Gas	NG
Foods & Fibers	
Cocoa	CC
Coffee	KC
Orange Juice	OJ
Sugar	SB
Cotton	CT
Lumber	LB
Grains & Oilseeds	
Corn	C_
Oats	O_
Soybeans	S_
Soybean Meal	SM
Soybean Oil	BO
Wheat	W_
Livestock	
Feeder Cattle	FC
Live Cattle	LC
Lean Hogs	LH
Precious Metals	
Gold	GC
Palladium	PA
Platinum	PL
Silver	SI

Panel B: Equity Indices	
Financial Index	BLM Symbol
S&P 500	SPX
Russell 3000	RAY

Note. This table provides an overview of the various commodity futures and equity indices examined. Panel A displays the composition of the five commodity futures sub-sectors and their respective Commodity Research Bureau (CRB) symbols. Panel B displays the two equity indices and their respective Bloomberg (BLM) symbols.

Table 3

Summary Statistics for Weekly Rates of Return for Equity Indices and Commodity Futures Sub-sectors (October 1992 - October 2013)

Panel A: Equity Indices

	S&P 500 Index	Russell 3000 Index
Mean	0.000567	0.000593
Median	0.001232	0.001436
Maximum	0.034318	0.034609
Minimum	-0.053787	-0.054679
Std. Dev.	0.008138	0.008344
Skewness	-0.665001	-0.730486
Kurtosis	6.772715	6.84484
Obs.	1111	1111

Panel B: Commodity Futures Sub-sectors

	Energy	Foods & Fibers	Grains & Oilseeds	Livestock	Precious Metals
Mean	0.000619	0.000328	0.000317	0.000232	0.000622
Median	0.001756	0.000181	-0.000033	0.000168	0.000965
Maximum	0.097980	0.043599	0.036699	0.029603	0.040602
Minimum	-0.067262	-0.061074	-0.058338	-0.034269	-0.054108
Std. Dev.	0.014677	0.012034	0.010841	0.007169	0.010641
Skewness	-0.225218	-0.022605	-0.175441	0.030680	-0.898585
Kurtosis	5.537885	4.354079	4.525559	4.710997	6.409541
Obs.	1111	1111	1111	1111	1111

Note. This table provides the summary statistics for the weekly rates of return for both equity indices and commodity futures sub-sectors over the period October 1992 to October 2013. Panel A displays the summary statistics for the unlevered rates of return for the S&P 500 and Russell 3000 index. All equity data is retrieved from Bloomberg. Equity index returns are calculated by taking the average value of daily index returns each week (Tuesday-Tuesday) and then taking the log difference on two consecutive weeks. Panel B displays the summary statistics for the rates of return for the various commodity futures sub-sectors. All commodity futures data is taken from the Commodity Research Bureau (CRB). Returns are calculated by taking the average value of daily individual commodity futures returns each week (Tuesday-Tuesday) and then taking the log difference on two consecutive weeks; the commodity futures sub-sectors returns are then calculated by taking an equally-weighted average of all weekly futures returns which comprise that particular sub-sector. One month prior to the expiration of each individual commodity futures contract we roll the futures price series over to the next-nearby futures contract.

Table 4

Summary Statistics for Time-Varying Correlation Measures between S&P 500 and Commodity Futures Sub-sectors (October 1992 - October 2013)

Panel A: Dynamic Conditional Correlations

	Energy	Foods & Fibers	Grains & Oilseeds	Livestock	Precious Metals
Mean	0.112896	0.129899	0.147074	0.067554	0.153452
Median	0.090886	0.130023	0.138171	0.065595	0.128660
Maximum	0.660127	0.289600	0.486961	0.555829	0.429127
Minimum	-0.395513	-0.046378	-0.177646	-0.185068	-0.068403
Std. Dev.	0.210793	0.072639	0.111749	0.080484	0.096989
Skewness	0.358478	-0.071368	0.016442	0.428084	0.708765
Kurtosis	2.817332	2.230820	2.779197	5.736523	3.015350
Obs.	1111	1111	1111	1111	1111
ADF level	-3.326754	-3.649157	-6.445035	-11.08973	-3.121095
ADF first diff.	-32.37508	-34.10594	-35.88812	-27.37567	-35.54447

Panel B: Normal Copula

	Energy	Foods & Fibers	Grains & Oilseeds	Livestock	Precious Metals
Mean	0.102890	0.127444	0.145129	0.067872	0.145482
Median	0.102108	0.124796	0.134144	0.064911	0.139893
Maximum	0.702986	0.360722	0.600300	0.432954	0.389318
Minimum	-0.414978	-0.076891	-0.236682	-0.174945	-0.123528
Std. Dev.	0.161305	0.052029	0.113093	0.072873	0.095861
Skewness	0.176781	0.076367	0.178573	0.601619	-0.000826
Kurtosis	4.069621	4.546517	3.633895	4.891108	2.635257
Obs.	1111	1111	1111	1111	1111
ADF level	-3.882332	-4.753266	-4.41872	-4.977293	-4.282546
ADF first diff.	-12.62296	-11.68946	-12.38269	-12.28725	-6.720328

Table 4 (cont.)

Summary Statistics for Time-Varying Correlation Measures between S&P 500 and Commodity Futures Sub-sectors (October 1992 - October 2013)

Panel C: Student's t-Copula

	Energy	Foods & Fibers	Grains & Oilseeds	Livestock	Precious Metals
Mean	0.123035	0.130249	0.151095	0.062444	0.147587
Median	0.085991	0.126618	0.151878	0.066166	0.131139
Maximum	0.662269	0.255172	0.491013	0.484562	0.435056
Minimum	-0.346019	-0.011289	-0.261398	-0.256117	-0.111110
Std. Dev.	0.214536	0.064784	0.140142	0.085255	0.115860
Skewness	0.561404	-0.070590	-0.169885	-0.190318	0.410189
Kurtosis	2.710581	1.945138	2.528013	3.944503	2.676566
Obs.	1111	1111	1111	1111	1111
ADF level	-2.418798	-1.692214	-6.607289	-14.27148	-3.44223
ADF first diff.	-31.92838	-33.53095	-35.56077	-15.7413	-35.33084

Panel D: Rotated-Gumbel Copula

	Energy	Foods & Fibers	Grains & Oilseeds	Livestock	Precious Metals
Mean	1.122599	1.082921	1.109963	1.030981	1.134628
Median	1.076721	1.082988	1.085280	1.021985	1.104915
Maximum	1.915124	1.100000	2.003947	1.294450	1.665708
Minimum	1.000100	1.073021	1.000100	1.000100	1.008838
Std. Dev.	0.127919	0.003298	0.100108	0.032059	0.112457
Skewness	1.379595	0.039253	1.493811	2.055222	2.634830
Kurtosis	5.028883	3.616748	8.623976	10.292510	10.646910
Obs.	1111	1111	1111	1111	1111
ADF level	-4.710499	-5.848515	-6.320574	-9.806826	-3.179535
ADF first diff.	-15.89283	-11.10609	-14.00002	-15.30717	-7.977814

Note. This table provides the summary statistics for the time-varying correlation measures between the S&P 500 and the five commodity futures sub-sectors over the full sample period (October 1992 to October 2013). Panel A provides the dynamic conditional correlations (DCC), while panels B, C, and D provide the correlations from normal, student's t, and rotated-gumbel copulas, respectively.

Table 5

Summary Statistics for Macroeconomic, Financial Market, and Speculation Variables (October 1992 - October 2013)

Panel A: Macroeconomic Variables

	Aruoba-Diebold-Scotti Index (ADSI)	Baltic Dry Shipping Index (BDSI)
Mean	-0.149949	2356.17
Median	-0.04516	1562
Maximum	1.80186	11573.4
Minimum	-3.9308	653.6
Std. Dev.	0.752847	1964.654
Skewness	-2.059075	2.253964
Kurtosis	9.81295	8.393444
Obs.	1111	1111
ADF level	-3.175834	-2.873605
ADF first diff.	-13.3703	-13.58968

Panel B: Financial Market Variables

	Market Volatility Index (VIX)	Yield Spread (YS)
Mean	20.39216	0.968392
Median	18.922	0.864
Maximum	72.72	3.448
Minimum	9.5775	0.526
Std. Dev.	8.32451	0.445833
Skewness	1.906206	3.044224
Kurtosis	9.05619	14.63892
Obs.	1111	1111
ADF level	-4.223237	-3.323553
ADF first diff.	-31.81519	-12.30402

Table 5 (cont.)

Summary Statistics for Macroeconomic, Financial Market, and Speculation Variables (October 1992 - October 2013)

Panel C: Sub-sector Excess Speculation Measures

	Energy (SPE_ENERGY)	Foods & Fibers (SPE_FOODFIB)	Grains & Oilseeds (SPE_GRAINS)	Livestock (SPE_LIVESTK)	Precious Metals (SPE_PMETALS)
Mean	0.333579	1.049820	1.052079	1.289389	0.489811
Median	0.226707	0.958957	0.778949	1.091181	0.450626
Maximum	0.949566	4.567558	13.753700	6.753103	1.450270
Minimum	0.000000	0.109335	0.234880	0.320550	0.071367
Std. Dev.	0.246275	0.477917	1.250135	0.729180	0.225018
Skewness	0.572599	1.947755	5.326990	2.175143	1.086559
Kurtosis	1.916844	10.410460	36.967110	10.532740	4.322239
Obs.	1111	1111	1111	1111	1111
ADF level	-4.018553	-5.845926	-9.445349	-7.066214	-7.437826
ADF first diff.	-26.27717	-25.95324	-14.2246	-31.94541	-31.70099

Note. This table provides the summary statistics for the macroeconomic, financial, and speculation variables over the period October 1992 to October 2013. Panel A displays the summary statistics of the weekly macroeconomic variables, the Aruoba-Diebold-Scotti Index (ADSI) tracks real business conditions at a high frequency and the Baltic Dry Shipping Index (BDSI) provides an assessment of the price of moving major raw commodity materials by sea. Panel B displays the summary statistics for the weekly financial market variables, the market volatility index (VIX) represents the market's expectation of stock market volatility and the Yield Spread (YS) is the difference between Moody's Aaa and Baa corporate bond yields, which represents a reflection of the overall broad corporate economy (and therefore credit quality and financial stress). Panel C displays the summary statistics regarding the calculation of the excess speculation index for each commodity futures sub-sector. Excess speculation for each individual commodity futures series is calculated via Working's "T" method based on weekly (Tuesday-Tuesday) speculation data provided by the US Commodity Futures Trading Commission (CFTC), and then aggregated to its respective sub-sector. The variables SPE_ENERGY, SPE_FOODFIB, SPE_GRAINS, SPE_LIVESTK, and SPE_PMETALS represent speculation in the energy, foods & fibers, grains & oilseeds, livestock, and precious metals commodity futures sub-sectors, respectively.

Table 6
Determinants of Dynamic Conditional Correlations between the S&P 500 and Commodity Futures Sub-sectors

	Oct. 1992 - Oct. 2013 (Full Sample Period)	Oct. 1992 - May 2003 (Sub-period A)	June 2003 - Oct. 2013 (Sub-period B)
Panel A: Energy			
Constant	0.8664	0.3754	0.0700
	(4.09)	(3.43)	(0.30)
ADSI	0.0838	-0.0068	0.1680
	(3.44)	(-1.29)	(6.26)
Log(BDSI)	-0.3531	-0.0870	-0.3038
	(-7.53)	(-2.96)	(-5.52)
Log(VIX)	0.0948	-0.0560	0.6800
	(1.22)	(-2.76)	(6.75)
YS	0.1492	-0.0007	0.1808
	(3.93)	(-0.06)	(3.78)
SPE_ENERGY	0.4429	-0.0730	0.2855
	(6.69)	(-1.18)	(2.76)
R^2	0.4672	0.0314	0.6032
Panel B: Foods & Fibers			
Constant	0.0654	0.0690	0.2246
	(0.73)	(2.00)	(24.40)
ADSI	0.0131	-0.0027	-0.0008
	(1.20)	(-1.39)	(-0.74)
Log(BDSI)	0.0293	-0.0091	-0.0012
	(1.36)	(-1.00)	(-0.59)
Log(VIX)	-0.1178	-0.0107	0.0075
	(-3.55)	(-1.57)	(1.35)
YS	0.0963	-0.0030	-0.0015
	(5.70)	(-0.46)	(-0.67)
SPE_FOODFIB	0.0268	-0.0002	0.0020
	(2.74)	(-0.14)	(2.06)
R^2	0.2535	0.0107	0.0153

Table 6 (cont.)

Determinants of Dynamic Conditional Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel C: Grains & Oilseeds			
Constant	0.1543	-0.1155	0.3955
	(1.14)	(-0.65)	(2.13)
ADSI	0.0357	0.0111	0.0836
	(2.58)	(1.02)	(3.96)
Log(BDSI)	-0.0233	0.0734	-0.1207
	(-0.74)	(1.40)	(-2.69)
Log(VIX)	-0.0386	-0.0209	0.1554
	(-0.63)	(-0.37)	(1.65)
YS	0.1258	0.0076	0.1473
	(5.90)	(0.23)	(3.61)
SPE_GRAINS	0.0016	0.0013	-0.1289
	(0.36)	(0.47)	(-3.63)
R^2	0.1188	0.0255	0.3499
Panel D: Livestock			
Constant	-0.0491	-0.2948	-0.0790
	(-0.66)	(-1.17)	(-0.68)
ADSI	0.0018	0.0138	-0.0286
	(0.25)	(1.11)	(-1.78)
Log(BDSI)	0.0015	0.0670	-0.0186
	(0.10)	(0.98)	(-0.65)
Log(VIX)	0.0361	0.0425	0.1699
	(1.10)	(0.77)	(3.06)
YS	0.0595	0.0561	0.0360
	(3.24)	(1.61)	(1.05)
SPE_LIVESTK	0.0063	0.0047	-0.0101
	(1.24)	(0.57)	(-1.20)
R^2	0.1198	0.0159	0.4034

Table 6 (cont.)

Determinants of Dynamic Conditional Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel E: Precious Metals			
Constant	-0.0068	0.0377	0.3272
	(-0.05)	(10952.00)	(2.58)
ADSI	0.0254	0.0000	0.0533
	(1.70)	(-0.042)	(3.85)
Log(BDSI)	0.0132	0.0000	-0.1080
	(0.49)	(-0.82)	(-3.76)
Log(VIX)	0.0416	0.0000	0.3203
	(0.88)	(-0.54)	(3.74)
YS	0.0574	0.0000	-0.0333
	(2.38)	(-0.40)	(-1.03)
SPE_PMETALS	0.0241	0.0000	-0.0627
	(0.94)	(0.59)	(-1.79)
R^2	0.0449	0.0026	0.3804

Note. This table provides the ordinary least squares (OLS) regression results for each of the commodity futures sub-sectors over the full sample period (October 1992 to October 2013) and two sub-periods (October 1992 to May 2003 and May 2003 to October 2013). In panels A, B, C, D, and E the dependent variable is the time-varying dynamic conditional correlation (DCC) between the weekly rates of return on the S&P 500 equity index and the equally-weighted weekly futures returns on the energy, foods & fibers, grains & oilseeds, livestock, and precious metals sub-sectors, respectively. The variables ADSI, BDSI, VIX, and YS represent the Aruoba-Diebold-Scotti Index, the Baltic Dry Shipping Index, the market volatility index, and yield spread, respectively. The variables SPE_ENERGY, SPE_FOODFIB, SPE_GRAINS, SPE_LIVESTK, and SPE_PMETALS represent speculation in the energy, foods & fibers, grains & oilseeds, livestock, and precious metals commodity futures sub-sectors, respectively. In all sample periods, Newey-West t-statistics are reported in parentheses below the corresponding coefficients, along with the R^2 of the regression.

Table 7
Determinants of Normal Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

	Oct. 1992 - Oct. 2013 (Full Sample Period)	Oct. 1992 - May 2003 (Sub-period A)	June 2003 - Oct. 2013 (Sub-period B)
Panel A: Energy			
Constant	0.4825	0.6770	0.0142
	(2.82)	(4.44)	(0.06)
ADSI	0.0313	-0.0110	0.1317
	(1.62)	(-1.51)	(5.04)
Log(BDSI)	-0.1956	-0.1746	-0.2319
	(-4.95)	(-4.13)	(-4.40)
Log(VIX)	0.0719	-0.0854	0.5585
	(1.02)	(-3.20)	(5.04)
YS	0.1175	-0.0012	0.1775
	(3.04)	(-0.07)	(3.33)
SPE_ENERGY	0.1766	-0.1571	0.1843
	(3.33)	(-2.10)	(1.78)
R^2	0.2730	0.0457	0.5380
Panel B: Foods & Fibers			
Constant	0.0717	-0.1896	0.1135
	(1.45)	(-1.60)	(2.32)
ADSI	0.0028	0.0101	0.0135
	(0.50)	(1.28)	(2.58)
Log(BDSI)	0.0090	0.0445	-0.0002
	(0.73)	(1.41)	(-0.01)
Log(VIX)	-0.0127	0.0655	0.0577
	(-0.66)	(2.60)	(2.43)
YS	0.0354	-0.0145	0.0282
	(3.37)	(-0.75)	(2.52)
SPE_FOODFIB	0.0084	0.0001	0.0150
	(1.22)	(0.02)	(2.38)
R^2	0.0792	0.0569	0.1733

Table 7 (cont.)

Determinants of Normal Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel C: Grains & Oilseeds			
Constant	0.0548	-0.0663	0.1793
	(0.41)	(-0.40)	(0.96)
ADSI	0.0406	0.0140	0.0768
	(3.10)	(1.36)	(3.84)
Log(BDSI)	-0.0099	0.0561	-0.0858
	(-0.32)	(1.14)	(-1.93)
Log(VIX)	0.0084	-0.0182	0.2246
	(0.13)	(-0.31)	(2.17)
YS	0.1219	0.0128	0.1304
	(4.92)	(0.40)	(3.13)
SPE_GRAINS	0.0001	0.0006	-0.1031
	(0.02)	(0.21)	(-3.09)
R^2	0.1168	0.0211	0.2816
Panel D: Livestock			
Constant	-0.0275	0.0022	-0.0692
	(-0.40)	(0.01)	(-0.48)
ADSI	0.0003	-0.0214	-0.0367
	(0.04)	(-1.41)	(-1.83)
Log(BDSI)	-0.0002	-0.0419	-0.0215
	(-0.02)	(-0.48)	(-0.59)
Log(VIX)	0.0291	0.0174	0.1672
	(0.95)	(0.24)	(2.34)
YS	0.0570	0.1588	0.0234
	(3.25)	(3.70)	(0.53)
SPE_LIVESTK	0.0029	-0.0095	-0.0141
	(0.62)	(-1.02)	(-1.25)
R^2	0.1421	0.2429	0.2859

Table 7 (cont.)

Determinants of Normal Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel E: Precious Metals			
Constant	0.0059	0.3020	0.1849
	(0.05)	(1.91)	(2.04)
ADSI	0.0100	-0.0268	0.0304
	(0.58)	(-2.66)	(2.85)
Log(BDSI)	0.0061	-0.0870	-0.0551
	(0.23)	(-1.90)	(-2.53)
Log(VIX)	0.0632	0.0504	0.2173
	(1.30)	(1.57)	(3.19)
YS	0.0354	-0.0643	0.0006
	(1.44)	(-2.78)	(0.02)
SPE_PMETALS	0.0119	-0.0173	0.0021
	(0.49)	(-1.37)	(0.10)
R^2	0.0376	0.1568	0.2118

Note. This table provides the ordinary least squares (OLS) regression results for each of the commodity futures sub-sectors over the full sample period (October 1992 to October 2013) and two sub-periods (October 1992 to May 2003 and May 2003 to October 2013). In panels A, B, C, D, and E the dependent variable is the time-varying normal copula correlation between the weekly rates of return on the S&P 500 equity index and the equally-weighted weekly futures returns on the energy, foods & fibers, grains & oilseeds, livestock, and precious metals sub-sectors, respectively. The variables ADSI, BDSI, VIX, and YS represent the Aruoba-Diebold-Scotti Index, the Baltic Dry Shipping Index, the market volatility index, and yield spread, respectively. The variables SPE_ENERGY, SPE_FOODFIB, SPE_GRAINS, SPE_LIVESTK, and SPE_PMETALS represent speculation in the energy, foods & fibers, grains & oilseeds, livestock, and precious metals commodity futures sub-sectors, respectively. In all sample periods, Newey-West t-statistics are reported in parentheses below the corresponding coefficients, along with the R^2 of the regression.

Table 8

Determinants of Student's t Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

	Oct. 1992 - Oct. 2013 (Full Sample Period)	Oct. 1992 - May 2003 (Sub-period A)	June 2003 - Oct. 2013 (Sub-period B)
Panel A: Energy			
Constant	1.0229	0.3580	0.3118
	(5.05)	(3.61)	(1.37)
ADSI	0.0875	-0.0062	0.1657
	(3.94)	(-1.29)	(6.07)
Log(BDSI)	-0.3938	-0.0792	-0.3826
	(-8.66)	(-2.92)	(-6.81)
Log(VIX)	0.0874	-0.0539	0.7034
	(1.15)	(-2.87)	(5.94)
YS	0.1054	0.0021	0.1117
	(2.76)	(0.19)	(1.88)
SPE_ENERGY	0.5449	-0.0584	0.4033
	(8.32)	(-0.99)	(4.67)
R^2	0.5285	0.0252	0.6566
Panel B: Foods & Fibers			
Constant	0.0413	-0.1741	0.2120
	(0.58)	(-1.78)	(2.62)
ADSI	0.0233	0.0102	0.0194
	(3.19)	(1.48)	(2.36)
Log(BDSI)	0.0436	0.0429	-0.0009
	(2.68)	(1.60)	(-0.04)
Log(VIX)	-0.1464	0.0624	-0.0194
	(-5.32)	(2.93)	(-0.57)
YS	0.1121	-0.0187	0.0458
	(8.53)	(-1.11)	(2.72)
SPE_FOODFIB	0.0277	0.0019	0.0083
	(4.05)	(0.32)	(0.85)
R^2	0.3810	0.0801	0.0649

Table 8 (cont.)

Determinants of Student's t Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel C: Grains & Oilseeds			
Constant	0.1984	-0.1549	0.3772
	(1.08)	(-0.57)	(1.58)
ADSI	0.0472	0.0104	0.1029
	(2.64)	(0.65)	(3.90)
Log(BDSI)	-0.0214	0.1117	-0.1348
	(-0.52)	(1.43)	(-2.36)
Log(VIX)	-0.0998	-0.0947	0.2152
	(-1.25)	(-1.17)	(1.82)
YS	0.1606	0.0464	0.1563
	(6.18)	(0.94)	(3.01)
SPE_GRAINS	-0.0002	0.0013	-0.1655
	(-0.03)	(0.33)	(-3.80)
R^2	0.0956	0.0377	0.3069
Panel D: Livestock			
Constant	-0.0284	-0.2231	-0.0398
	(-0.40)	(-0.94)	(-0.30)
ADSI	0.0025	0.0102	-0.0288
	(0.33)	(0.89)	(-1.62)
Log(BDSI)	0.0027	0.0514	-0.0296
	(0.17)	(0.80)	(-0.91)
Log(VIX)	0.0235	0.0355	0.1662
	(0.73)	(0.69)	(2.48)
YS	0.0446	0.0386	0.0179
	(2.88)	(1.23)	(0.46)
SPE_LIVESTK	0.0055	0.0054	-0.0114
	(1.11)	(0.67)	(-1.14)
R^2	0.0565	0.0090	0.2674

Table 8 (cont.)

Determinants of Student's t Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel E: Precious Metals			
Constant	0.0636	-0.0168	0.5052
	(0.42)	(-0.34)	(3.93)
ADSI	0.0258	0.0035	0.0480
	(1.36)	(1.11)	(3.26)
Log(BDSI)	-0.0028	0.0141	-0.1391
	(-0.09)	(1.03)	(-4.94)
Log(VIX)	0.0101	0.0037	0.2683
	(0.18)	(0.32)	(2.96)
YS	0.0733	0.0051	-0.0498
	(2.48)	(0.74)	(-1.47)
SPE_PMETALS	0.0281	0.0018	-0.0638
	(0.87)	(0.37)	(-1.63)
R^2	0.0413	0.0047	0.4162

Note. This table provides the ordinary least squares (OLS) regression results for each of the commodity futures sub-sectors over the full sample period (October 1992 to October 2013) and two sub-periods (October 1992 to May 2003 and May 2003 to October 2013). In panels A, B, C, D, and E the dependent variable is the time-varying student's t copula correlation between the weekly rates of return on the S&P 500 equity index and the equally-weighted weekly futures returns on the energy, foods & fibers, grains & oilseeds, livestock, and precious metals sub-sectors, respectively. The variables ADSI, BDSI, VIX, and YS represent the Aruoba-Diebold-Scotti Index, the Baltic Dry Shipping Index, the market volatility index, and yield spread, respectively. The variables SPE_ENERGY, SPE_FOODFIB, SPE_GRAINS, SPE_LIVESTK, and SPE_PMETALS represent speculation in the energy, foods & fibers, grains & oilseeds, livestock, and precious metals commodity futures sub-sectors, respectively. In all sample periods, Newey-West t-statistics are reported in parentheses below the corresponding coefficients, along with the R^2 of the regression.

Table 9

Determinants of Rotated-Gumbel Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

	Oct. 1992 - Oct. 2013 (Full Sample Period)	Oct. 1992 - May 2003 (Sub-period A)	June 2003 - Oct. 2013 (Sub-period B)
Panel A: Energy			
Constant	1.5373	0.2511	1.2121
	(11.99)	(0.53)	(5.67)
ADSI	0.0196	-0.0148	0.1028
	(1.32)	(-0.71)	(3.62)
Log(BDSI)	-0.1427	0.2942	-0.2173
	(-5.08)	(2.06)	(-3.86)
Log(VIX)	-0.0598	-0.1108	0.4467
	(-1.10)	(-1.30)	(3.11)
YS	0.0710	0.0353	0.0925
	(2.82)	(0.85)	(1.39)
SPE_ENERGY	0.1879	0.2008	0.2291
	(4.12)	(0.91)	(2.45)
R^2	0.2208	0.0871	0.3802
Panel B: Foods & Fibers			
Constant	1.0875	0.9724	1.1769
	(271.79)	(15.84)	(28.15)
ADSI	0.0003	0.0036	0.0113
	(0.75)	(0.93)	(2.30)
Log(BDSI)	0.0002	0.0058	0.0011
	(0.17)	(0.34)	(0.11)
Log(VIX)	-0.0060	0.0415	-0.0491
	(-3.74)	(2.50)	(-2.45)
YS	0.0030	-0.0200	0.0342
	(3.66)	(-2.08)	(2.90)
SPE_FOODFIB	-0.0002	0.0018	0.0029
	(-0.61)	(0.55)	(0.53)
R^2	0.0913	0.0772	0.0800

Table 9 (cont.)

Determinants of Rotated-Gumbel Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel C: Grains & Oilseeds			
Constant	1.2206	1.1421	1.3700
	(10.72)	(4.63)	(7.64)
ADSI	0.0224	-0.0030	0.0549
	(1.96)	(-1.23)	(2.56)
Log(BDSI)	-0.0202	0.0088	-0.0799
	(-0.89)	(0.89)	(-1.95)
Log(VIX)	-0.0918	0.0069	0.0655
	(-1.86)	(0.11)	(0.62)
YS	0.0833	-0.1143	0.0842
	(4.53)	(-1.97)	(1.91)
SPE_GRAINS	-0.0041	0.0824	-0.1157
	(-1.26)	(2.33)	(-3.60)
R^2	0.0595	0.0467	0.1559
Panel D: Livestock			
Constant	1.0841	1.0021	1.1662
	(35.59)	(61.75)	(13.88)
ADSI	-0.0017	0.0010	-0.0223
	(-0.56)	(0.89)	(-1.89)
Log(BDSI)	-0.0130	-0.0071	-0.0491
	(-1.97)	(-1.25)	(-1.99)
Log(VIX)	-0.0276	0.0159	0.0435
	(-2.24)	(2.27)	(0.86)
YS	0.0198	-0.0036	-0.0132
	(2.90)	(-1.62)	(-0.43)
SPE_LIVESTK	0.0040	0.0038	-0.0052
	(1.56)	(1.48)	(-0.83)
R^2	0.0673	0.0891	0.1433

Table 9 (cont.)

Determinants of Rotated-Gumbel Copula Correlations between the S&P 500 and Commodity Futures Sub-sectors

Panel E: Precious Metals			
Constant	0.9482	0.8743	1.3374
	(6.48)	(14.30)	(7.13)
ADSI	0.0352	0.0105	0.0483
	(1.91)	(3.26)	(2.04)
Log(BDSI)	0.0321	0.0427	-0.0824
	(1.10)	(2.69)	(-2.24)
Log(VIX)	0.0286	0.0170	0.2171
	(0.55)	(1.15)	(1.75)
YS	0.0665	0.0053	-0.0170
	(2.57)	(0.75)	(-0.37)
SPE_PMETALS	-0.0292	0.0005	-0.1252
	(-1.03)	(0.08)	(-2.43)
R^2	0.0457	0.1156	0.2151

Note. This table provides the ordinary least squares (OLS) regression results for each of the commodity futures sub-sectors over the full sample period (October 1992 to October 2013) and two sub-periods (October 1992 to May 2003 and May 2003 to October 2013). In panels A, B, C, D, and E the dependent variable is the time-varying rotated-gumbel copula correlation between the weekly rates of return on the S&P 500 equity index and the equally-weighted weekly futures returns on the energy, foods & fibers, grains & oilseeds, livestock, and precious metals sub-sectors, respectively. The variables ADSI, BDSI, VIX, and YS represent the Aruoba-Diebold-Scotti Index, the Baltic Dry Shipping Index, the market volatility index, and yield spread, respectively. The variables SPE_ENERGY, SPE_FOODFIB, SPE_GRAINS, SPE_LIVESTK, and SPE_PMETALS represent speculation in the energy, foods & fibers, grains & oilseeds, livestock, and precious metals commodity futures sub-sectors, respectively. In all sample periods, Newey-West t-statistics are reported below the coefficients in parentheses, along with the corresponding R^2 of the regression.

Figure 1

Dynamic Conditional Correlation between S&P 500 and Commodity Sub-sectors

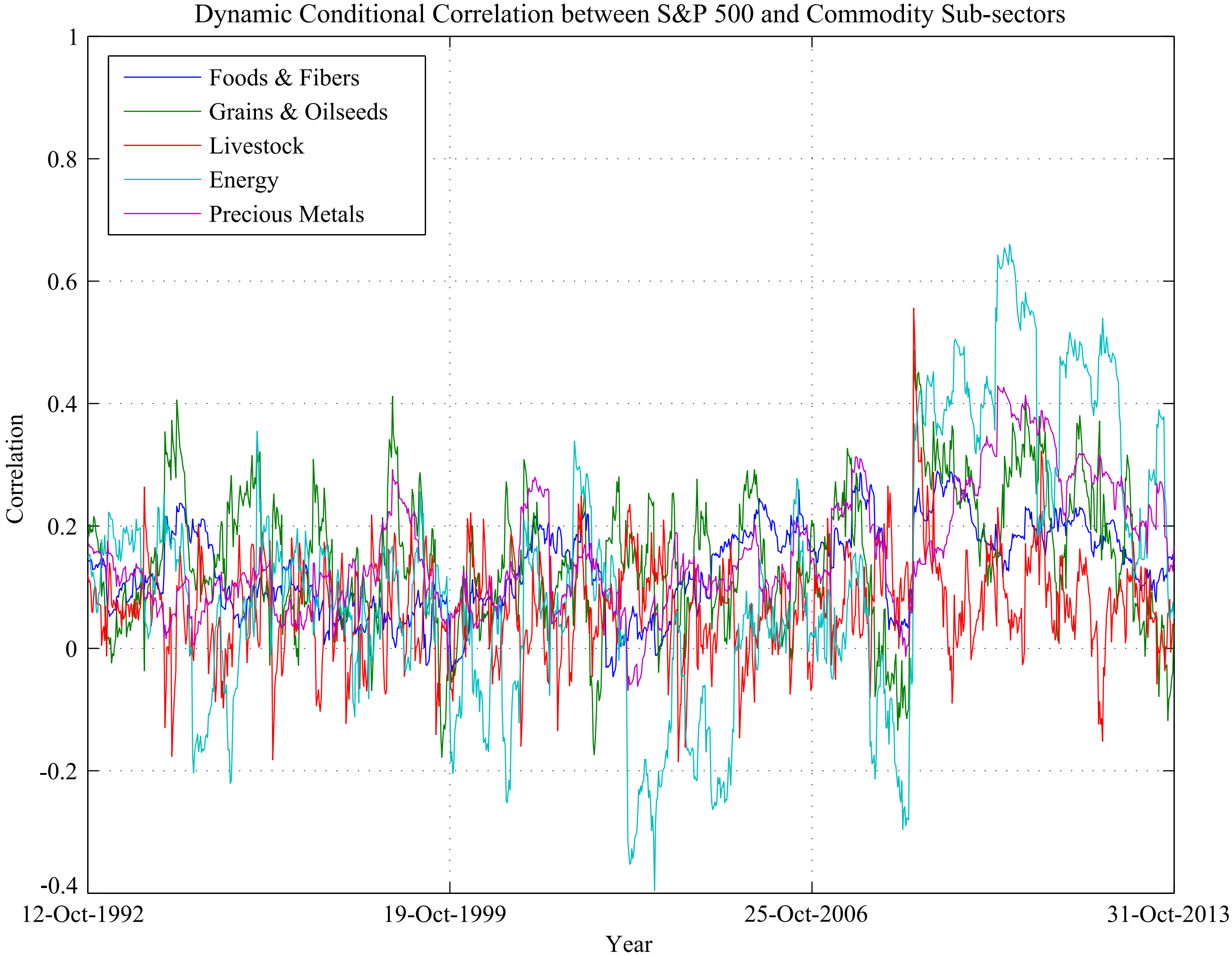


Figure 2A

Normal Copula Correlation between S&P 500 and Commodity Sub-sectors

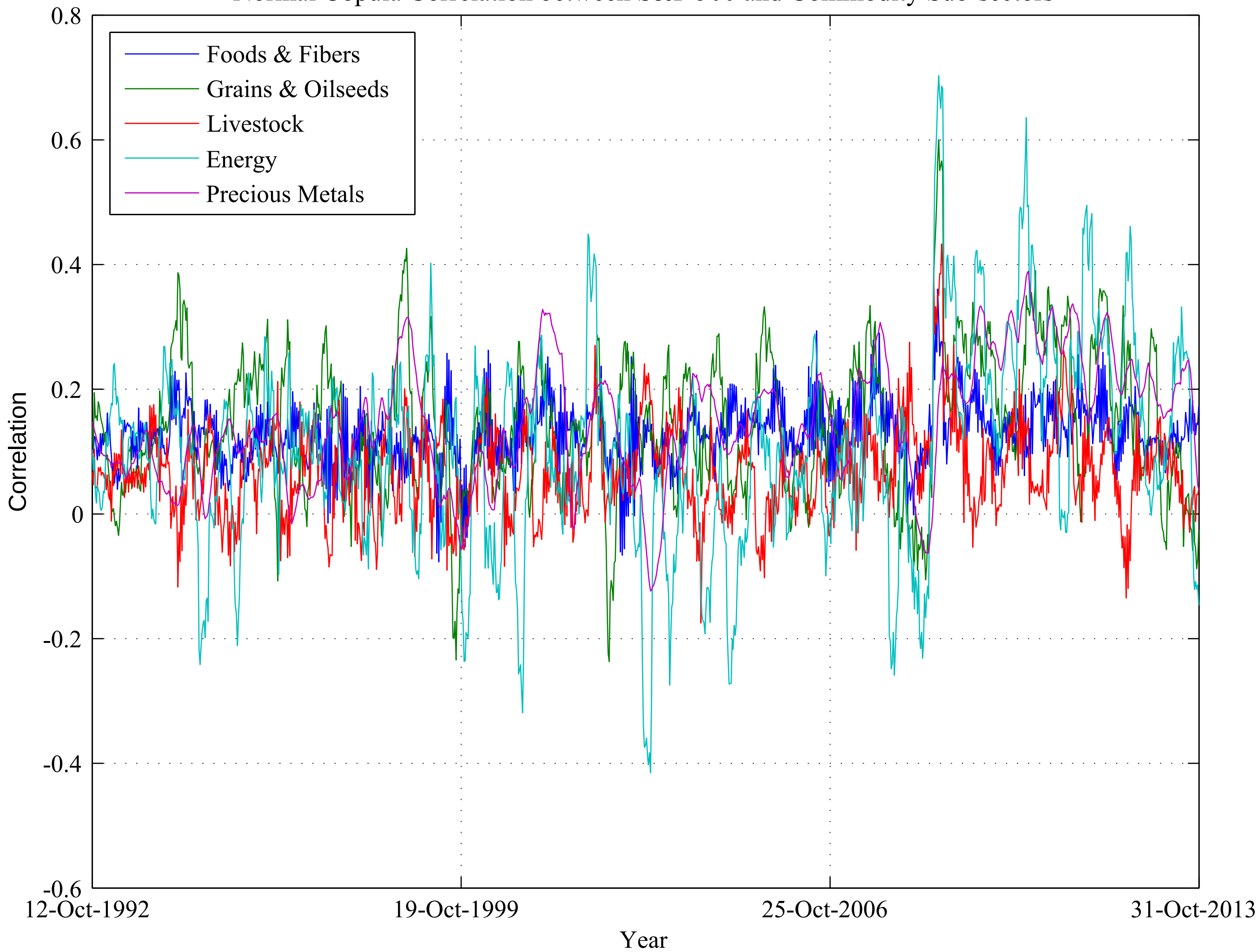


Figure 2B

Student's t Copula Correlation between S&P 500 and Commodity Sub-sectors

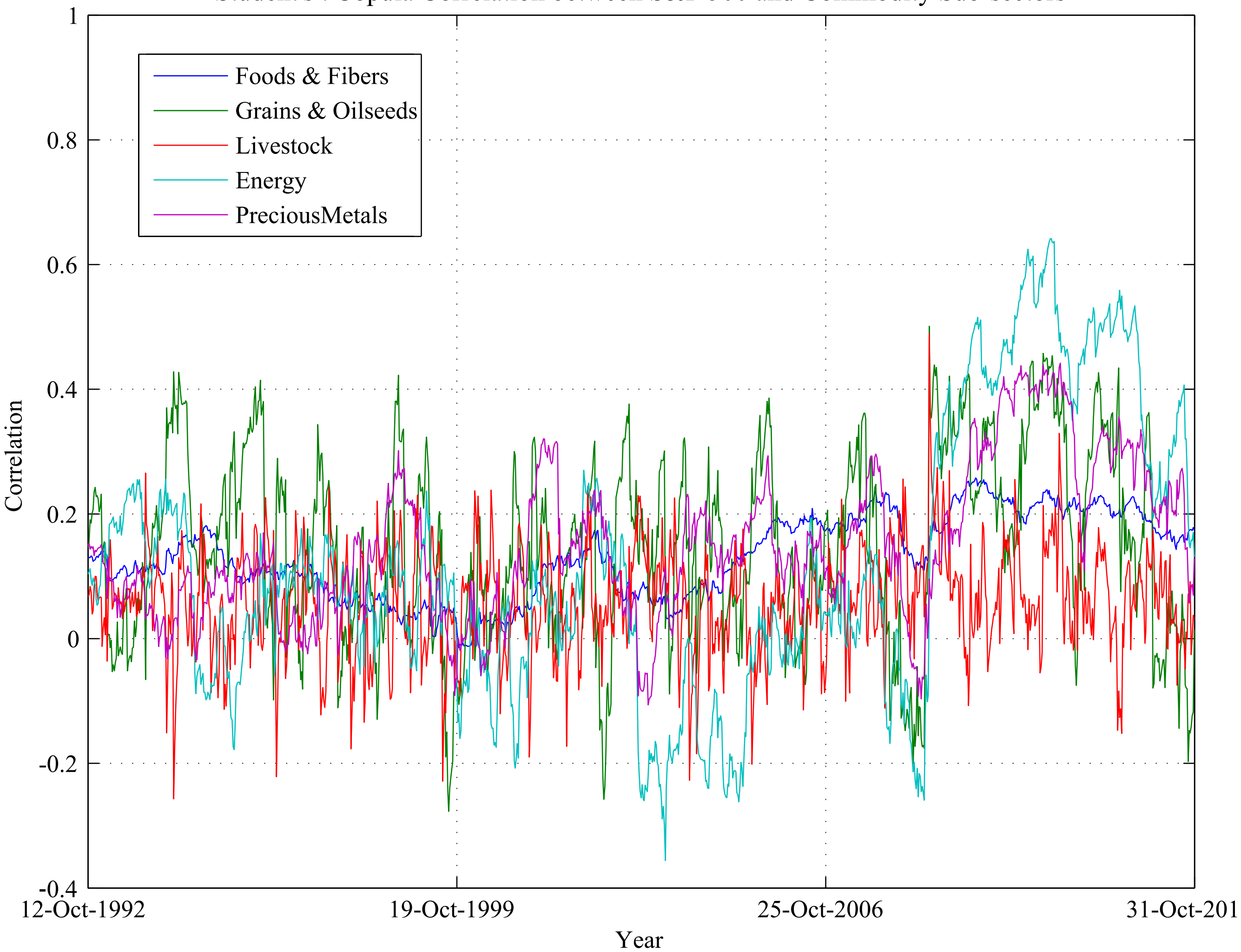
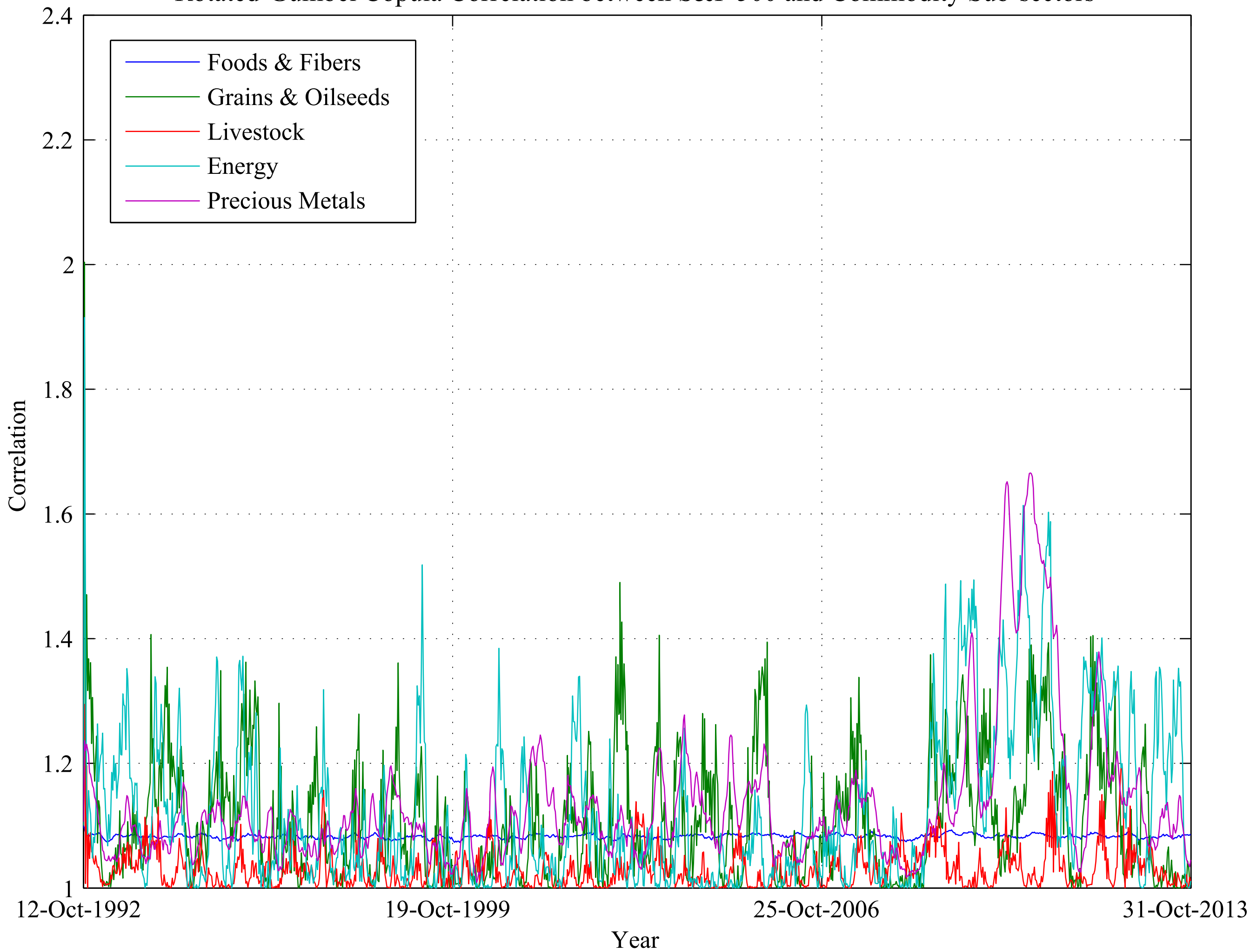


Figure 2C

Rotated-Gumbel Copula Correlation between S&P 500 and Commodity Sub-sectors



Appendix A

Table A1

Best Fit Copulas based on Log Likelihood

	Energy	Foods & Fibers	Grains & Oilseeds	Livestock	Precious Metals
Panel A: S&P500 Full Sample Period (Oct. 1992 - Oct. 2013)					
Normal Copula	-22.7520	-10.8940	-19.7820	-5.6022	-17.6860
Rotated-Gumbel Copula	-27.8230	-10.9760	-21.3130	-4.4363	-20.8580
Student's t Copula	-35.0780	-14.0970	-22.3190	-5.8891	-23.2140
Panel B: S&P 500 Sub-period A (Oct. 1992 - May 2003)					
Normal Copula	-3.3075	-0.4371	-4.0944	-8.9077	-0.9961
Rotated-Gumbel Copula	-6.0440	-1.5423	-6.6938	-0.3601	-1.1129
Student's t Copula	-1.7839	-2.9272	-5.0788	-2.1084	-1.8055
Panel C: S&P 500 Sub-period B (June 2003 - Oct. 2013)					
Normal Copula	-26.7750	-15.5100	-19.7590	-8.4453	-20.5390
Rotated-Gumbel Copula	-33.5680	-14.5960	-17.0030	-5.3183	-26.7310
Student's t Copula	-34.8680	-15.7570	-20.4800	-6.7192	-23.7520
Panel D: Russell 3000 Full Sample Period (Oct. 1992 - Oct. 2013)					
Normal Copula	-23.4750	-13.1450	-19.9340	-6.5967	-19.4270
Rotated-Gumbel Copula	-28.5450	-12.8980	-20.8950	-4.5830	-22.8850
Student's t Copula	-34.9680	-15.3650	-22.1140	-6.7607	-25.8730
Panel E: Russell 3000 Sub-period A (Oct. 1992 - May 2003)					
Normal Copula	-0.6834	-0.5059	-4.1525	-10.5930	-0.8424
Rotated-Gumbel Copula	-4.3460	-1.6040	-6.1298	-0.7909	-1.0866
Student's t Copula	-1.8144	-3.7653	-4.9042	-2.0195	-2.1645
Panel F: Russell 3000 Sub-period B (June 2003 - Oct. 2013)					
Normal Copula	-27.6470	-15.7140	-19.6630	-9.2760	-24.2270
Rotated-Gumbel Copula	-34.7970	-15.6770	-16.7040	-5.7880	-29.5610
Student's t Copula	-35.5280	-16.0390	-20.2030	-7.6272	-26.3960

Note. This table provides the best fit measure for the copula functions, for each sub-sector and sample period, based on the log-likelihood criteria.