Links Between Commodity Futures And Stock Market: Diversification Benefits, Financialization And Financial Crises

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ABSTRACT

In this paper, we analyze time-varying correlations between commodity markets and S&P 500 index, employing a recent and novel technique: asymmetric dynamic conditional correlation (ADCC) model. Using weekly data from January 3, 1992 to December 27, 2013, we provide evidence of highly volatile correlations, which substantially increase after the 2007-2008 financial crisis. We also find that conditional correlations and variances are positively linked in overall, which implies deterioration in diversification benefits. Finally, we examine the impacts of financial crises on the conditional correlations and find that external shocks have different effects on the correlations. Our results have potential implications for investors, portfolio managers, commodity producers and policy makers.

Keywords: Commodity indices, S&P 500, Diversification, Financial Crises, ADCC-GARCH Model, Financialization,

JEL Classification: C32; G10

I. INTRODUCTION

As a result of increased financial activity in commodity markets, the financialization process of commodities and their correlations with traditional asset classes are subjects of an ongoing debate.[1] In the report of the G20 Study Group on Commodities, it is noted that

"*The estimated market value of commodity-related assets under management has grown significantly since 2005 and has reached more than 410 billion USD in the first quarter of 2011. This compares with nearly 270 billion USD when commodity prices peaked in mid-2008. Inflows into commodity-related investments have been strong since 2009, averaging about 15 billion USD per quarter.*"

The participation of financial investors in commodity markets stems from several reasons. First, investors use commodities for strategic and tactical asset allocations and they benefit from the role of commodities as risk diversifiers, improving risk-return characteristics of their portfolios (Erb and Harvey, 2006; Gao and Liu, 2014). Second, commodities are potential inflation hedgers, as the inflation rate is heavily contingent on the prices of all physical commodities. (Edwards and Park, 1996; Jensen et al., 2000). Third, possible arbitrage opportunities arising from trading in different markets and new investment strategies whet investors' appetite. For these reasons, increased number of financial players in commodity markets can drive commodity prices, apart from demand-side and supply-side factors. In this regard, comprehending the role of financial investors and the drivers of price swings in commodities are important for policy makers to make effective policy decisions.

There is a strand of literature investigating the financialization process of commodities and their correlations with stock markets. The studies in the field mainly concentrate on the effects of oil prices on stock returns. In a microeconomic view, increasing oil prices adversely affects earnings of firms using oil as an input in the production process. From the macroeconomic perspective, oil price hikes

[1] As suggested by Creti et al. (2013), the financialization of commodities refer to the increasing role of financial activity in commodities and as a result, the price of a commodity is not only determined by its supply and demand, but also by financial investors' trading positions and their behavior in derivative markets.

imply inflationary pressures and central banks, as a response, raise interest rates to control the inflation. Rising interest rates leads to stock price declines, affecting the discount rates in the equity pricing formulation. Many scholars provide evidence of significant impacts of oil prices on stock returns. (Sadorsky, 1999; Arouri, 2011; Filis et al., 2011; Fan and Jahan-Parvar, 2012; Park and Ratti, 2008). Their results depend on whether the countries under investigation are oil-importers or oil-exporters; as well as, sector-specific differences and the origins of oil price shocks (demand-side or supply side).

Apart from oil-stock markets link, previous studies in the existing literature cite mixed results for the links between commodities and stock markets. Creti et al. (2013) examine the correlations between 25 individual commodities and S&P 500 index within the framework of dynamic conditional correlation (DCC) GARCH model.[2] They find that the correlations are highly volatile over the period from January 2001 to November 2011, especially after the 2007-2008 financial crisis, emphasizing the financialization of commodity markets. This reduces possible diversification benefits from commodities in portfolios. Using double smooth transition conditional correlation (DSTCC-GARCH) models, Silvennoinen and Thorp (2013) present evidence of no weakening correlation between commodities and conventional stock and bond returns. Their results point out closer integration of commodity and financial markets. Cheung and Miu (2010) examine diversification benefits of commodity futures for US and Canadian investors. They demonstrate that the benefits are not found when the US and Canadian stock markets are bearish and diversification is needed most. Daskalaki and Skiadopoulos (2011) employ mean-variance and non mean-variance spanning tests and evidence the increasing financialization of commodities, reflecting deterioration of the potential diversification benefits. In the context of the financialization issue, Tang and Xiong (2010) find that the correlations between commodities in the major commodity indexes are substantially larger than those not included in the indexes.

As indicated by the aforementioned studies, reducing diversification benefits of commodities, especially in times of market stress, would impede investors to select commodities as refuge assets for portfolio rebalancing. However, some researchers document contrary results. Büyükşahin et al. (2010) explore the correlation dynamics between S&P GSCI commodity indices and S&P 500 from January 1991 to May 2008. They suggest no evidence of a rise in correlations during periods of extreme returns, demonstrating that commodities provide portfolio diversification benefits to equity investors. Chong and Miffre (2010) analyze the conditional correlations between 25 commodity futures and 13 stock and fixed-income indices from January 1981 to December 2006. They depict that the correlations with the global equity returns decrease in times of market turbulence, pointing out the diversification benefits when stock market volatility is above average. For fixed income instruments, they document that commodity futures are good hedgers against short-term interest rate increases, while inclusion of commodities to Treasury-bond portfolios does not reduce risk in times of extreme volatility in bond markets. Gorton and Rouwenhorst (2006) construct an equally-weighted index of commodity futures and report negative correlations of commodities with stocks and bonds. They assert that commodity futures provide effective diversification of both stock and bond portfolios. However, we should note that study periods of the mentioned studies, which find support of using commodities as a means of diversification do not cover the 2007-2008 financial crisis.

The objective of this paper is to provide additional insights for the links between commodity markets and S&P 500, putting emphasis on diversification benefits and the financialization process of commodity markets. For this, we utilize a recent method - asymmetric dynamic conditional correlation (ADCC) proposed by Cappiello et al. (2006). Our motivation is to provide possible answers for several unresolved questions: 1) Do the correlations between commodity and stock markets rise or fall in episodes of extreme volatility? and accordingly, 2) As postulated by some researchers, do commodity markets actually provide diversification benefits, particularly during times of market stress? 3) Do the asymmetric behaviors of time-varying correlations between commodity and stock markets exist? 4) What is the degree of correlations during financial crises?

[2] Computational advantages over other multivariate GARCH models make the DCC framework widely used among many researchers. As for computational advantages, Engle (2002) asserts that the number of parameters to be estimated in the correlation process is independent of the number of series to be correlated. Thus potentially very large correlation matrices can be estimated.

The remainder of this paper is as follows: Part 2 describes the empirical model. Part 3 analyzes characteristics of data. Part 4 presents empirical results and Part 5 concludes.

II. METHODOLOGY

To examine correlation dynamics of commodity and stock returns, we employ asymmetric dynamic conditional correlation (ADCC) model proposed by Cappiello et al. (2006). ADCC model is a generalization of DCC-GARCH model of Engle (2002), introducing asset-specific correlation parameters and conditional asymmetries in correlation. Suppose that the $k\times 1$ vector of returns, r_t is normally distributed with zero mean and conditional covariance matrix, H_t:

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

where Ω_{t-1} represents the information set at t-1.

We conduct ADCC model, using the following two stage estimation procedure. In the first step, we fit univariate exponential GARCH – *EGARCH (p, q)* model of Nelson (1991). For this, we estimate the equation below:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{i=1}^{q}\left(\alpha_i \left|z_{t-i}\right| + \gamma z_{t-i}\right) + \sum_{i=1}^{p}\beta_i \log\left(\sigma_{t-1}^2\right) \tag{2}$$

where z_t is standardized residuals, calculated as ε_t / σ_t. The logarithmic form of the EGARCH model ensures the non-negativity of the conditional variance without the need to artificially impose constraints on the model parameters. Also, asymmetric effects are allowed under EGARCH formulation, by the term z_{t-i}. When $\gamma>0$, good news have a larger impact on conditional volatility and the total effect of z_{t-i} is $(1+\gamma_i)\left|\varepsilon_{t-i}\right|$. If $\gamma<0$, bad news generates more volatility and the total effect is $(1-\gamma_i)\left|\varepsilon_{t-i}\right|$.

In the second stage, we estimate the time-varying conditional correlations. The covariance matrix, H_t can be written as;

$$H_t = D_t P_t D_t \tag{3}$$

where $D_t = diag\{\sigma_{it}\}$ is a diagonal matrix with the ith diagonal element which accounts for time-varying standard deviations generated from the EGARCH model and $P_t = \{\rho_{ij,t}\}$ is the conditional correlation matrix. Using the standardized residuals matrix, Z_t, the asymmetric generalized DCC (AG-DCC) model can be expressed as:

$$Q_t = \left(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G\right) + A'z_{t-1}z'_{t-1}A + G'\eta_{t-1}\eta'_{t-1}G + B'Q_{t-1}B \tag{4}$$

where A, B and G are $k\times k$ parameter matrices. $\bar{Q}$ and $\bar{N}$ represent the unconditional correlation matrices of z_t and η_t, respectively and $\bar{N} = E\left[\eta_t \eta_t'\right]$.

The asymmetric impacts in correlations are given by:

$$\eta_t = I\left[z_t < 0\right] \circ z_t \tag{5}$$

where $I[.]$ is a $k\times 1$ indicator function that takes a value of 1 if the argument is true and 0 otherwise, "$\circ$" is the Hadamard product (element-by-element matrix multiplication). The asymmetry indicates a higher correlation coefficient following joint bad news than following joint good news.

Next we compute the correlation matrix P_t, using the equation below:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (6)$$

where $Q_t^* = \sqrt{q_{ii,t}}$ symbolizes diagonal matrix with the square root of the *i*th diagonal element of Q_t on its *i*th diagonal position.

Finally, we utilize Quassi Maximum Likelihood (QMLE) in the both first and second stage estimations. Since, it produces robust standard errors even if the assumption of conditional normality is violated.

III. DATA AND PRELIMINARY ANALYSIS

We use weekly data of commodity index (Dow Jones-UBS), its sub-indices and S&P 500 stock index from January 3, 1992 to December 27, 2013.[3,4] All the price series are quoted in US dollars and converted to log return series, computed as $R_t = log\ (P_t\ /\ P_{t-1})$. The source of the data is Bloomberg. The summary statistics and preliminary statistical tests of the return series are reported in Table 1.

Table 1. Descriptive statistics of the return series

	DJUBS	DJ-ENERGY	DJ-AGRI.	DJ-PREC.	DJ-LİVE.	DJ-IND.	S&P500
Mean	0.087	0.066	0.028	0.119	-0.033	0.100	0.128
Std. Dev.	2.108	3.965	2.511	2.614	1.955	2.961	2.369
Skew.	-0.913	-0.464	-0.326	-0.601	-0.331	-0.525	-0.779
Kurt.	7.480	4.698	5.959	6.269	4.915	5.714	10.032
J-B.	1119.06[a]	1790.27[a]	438.91[a]	5800.04[a]	196.34[a]	404.82[a]	2479.67[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q (10)	28.478[a]	21.079[b]	17.878[b]	14.077	20.289[b]	18.755[b]	33.397[a]
	(0.001)	(0.020)	(0.047)	(0.169)	(0.026)	(0.043)	(0.000)
Q^2 (10)	366.565[a]	123.627[a]	407.351[a]	199.912[a]	64.260[a]	406.764[a]	303.114[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH (10)	20.958[a]	8.574[a]	20.641[a]	11.583[a]	4.634[a]	19.540[a]	20.139[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PP	-33.857	-33.644	-34.145	-35.176	-35.417	-34.052	-36.704
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: (a) and (b) denote statistical significance at the 1% and 5% levels, respectively. *Q (10)* and *Q^2 (10)* are the Ljung-Box test statistics. J-B and PP stands for Jarque-Bera normality test and Phillips-Perron unit root test, respectively. P-values are in the parentheses

The results show that precious metals group has the highest average return and the energy group has the highest standard deviation. All the return series are negatively skewed, which contradicts the findings of Gorton and Rouwenhorst (2004). The value of skewness, kurtosis and Jarque-Bera statistics indicate non-normal and leptokurtic distributions. As suggested by Ljung-Box tests, the null hypotheses of no serial correlation in the raw and squared returns up to 10th lag are rejected at the 1% level.[5] We also test the presence of ARCH effects for all the return series via ARCH Lagrange Multiplier (LM) test and the test statistics provide evidence of time-varying volatility characterizations. Stationarity is checked by Phillips-Perron (1988) tests, which evince the rejections of unit-root hypotheses.

[3] As an alternative, we would use Standard & Poor's Goldman Sachs Commodity Index (S&P GSCI) which is tilted toward energy-related commodities. However, the DJ-UBS Commodity Index, made up of exchange-traded fully collateralized futures on physical commodities, represents a more diversified benchmark for the commodity futures.
[4] The sub-indices used are Energy, Agriculture, Precious Metals, Livestock and Industrial Metals.
[5] See Ljung and Box (1978)

IV. EMPIRICAL RESULTS

IV. 1. Asymmetric DCC-ADCC (1, 1) model

As the first step, we fit the univariate EGARCH (1, 1) models to the each of the series.[6] Table 2 reports the empirical results of the EGARCH model. The parameters *a* and *β* are all statistically significant at the 1% level, demonstrating that all past news and past volatilities have a significant impact on the current volatility. The parameters *a* range from 0.120 for the energy index to 0.292 for the agriculture index. The parameters *β*, which quantify the degree of persistence in volatility are from 0.947 for the agriculture index to 0.991 for DJUBS Composite index. This result brings the conclusion that shocks to volatilities are more persistent. The asymmetric news impact coefficients γ are statistically insignificant, except for precious metals, livestocks and S&P 500. The sign of the coefficient is positive for precious metals group, which is linked to the perception of investors that upward price movements in precious metals are signals of increased uncertainty in equity markets and future unfavorable macroeconomic conditions, inducing higher volatility in the precious metals group.

In table 2, we also document the residuals' diagnostic tests, which are used to examine whether the univariate models are correctly specified. The Ljung-Box tests applied to the raw and squared residuals indicate no serial correlations up to 10th lag. The ARCH-LM tests suggest that there are no remaining ARCH effects in the models' residuals.

Table 2. EGARCH model results

	DJUBS	DJ-ENERGY	DJ-AGRI.	DJ-PREC.	DJ-LIVE.	DJ-IND.	S&P500
ω	-0.115[a]	-0.054[b]	-0.139[a]	-0.104[a]	-0.040[a]	-0.092[a]	-0.099[a]
	(0.022)	(0.024)	(0.033)	(0.003)	(0.001)	(0.019)	(0.004)
a	0.161[a]	0.120[a]	0.292[a]	0.228[a]	0.122[a]	0.153[a]	0.217[a]
	(0.030)	(0.028)	(0.043)	(0.031)	(0.001)	(0.045)	(0.006)
β	0.991[a]	0.984[a]	0.947[a]	0.959[a]	0.955[a]	0.986[a]	0.947[a]
	(0.005)	(0.008)	(0.018)	(0.012)	(0.001)	(0.008)	(0.003)
γ	0.017	0.005	0.026	0.085[a]	-0.076[a]	-0.009	-0.173[a]
	(0.015)	(0.015)	(0.023)	(0.015)	(0.018)	(0.015)	(0.016)
L	-2354.94	-3152.41	-2575.20	-2618.28	-2352.32	-2768.21	-2415.42
Q (10)	14.111	10.599	10.025	10.582	11.002	14.981	16.184
	[0.167]	[0.389]	[0.438]	[0.390]	[0.210]	[0.132]	[0.094]
Q^2 *(10)*	9.024	18.146	4.351	10.924	6.250	10.070	9.214
	[0.529]	[0.052]	[0.930]	[0.757]	[0.793]	[0.434]	[0.511]
ARCH (10)	0.912	0.930	0.430	0.578	0.609	0.964	0.966
	[0.520]	[0.460]	[0.932]	[0.716]	[0.807]	[0.472]	[0.471]

Notes: (a) and (b) denote statistical significance at the 1% and 5% levels, respectively. *Q (10)* and Q^2 *(10)* are the Ljung-Box test statistics. L denotes log-likelihood. Robust standard errors are in the parentheses and the p-values are in the brackets.

The second step is to estimate the asymmetric DCC (ADCC) models. Table 3 presents the results of these models. The parameters of standardized residuals *(a)* are statistically significant at the 1% level for DJUBS-S&P 500 and precious metals-S&P 500 pairs and at the 5% level for energy-S&P 500 pair. The estimates of innovations in the dynamics of conditional correlation matrix *(b)* are all significant at the 1% level for all the pairs and ranged between 0.785 and 0.989, indicating that shocks to correlations are highly persistent. The asymmetry coefficients *(g)* are statistically significant at the 1% level for all the pairs, except for the correlations of precious metals and livestock with the stock market. The statistically significant asymmetry terms depict that the conditional correlations between commodity and stock indices are affected more by joint bad news than by joint good news. In other words, the

[6] We select EGARCH (1, 1) model according to Schwarz Information Criteria (SIC) and the value of the log-likelihoods.

correlations tend to increase more when both commodity and stock markets are turning down than when they are rising. This posits the strong interdependence between the commodity markets (DJUBSCI, energy, agriculture and industrial metals) and the S&P 500 index.

Table 3. ADCC model results

	DJUBS-SP500	DJENERGY-SP500	DJAGRI-SP500	DJPREC-SP500	DJLIVE-SP500	DJIND-SP500
a	0.159[a]	0.146[b]	0.110	-0.137[a]	0.186	0.082
	(0.045)	(0.063)	(0.080)	(0.034)	(0.131)	(0.048)
b	0.968[a]	0.972[a]	0.960[a]	0.969[a]	0.785[a]	0.989[a]
	(0.012)	(0.014)	(0.018)	(0.011)	(0.191)	(0.004)
g	-0.213[a]	0.198[a]	0.192[a]	0.166	0.197	0.157[a]
	(0.053)	(0.053)	(0.058)	(0.089)	(0.172)	(0.035)

Notes: (a) and (b) denote statistical significance at the 1% and 5% levels, respectively. Robust standard errors are in the parentheses.

The graphs of the time varying correlations are presented in Figure 1. From these graphs, several inferences can be made as follows: First, the correlations are highly volatile over the whole period. This volatility notably increases and bursts to a new high level following the 2007-2008 financial crisis. Second, the correlations exhibit the largest drop at the times of the financial crisis, except for the correlations of the livestock index with the S&P 500, indicating the "flight-to-quality" phenomenon. Investors gravitate towards safer investments during episodes of extreme stock market volatility. Third, correlations fluctuate between -0.2 and 0.6 in overall. The commodity group that is the most negatively correlated with the stock market during the 2007-2008 financial crisis, is precious metals, which can be treated as the "safest" assets.[7] Moreover, the correlations are high and positive during the period from mid-2008 to the end of 2013, in which the severe market crises are experienced. During this "increased uncertainty" era, investors imitate other market participants' trading strategies (herding behavior), leading to deviation of commodity prices from their fundamental values and hence increase in the correlations. Last, the increased correlations in the last five years also reflect the growing financialization of commodity markets, which manifests that commodity prices are not only affected by the principle supply and demand factors, but also by financial trading activities.

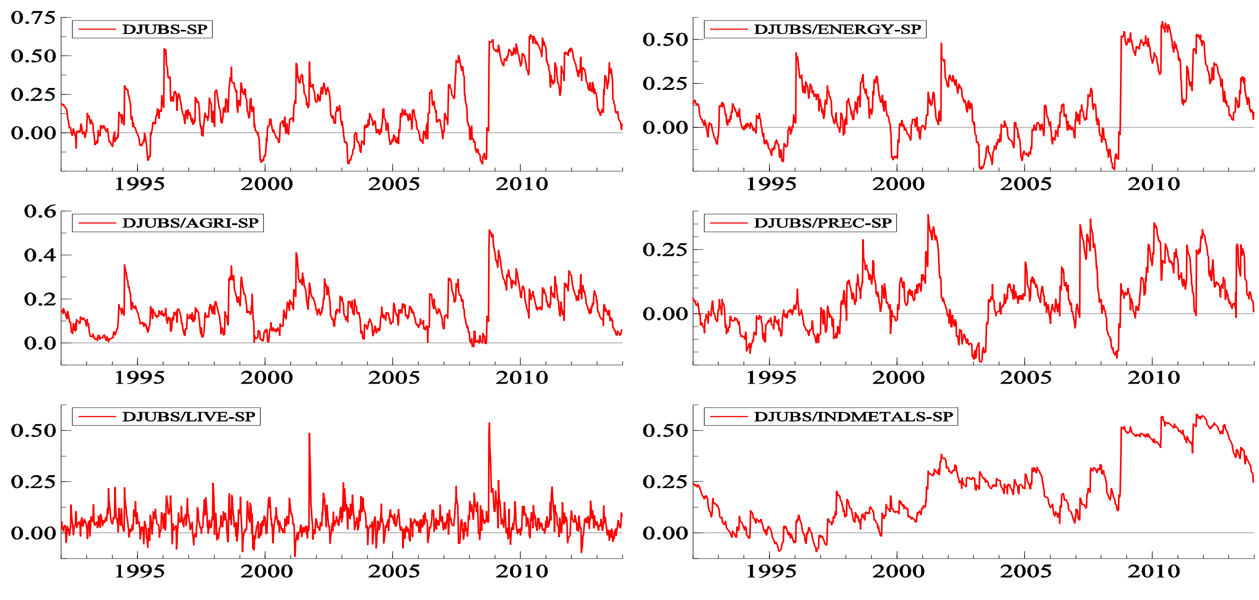

Figure 1. Time-varying Correlations

[7] Baur and Lucey (2010) define safe haven assets as assets that are uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil.

IV. 2. Long Run Risks

In this section, we investigate the nexus between the conditional volatilities and conditional correlations. In other words, we analyze whether the correlations are higher during volatile periods. For this, we run the following regression given as:

$$\rho_{ij,t} = \psi + \xi_1 \sigma_{i,t} + \xi_2 \sigma_{j,t} + \varepsilon_{ij,t} \qquad (7)$$

where, $\rho_{ij,t}$, $\sigma_{i,t}$ and $\sigma_{j,t}$ are the conditional correlations between the commodity index and SP500, the conditional variance of the commodity index and the conditional volatility of the S&P 500 index, respectively. All the variables used in the regression are generated from the ADCC models. A positive coefficient ξ_1 indicates that correlations are stronger in the periods of high commodity market volatility (e.g. commodity price boom during 2006-2008); while a positive coefficient ξ_2 suggests that the correlations rise with the stock market volatility.

In table 4, we document the results of the regressions. Positive and statistically significant coefficients are found for the pairs, excluding ξ_1 for the pairs of energy-S&P 500 and livestock-S&P 500 and ξ_2 for precious metals-S&P 500 pair. This suggests that the correlations get higher during extreme volatility episodes. For the precious metals group, the volatility of the stock market does not have an explanatory power on the correlations, highlighting the safe haven property of precious metals. The highest sensitivity to the stock market volatility is observed for the energy group. This can be attributed to outweigh of oil in the energy commodity index composition. Oil is the most related commodity with the stock market due to its effects on production costs, profitability of companies and hence shareholders' value. The overall results indicate closer integration of some commodity indices and stock markets and consequently, imply that diversification benefits of commodities may reduce during periods of extreme volatility.

Table 4. Conditional correlations and conditional volatilities

	DJUBS-SP	DJENERGY-SP	DJAGRI-SP	DJPREC-SP	DJLIVE-SP	DJIND-SP
ψ	0.069[a]	0.085[a]	0.094[a]	0.023[a]	0.033[a]	0.103[a]
	(0.008)	(0.012)	(0.003)	(0.006)	(0.004)	(0.008)
ξ_1	0.017[a]	-0.002[a]	0.003[a]	0.004[a]	0.000	0.010[a]
	(0.001)	(0.006)	(0.000)	(0.000)	(0.001)	(0.000)
ξ_2	0.004[a]	0.011[a]	0.005[a]	0.000	0.003[a]	0.003[a]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.168	0.134	0.261	0.035	0.173	0.214

Notes: (a) and (b) denote statistical significance at the 1% and 5% levels, respectively. Robust standard errors are in the parentheses.

IV. 3. Financial Crises

The last section explores the impacts of financial crises on the conditional correlations between the commodity indices and the stock market. This analysis provides further understanding of the correlation dynamics, allowing us to examine whether commodities can be seen as "refuge assets" in times of financial crises. We incorporate three dummy variables for the Asian and Russian crises, the tech bubble and the sub-prime mortgage crisis. The regression equation is given as follows:

$$\rho_{ij,t} = \varphi + \delta_1 dummy1_t + \delta_2 dummy2_t + \delta_3 dummy3_t + v_t \qquad (8)$$

The value of dummy variables is equal to one for the periods of crises and zero otherwise. *dummy 1*, *dummy2* and *dummy3* represent the Asian and Russian crises (November 21, 1997 -October 30, 1998), the tech bubble (March 3, 2000 – September 27, 2002) and subprime mortgage crisis (August 9, 2007 – February 12, 2009).

Table 5 reports the regression results. Asian and Russian crises *(δ_1)* and dot-com bubble *(δ_2)* dummy coefficients are found to be positive and significant for the correlations of agriculture and precious metals indices with the stock market. For industrials index- stock market pair, we document a negative coefficient for Asian and Russian crises *(δ_1)* and a positive coefficient for dot-com bubble *(δ_2)*. This suggests that the correlations of agriculture and precious metals indices with the stock market are stronger during these crises, while we find weakened correlations between industrials index and stock market during the tech bubble.

During the 2007-2008 financial crisis, the correlations of livestock and industrials indices with the stock market increase, evidenced by positive and statistically significant dummy coefficients. In the same period, we find a negative dummy coefficient for the energy index-S&P500 correlations, which suggests that the correlations of energy index with the stock market are lower during the crisis. Overall, our results from this section suggest the different impacts of external shocks on the correlations, as a result of changing supply-demand conditions and investor sentiment in times of market stress.

Table 5. Correlations during the crises

	DJUBS-SP	DJENERGY-SP	DJAGRI-SP	DJPREC-SP	DJLIVE-SP	DJIND-SP
φ	0.170	0.112	0.140	0.051	0.051	0.217
	(0.006)	(0.006)	(0.003)	(0.003)	(0.002)	(0.005)
δ_1	0.035	0.020	0.025[c]	0.054[a]	0.011	-0.126[b]
	(0.028)	(0.027)	(0.013)	(0.016)	(0.008)	(0.025)
δ_2	0.003	0.011	0.031[a]	0.032[a]	-0.001	0.002[a]
	(0.018)	(0.017)	(0.008)	(0.010)	(0.005)	(0.015)
δ_3	-0.007	-0.038[c]	0.011	-0.018	0.049[a]	0.082[b]
	(0.023)	(0.022)	(0.010)	(0.013)	(0.006)	(0.020)

Notes: (a) and (b) denote statistical significance at the 1% and 5% levels, respectively. Standard errors are in the parentheses.

5. Conclusion

This paper investigates the time-varying correlations between Dow Jones commodity indices and S&P 500 index within the framework of asymmetric dynamic conditional correlation (ADCC) model, which allows us to examine the existence of joint bad/good news' impacts on the conditional correlations. Using weekly data from January 3, 1992 to December 27, 2013, we draw several conclusions: First, the ADCC model results provide that the correlations of energy, agriculture and industrial metals commodity indices with the S&P 500 index tend to increase more when both commodity and stock markets are turning down than when they are rising, which emphasizes the strong interdependence. Second, analyzing time-varying correlations, we find that the correlations considerably rise after the 2007-2008 financial crisis. This can be linked to investors' herding behavior in times of increased uncertainty, conducing commodity prices to deviate from their fundamental values and the phenomenon known as "financialization". Third, we examine whether the correlations are higher during turbulent periods by OLS regressions. The regression results demonstrate that the correlations, except for the correlation of precious metals group with the S&P 500, increase during times of high stock market volatility. This indicates that diversification benefits of commodities may deteriorate during periods of extreme volatility. Finally, the degree of correlations is evaluated during the Asian and Russian crises, the tech bubble and the sub-prime mortgage crisis. The findings suggest that the market crises have distinct effects on the correlations.

The findings of this paper provide additional insights for investors, commodity producers and policy makers. Commodity indices have attracted investors' attention in the past years; however investors should keep a close eye on the comovements between commodity indices and the stock markets to efficiently diversify their portfolios. The producers should carefully assess price deviations originating from the commodity exchanges as a result of the financialization process and they should implement proper hedging strategies. Understanding the key drivers of commodity prices and volatilities is also important for policy makers to make effective and optimal policy decisions about restrictions on commodity trade and derivative markets.

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