Conditional Correlation and Volatility in Commodity Futures and Traditional Asset Markets

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The article studies the conditional correlations between 25 commodity futures and 13 stock and fixed-income indices. Conditional correlations with equity returns fell over time, a sign that commodity futures have become better tools for strategic asset allocation. The correlations between the S&P500 and 11 commodities also fell in periods of above average volatility in equity markets. We see this as welcome news to long institutional investors as they need the benefits of diversification most in periods of high volatility in equity markets. Similarly, the results suggest that adding commodity futures to Treasury-bill portfolios reduces risk further in volatile interest rate environments.

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The impressive rise in commodity prices from 2002 and their subsequent fall since July 2008 has revived the debate on the role of commodities for strategic and tactical asset allocations. Commonly accepted benefits include the equity-like return of commodity indices, the role of commodity futures as risk diversifier and inflation hedge, their low transaction costs and high potential for alpha generation through long-short dynamic trading.[1] These stylized facts have been very well received by commodity marketers and are at the root of most commodity sales pitches. This paper adds to the debate by analyzing the conditional return correlation between commodity futures and traditional assets, such as global equities and fixed income securities. It is well-known indeed that the strategic decision to include commodity futures in a well-diversified portfolio is not solely based on the temporal risk-return characteristics of the contracts. The decision also depends on how commodity futures correlate with the rest of the portfolio over time and in periods of above average volatility in traditional markets. This is precisely what this paper intends to study.

The results indicate that correlations between commodity futures and S&P500 returns fell over time and thus the risk reduction obtained by adding commodity futures to an equity portfolio has increased since the 1980s. Ultimately, this implies that commodity futures have become better portfolio diversifiers and better instruments for strategic asset allocation. Correlations between 11 commodity futures and the S&P500 returns also tend to fall in turbulent periods; namely, when the risk of equity markets increases. This is good news to institutional investors with long positions in equities and in those 11 commodity futures as it is precisely when market volatility is high that the benefits of diversification are most appreciated. Interestingly, the evidence from the stock market can be extended to short-term interest rate securities, whereby their conditional correlations with commodities have a tendency to fall in volatile interest rate markets. The opposite applies to long-term global fixed income securities for which conditional correlations tend to rise with the volatility of global fixed income markets. This suggests that adding commodity futures to a long-term fixed income global portfolio will not reduce risk further in periods of high price volatility in the fixed income market.

The decrease in return correlations between some commodity and equities (or Treasury-bills) that we observe in periods of market stress could be interpreted as a flight-to-quality. Namely, investors in equities and Treasury-bills, in times of panic in these markets, treat commodity futures (such as precious metals) as refuge securities. They stop their losses by selling their traditional asset portfolios and re-invest the proceeds in commodity futures. The increase in volatility in stock and Treasury-bill markets then generates an upsurge of interest in commodity futures markets that could explain the decrease in correlations that we observe during market stress.[2] Alternatively, our results could be explained through the different impacts that major events have on commodity and equity returns. A hurricane, a war or a sudden rise in inflation, for example, increases the volatility of equity markets. Simultaneously, it increases commodity prices while decreasing equity prices. Thus, and as observed in this paper, an upsurge in market risk could occur at the same time as a decrease in return correlation between equities and commodities.

METHODOLOGY

By far the most successful volatility forecasting model is the generalized autoregressive conditional heteroscedasticity model, GARCH(1,1) (Hansen and Lunde [2005]), developed by Bollerslev [1986]. It describes the volatility dynamics of almost any financial return series, across markets and asset groups (Engle [2004]). The GARCH(1,1) variance, $h_{ii,t}$, is represented by

$$x_{i,t} = \mu + \varepsilon_{i,t}\,,\ \ \varepsilon_{i,t} \sim N(0, h_{ii,t})\,,$$

$$h_{ii,t} = \gamma_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \quad i = 1,\ldots,N$$

subject to $\gamma_i > 0, \alpha_i, \beta_i \geq 0, \alpha_i + \beta_i < 1$. α and β determine the short run dynamics of the resulting volatility time series. A large β indicates that shocks to conditional variance take a long time to dissipate; that is, volatility is said to be “persistent.” A large α indicates that volatility reacts intensely to recent market movements.

In estimating the conditional correlation, we employ the dynamic conditional correlation model (DCC) of Engle [2002]. Upon estimating the GARCH(1,1) model and employing its resulting standardized residuals, a time-varying correlation matrix is estimated via the DCC(1,1). Hence, the covariance matrix can be expressed as $H_t \equiv D_t R_t D_t$, where $D_t = diag\left(h_{11,t}^{1/2} \ldots h_{NN,t}^{1/2}\right)$ is a diagonal matrix of univariate GARCH volatilities and $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is the time varying correlation matrix, with $Q_t = \left(q_{ij,t}\right)$ as described by

$$Q_t = (1 - a - b)\overline{Q} + a\left(\Xi_{t-1}\Xi_{t-1}'\right) + bQ_{t-1}$$

$\overline{Q}$ is the $N \times N$ unconditional covariance matrix of standardized residuals, $\Xi_t = x_t / \sqrt{h_t}$ resulting from the first stage estimation, $Q_t^* = \left(q_{ii,t}^*\right) = \left(\sqrt{q_{ii,t}}\right)$ is a diagonal matrix composed of the square root of the *i*th diagonal elements of Q_t, and *a* and *b* are non-negative coefficients satisfying $a + b < 1$. Rewriting $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$, the conditional correlation between assets *i* and *j* at time *t* can then be expressed as $\rho_{ij,t} = \dfrac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$.

We can use this framework to analyze the conditional returns correlations between commodity futures and traditional assets. First, we investigate how they changed over time by simply regressing them on a constant and a time trend. Second, we study the relation between conditional correlations and conditional volatilities by regressing the former on the latter as follows

$$\rho_{TC,t} = \alpha + \beta_T \sqrt{h_{T,t}} + \beta_C \sqrt{h_{C,t}} + \varepsilon_t \qquad (1)$$

where the subscripts *T* and *C* refer to traditional asset class and commodity futures, respectively. Taking the S&P500 index as an example, a positive β_T suggests that conditional return correlations between the S&P500 index and commodity futures rise with the volatility of equity markets. If so, the evidence from international stock markets (Solnik *et al.* [1996]; Longin and Solnik [2001]) can be extrapolated to equity and commodity futures markets. On the other hand, a negative β_T indicates that correlations between commodity futures and equity returns fall in periods of high volatility in equity markets. This result implies that the usefulness of commodity futures as a diversification tool increases in periods of above average market volatility.

DATA

The data, obtained from Datastream International, comprise returns of 25 commodities and 13 traditional asset classes. The choice of the equity and bond indices was dictated by the fact that they represent a substantial proportion of the asset allocation of a well-diversified global asset manager. Based on this criterion, 7 equity asset classes (4 from the US and 3 from global markets) were shortlisted. They are the S&P500 composite index, the Russell 2000 Index, the Russell 1000 Value Index, the

Russell 1000 Growth Index, the MSCI Europe Index, the MSCI Asia Pacific Index and the MSCI Latin America Index. As for the fixed income markets, we concentrate our attention on 6 bond indices from JP Morgan: US Cash with 6-month maturity, US Cash with 12-month maturity, United States Government Securities, Global Asia, Global Africa and Global Europe.

The dataset also consists of closing prices on the nearby and second nearby contracts of 25 commodities. We consider 11 agricultural futures (cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar and wheat), 5 energy futures (crude oil, heating oil, lumber, natural gas and unleaded gas), 4 livestock futures (feeder cattle, frozen pork bellies, lean hogs and live cattle) and 5 metal futures (copper, gold, palladium, platinum and silver). To compile futures prices into a series of futures return, we collect the settlement prices on the nearest maturity futures contract, except in the maturity month when the price on the second nearest futures is used. Futures returns are then computed as the log difference in the settlement prices.

At the roll-over date, one could adjust the price level *ex-post* to eliminate the price gap between the futures contract that is closed out and the futures contract that is entered into. We favor a correction-free approach instead. The reasons for using unadjusted price series are twofold. First, as real transaction prices are used in practice, long-only asset managers and institutional investors care about unadjusted prices as they reflect the actual performance of the asset. Second, as roll-returns have been shown to be the main driver of total returns (Erb and Harvey, 2006), adjusting the price levels on the roll-over date might eliminate part of the profits of long backwardated positions or part of the losses of long contangoed positions. These positive and negative roll-returns are important source of performance (or lack thereof) to long-only asset managers and are thus part of our analysis.

The frequency of the data is weekly.[3] To avoid week-end effect, thin trading effect and maturity effect, we collect Wednesday settlement prices on the nearest maturity futures contract, except in maturity months when prices on the second nearest futures are used. The dataset spans the period January 1, 1981 to December 27, 2006 for most series, totaling 1,356 return observations. For series with fewer observations, details of starting dates are reported in Exhibit 1. Exhibit 1 also presents summary statistics for the 25 commodity futures returns and the excess returns on the traditional asset classes.[4] The results confirm some stylized facts about commodity futures, such as their zero mean return (Erb and Harvey [2006]) and high volatility (26.83% a year on average). With only a few commodities having higher reward-to-risk ratios than those reported for stocks and bonds, the results also confirm the general belief that commodity futures are poor stand-alone investments. Finally, the return distribution of commodity futures departs from normality, with strong evidence of positive excess kurtosis.

<< Insert Exhibit 1 around here >>

Exhibit 2 presents unconditional correlations between commodity futures and traditional asset classes. As previously reported (Jensen *et al.* [2000]; Erb and Harvey [2006]), correlations with S&P500 returns are very low, ranging from -0.0206 for unleaded gas to 0.0948 for lumber, with a mean at 0.0139. The return correlations with other equity indices are equally low at 0.0287 on average. Those with bonds are even lower (at 0.0034 on average). It is clear that commodity futures returns behave independently from global stock and bond returns. This feature is sought after by risk-averse investors who use commodities for the diversification of risk.

<< Insert Exhibit 2 around here >>

EMPIRICAL RESULTS

Conditional Correlation and Conditional Volatility in Equity Markets

Exhibit 3 presents summary statistics of conditional correlations estimated from our DCC model. The results warrant three comments. First, the average conditional correlation (at 0.0408 in Exhibit 3) with the S&P500 index is of the same magnitude as the average unconditional correlation (at 0.0139 in Exhibit 2). The conditional correlations are also, for the most part, insignificant at the 5% level. Second, there is considerable divergence in the volatilities of the conditional correlations, with standard deviations ranging from 2.25% for lean hogs to 16.49% for gold. Third, and possibly most importantly, regressions of conditional correlations on a time trend reveal a fall over time in conditional correlations for 19 (20) out of 25 commodities at the 5% (10%) level. The remaining coefficients are positive and significant for 4 commodities (coffee, crude oil, unleaded gas and live cattle) or insignificant for heating oil. With an average fall by 5.81% over the period 1981-2006, the decrease in correlation, measured as $\Delta\rho^5$ in Exhibit 3, is significant in economic terms too. The decrease in correlation is particularly noticeable for precious metals, such as silver

($\Delta\rho$ = -28.38%), gold ($\Delta\rho$ = -18.8%) and platinum ($\Delta\rho$ = -17.72%), suggesting that these markets and the S&P500 index have become more segmented. As a result, the diversification benefits of being long equities and commodity futures and the importance of commodity futures for strategic asset allocation have increased. The results of Exhibit 4—namely, the fact that correlations decrease in period of high market volatility—could explain the observed decrease in correlation over time. We turn our attention to this now.

<< Insert Exhibit 3 around here >>

Exhibit 4 looks at the relation between conditional correlations and conditional market volatility. Eleven β_T coefficients on $\sqrt{h_{T,t}}$ in equation (1) are negative at the 5% level, indicating that conditional correlations between these 11 commodity futures and S&P500 returns fall in periods when market risk rises. This is good news to institutional investors with long positions in these commodity futures and in equities as it is precisely when market volatility is high that benefits of diversification are most needed.[6]

<< Insert Exhibit 4 around here >>

Take, for example, Exhibit 5, where we plot the conditional correlations between gold futures returns and the S&P500 excess returns against the conditional volatilities of the S&P500 excess returns. The conditional correlations were very volatile over the period, ranging from a low of -0.33 in October 1990 to a high of 0.56 in October 1982. The conditional correlation plunges, when the S&P500 volatility experiences a spike. For example, it was as low as -0.20 in October 1987 and -0.23 in October 2002 (relative to an average of 0). At those times, the stock market volatility rose to highs of 41.66% and 34.26% a year, respectively. On the other hand, when the S&P500 volatility decreases (such as in 1985 and 2005-2006), conditional correlations tend to be above average (0.13 in 1985 and 0.11 in 2005-2006). As a result, the correlation between the two series in Exhibit 5 is reliably negative at -0.18 (t-statistic of -6.55). This implies that gold futures contracts possess diversification properties in times of increased market stress. Exhibit 5 also depicts a straight line that is fitted on the conditional correlations to illustrate how they changed over time. Clearly the line is downward-sloping, suggesting, as in Exhibit 3, that the correlation between S&P500 and gold futures returns fell over the period analyzed.

<< Insert Exhibit 5 around here >>

Across the 11 commodity futures for which β_T is negative at the 5% level, the average β_T coefficient in (1) is -2.1645. Namely, a 1% rise in market risk leads, on average, to a 2.16% fall in correlation.[7] This ultimately indicates that higher volatility in the S&P500 index implies, other things being equal, a higher allocation to these 11 commodity futures. Investors, by allocating higher portfolio weights to these 11 commodity futures during turbulent periods, can benefit more from the decrease in correlation and the enhanced risk reduction that ensues. The β_T coefficients are particularly low, and statistically significant, for precious metals such as gold (β_T = -6.9796, *t*-statistic of -16.20), platinum (β_T = -1.5638, *t*-statistic of -5.66) and silver (β_T = -1.5979, *t*-statistic of -4.28). Some agricultural commodities (cocoa, corn, orange juice, soybean meal) tend to do well, relatively speaking, when equity market volatility rises too. These futures contracts are the best candidates for inclusion in equity portfolios in periods of market turbulence. In the case of gold, its low β_T coefficient is accompanied by a negative, albeit insignificant, unconditional and conditional correlations with, and a comparable volatility to, the S&P500 index (Exhibits 1, 2 and 3), therefore enhancing its diversification properties even further and living up to its reputation as a good hedge in times of market stress.

Note however that the conclusion of a negative relation between conditional correlation and S&P500 volatility is not consistent throughout the cross section. The evidence in Exhibit 4 suggests that the slope coefficient β_T of equation (1) is negative for 11 commodities, positive for 10 and zero for 4 at the 5% level.[8] The different impact that market volatility has on conditional correlation confirms the general belief that commodities behave differently from one another (Erb and Harvey [2006]) and cannot be treated as perfect substitutes. Exhibit 6 presents an example of a positive relation between conditional correlation and conditional S&P500 volatility (that of the feeder cattle), where the correlation between the series portrayed equals 51.35% with a *t*-statistics of 22.02.

<< Insert Exhibit 6 around here >>

Exhibit 7 focuses on equity indices other than the S&P500 index. By and large, the evidence from Exhibit 4 seems to apply to a wider cross section of equity indices. For example, β_T tends to be negative for metal futures and positive for energy futures. This suggests as in Exhibit 4 that for metals, conditional correlations tend to fall in periods of high volatility in equity markets, while for energy futures, conditional correlation and market volatility move hand in hand.

<< Insert Exhibit 7 around here >>

Three Economic Rationales for the Observed Results

Flight-to-quality is a possible economic rationale for the observed decrease in correlations in periods of high volatility in equity markets. Put differently, institutional investors may view commodity futures (such as precious metals) as refuge securities in uncertain times in stock markets. Our results are indeed consistent with the notion that, when market risk rises, institutional investors sell their shares to stop the loss in value of their equity portfolio and invest the proceeds in refuge assets. At times when equity markets experience high volatility, the stop-loss orders of equity asset managers and the subsequent re-allocation of resources towards commodity futures, such as gold, platinum or silver, put more downward pressure on equity prices than on commodity futures prices. This, in turn, could explain the decrease in correlation between commodity futures and equity returns that we observe in periods of high market volatility.

Another plausible explanation for our finding is based on the difference that major events have on the two types of securities. Specifically, Exhibit 1 shows that agricultural commodity futures frequently have positively skewed return distributions because events such as hurricanes or wars positively affect commodity prices. In contrast, such events create turmoil in equity markets and negative skewness in their return distribution (as in Exhibit 1, Panel E). Similarly, a rise in unexpected inflation is treated as welcome news in commodity markets, while it has a negative impact on the value of equities. Therefore, one may expect that the same events (a war, a climatic phenomenon or an unexpected rise in inflation) create simultaneously some instability in equity markets and a decrease in return correlation between commodities and traditional asset classes. This is precisely what our results suggest.

A third explanation relates to the fact that commodities are inputs for most firms and thus an increase in commodity prices tends to increase firms' costs and uncertainty. As a result, higher commodity prices are seen as good news to long investors in commodity futures and as bad news to equity holders, creating higher stock market volatility. This explanation too can account for the observed inverse relationship between correlation and stock market volatility.

Conditional Correlation and Conditional Volatility in Fixed Income Markets

Institutional investors do not just hold equities and commodity futures. To a large extent, their asset mix includes US Treasury-bonds, Treasury-bills and international fixed income securities. A thorough analysis of the temporal variations between commodity futures and a much broader range of assets is therefore warranted. With this in mind, Exhibit 8 studies the co-movements between commodity futures returns and the returns of global bond indices by reporting the coefficient β_T on the conditional fixed income volatilities as in (1).

<< Insert Exhibit 8 around here >>

In periods of falling short-term interest rates (presumably a sign of economic downturn), the return on Treasury-bill securities with 6-month and 12-month maturity increases. The negative β_T coefficients on the conditional volatility of Treasury-bill suggest that this rise in Treasury-bill volatility is accompanied by a sharp decrease in the return correlation between Treasury-bills and most commodities. This result suggests that in falling interest rate environments, short-term fixed income securities become more uncorrelated with commodity futures, making the latter better tools for risk diversification. Vice versa, following the announcement of a tightening of monetary policy through rising short-term interest rates, Treasury-bill securities typically tend to underperform. The negative β_T coefficients on the conditional volatility of Treasury-bill suggest that simultaneously commodity futures tend to be more uncorrelated than average with short-term fixed income securities and thus tend to serve as better hedge against interest rate risk.

The decrease in conditional correlations in volatile interest rate environments is particularly sharp for precious metals, energy and some agricultural commodities such as corn, soybean meal, soybean oil, soybeans and sugar. For example, β_T can be as low as -716.94 for silver and 6-month Treasury-bills, suggesting that, other things being equal, a 1% rise in the volatility of short-term Treasury securities leads to a sharp fall of 7.16% in return correlation between silver and 6-month Treasury-bills. Along the same line, Exhibit 9 plots the conditional return correlation between crude oil and 6-month Treasury-bills versus the conditional volatility of 6-month Treasury-bills. Clearly, a rise in Treasury-bill volatility goes hand in hand with a fall in conditional correlation, the correlation between the two series being as low as -32.64% (*t*-statistic of -11.42).

<< Insert Exhibit 9 around here >>

In contrast to the results reported thus far for both short-term Treasury securities and equity indices, the slope coefficient from regressions of conditional correlations on conditional Treasury-bond volatilities in Exhibit 8 is positive on the whole at 3.351. That is, when volatility in the US Treasury-bond market increases, correlation between Treasury-bond and commodity futures returns on average tends to rise. At the 5% level, β_T is positive for 12 (mainly agricultural) commodity futures and negative for 8. The inference for the JPM Global Asia, Africa and Europe indices are in line with those reported for the JPM US Treasury-bond index. Namely, conditional correlations tend to rise with the volatility of long-term fixed-income securities. This suggests that unlike stocks and short-term interest rate instruments, the benefits of diversification coming from commodities have less impact in periods when long-term interest rates are highly volatile.

Robustness Check

The results presented in Exhibits 4 to 9 study the relationship between conditional correlation and volatility, where both are measured at a weekly frequency. It has been shown however that the lower the frequency of observations, the noisier the estimate of the unobserved true volatility (Andersen *et al.* [2005]). In other words, the weekly frequency used thus far may lead to error-prone estimates of conditional correlation and volatility and thus to incorrect inference of the impact of the later on the former.[9] To address this concern, we would want ideally to use intraday data but these are not available at our institutions. On balance, we choose therefore to use daily data. Exhibit 10 tests the sensitivity of the S&P500 and US Treasury-bond results of Exhibits 4 and 8 to the data frequency.

<< Insert Exhibit 10 around here >>

Columns 2 and 3 of Exhibit 10 look at the daily relationship between conditional correlation and volatility for the S&P500 index. The results indicate that for 18 out of 25 commodities the results at the weekly horizon are consistent with those at the daily horizon and thus that the inference regarding the relation between conditional volatility and conditional correlation is for the most part not sensitive to the frequency of the data. This is the case for 10 commodities (cocoa, coffee, corn, oats (at the 10% level), orange juice, soybean meal, frozen pork bellies, gold, platinum and silver) for which the slope coefficients β_T in (1) are negative and significant in both Exhibits 4 and 10 and for 8 commodities (soybean oil, sugar, wheat, crude oil, lumber, natural gas, feeder cattle and lean hogs) for which the slope coefficients β_T in (1) are positive and significant in both exhibits. For the remaining 7 commodities, the evidence is not as clear-cut since the β_T coefficients between Exhibits 4 and 10 either switch signs (cotton, unleaded gas, live cattle and copper) or turn from insignificant to significant (soybeans, heating oil and palladium). On the whole, β_T in Exhibit 10 is negative for 14 commodities and positive for 11 (with an average of -2.1607 and 1.7328, respectively) at the 5% level. Note also that the average coefficients of negative and positive β_T's at the daily horizon (-2.1607 and 1.7328) are in the vicinity of those at the weekly horizon (-2.1645 and 1.6084), suggesting once again that the results are robust to the frequency of the data.

Columns 4 and 5 of Exhibit 10 focus on the relationship between conditional correlation and US Treasury-bond volatility at a daily frequency. While comparing these results to those reported in Exhibit 8, we note that 4 commodities maintain their statistically significant negative slope coefficients (cotton, feeder cattle, copper and palladium), 8 commodities maintain their statistically significant positive coefficients (corn, soybean meal, soybean oil, soybeans, wheat, crude oil, heating oil and gold), while the β_T of the remaining commodities either lose their statistical significance (5), gain statistical significance (4) or switch signs at the 5% level (4). Overall, β_T in Columns 4 and 5 of Exhibit 10 is negative for 9 commodities and positive for 11 (in close proximity to the 8 and 12 commodities with negative and positive β_T in Exhibit 8). So while we note a few discrepancies between the daily and weekly results, the general picture of a mainly positive relationship between conditional correlation and conditional T-bond volatility evidenced in Exhibit 8 prevails in Exhibit 10 too.

CONCLUSIONS

The paper studies the way returns on commodity futures co-vary over time with those of traditional asset classes (as proxied by global stock and bond indices). We find that the conditional return correlations between the S&P500 index and commodity futures fell over time. This suggests that commodity futures and equity markets have become more segmented and, thus, commodity futures have become over time better tools for strategic asset allocation. We also observe that for more than half of our cross section, the conditional correlations between commodity futures and global equity returns fell in periods of market turbulence. We see this as good news to institutional investors with long positions in equities and in these commodity futures. Indeed, it is precisely when stock market volatility is high that benefits of diversification are most appreciated. This is particularly true of precious metals, which emerge as excellent risk diversifiers in periods of high volatility in equity markets, irrespectively of the data frequency. Possible explanations for this finding include the fact that: i) institutional investors treat commodity futures (such as precious metals) as refuge assets in periods of high market volatility and ii) the differing effects that major events (such as hurricane or a rise in unexpected inflation) have on the prices of commodity futures and equities. It is important to note however that the evidence is not uniform across commodities and that for some commodities, conditional correlation rises with the volatility of equity markets. This is somehow to be expected since commodities behave differently from one another (Erb and Harvey [2006]) and cannot be treated as substitutes.

The paper also studies the temporal variation in the conditional return correlations between commodities and interest-rate securities and relates it to the conditional volatility of fixed-income instruments. In line with the results for international stock markets, we report that commodity futures serve as a good hedge against the risk that short-term interest rate may rise. However, the evidence from the long-term fixed income securities is different: Adding commodity futures to a US or global Treasury-bond portfolio does not reduce risk further in periods of high volatility in bond markets.

Finally, our analysis could be further refined to account for the fact that institutional investors also hold corporate bonds of different grades and maturities, real estate, artwork or hedge funds as part of their asset allocation. A thorough analysis of the temporal variations between commodity futures and this broader range of assets might therefore be of interest. We offer this as a possible avenue for future research.

Exhibit 1
Descriptive Statistics of Returns

The exhibit reports the annualized mean and standard deviation of returns for 25 commodity futures (split into 4 styles) and 13 traditional asset classes. *, ** and *** indicate significance at the 1, 5 and 10% levels, respectively.

	Mean	Standard Deviation	Reward-to-Risk Ratio	Skewness	Excess Kurtosis	Jarque-Bera Test	Sample begins
Panel A: Agricultural Commodities							
Cocoa	-0.0855	0.2860	-0.2990	0.2046 *	1.0557 *	72.44 *	Jan-81
Coffee	-0.0353	0.3668	-0.0963	0.4983 *	5.6113 *	1835.14 *	Jan-81
Corn	-0.0944 *	0.2072	-0.4557	0.5469 *	3.9090 *	930.94 *	Jan-81
Cotton	-0.0444	0.2249	-0.1972	0.0946	0.9708 *	55.27 *	Jan-81
Oats	-0.0577	0.4708	-0.1226	0.0339	1.4525 *	74.70 *	Jan-81
Orange juice	-0.0770	0.2911	-0.2643	0.3821 *	2.8901 *	504.16 *	Jan-81
Soybean meal	-0.0736	0.2814	-0.2614	-0.2648 *	4.6935 *	1260.45 *	Jan-81
Soybean oil	0.0060	0.2288	0.0262	0.0648	1.9587 *	217.70 *	Jan-81
Soybeans	-0.0519	0.2300	-0.2257	0.1385 **	1.2935 *	98.87 *	Jan-81
Sugar	-0.0416	0.2074	-0.2005	-0.0334	2.2875 *	295.89 *	Jan-81
Wheat	0.1660 **	0.3593	0.4620	0.0138	3.2569 *	507.41 *	Jan-81
Panel B: Energy Commodities							
Crude oil	0.0959	0.3148	0.3047	-0.5177 *	5.0167 *	1354.61 *	Apr-83
Heating oil	0.0956	0.3173	0.3015	-0.0181	4.2445 *	1017.98 *	Jan-81
Lumber	-0.0910	0.2865	-0.3178	0.0758	0.5077 *	15.86 *	Jan-81
Natural gas	-0.0346	0.2052	-0.1686	-0.1385	2.3873 *	116.24 *	Oct-90
Unleaded gas	-0.0914	0.3526	-0.2593	-0.0632	1.4211 *	115.00 *	Jan-85
Panel C: Livestock Commodities							
Feeder cattle	0.0294	0.1357	0.2168	-0.5831 *	6.9730 *	2824.02 *	Jan-81
Frozen pork bellies	-0.0424	0.3473	-0.1221	0.0972	1.3166 *	100.07 *	Jan-81
Lean hogs	0.0178	0.2310	0.0770	-0.4495 *	2.2151 *	322.89 *	Jan-81
Live cattle	0.0481 ***	0.1467	0.3277	-0.5766 *	6.5585 *	2505.41 *	Jan-81
Panel D: Metal Commodities							
Copper	0.0735	0.2258	0.3253	-0.0794	2.1587 *	174.91 *	Nov-89
Gold	-0.0543	0.1703	-0.3188	0.3673 *	6.7636 *	2615.17 *	Jan-81
Palladium	-0.0020	0.2700	-0.0073	0.3536 *	4.0013 *	932.84 *	Jan-81
Platinum	0.0177	0.3090	0.0572	-0.0875	2.4263 *	334.34 *	Jan-81
Silver	0.0021	0.2425	0.0086	0.0528	3.8253 *	827.40 *	Jan-81
Panel E: Traditional Asset Classes (Excess Return)							
S&P500	0.0410	0.1549	0.2644	-0.3097 *	3.7781 *	828.17 *	Jan-81
Russell 2000	0.0602	0.1723	0.3494	-0.3209 *	1.8071 *	151.69 *	Jan-88
Russell 1000 value	0.0676 ***	0.1419	0.4762	0.0338	2.9313 *	299.11 *	Jan-91
Russell 1000 growth	0.0539	0.1778	0.3030	-0.2499 *	2.6818 *	258.92 *	Jan-91
MSCI Europe equity	0.0495	0.1597	0.3100	-0.3467 *	2.5546 *	289.02 *	Jan-88
MSCI Asia Pacific equity	-0.0154	0.1892	-0.0814	0.0922	1.1874 *	59.56 *	Jan-88
MSCI Latin America equity	0.1577 *	0.2804	0.5625	-0.6212 *	2.9839 *	429.20 *	Feb-88
JPM US 6-month T-bill	0.0011 **	0.0025	0.4571	0.2549 *	2.4875 *	294.15 *	Jan-86
JPM US 12-month T-bill	0.0045 *	0.0080	0.5549	0.0698	2.1238 *	206.68 *	Jan-86
JPM US T-Bond	0.0194 **	0.0445	0.4349	-0.1445 ***	1.2368 *	73.60 *	Jan-86
JPM Global Asia bond	0.0458 **	0.0720	0.6363	-1.2935 *	10.3675 *	3220.78 *	Jan-94
JPM Global Africa bond	0.0831 **	0.1431	0.5809	-2.1832 *	18.4805 *	10171.72 *	Jan-94
JPM Global Europe bond	0.1128 **	0.1996	0.5650	-1.7390 *	12.3309 *	4630.33 *	Jan-94
Panel F: Average							
Commodity	-0.0130	0.2683	-0.0484	0.0045	3.1678	764.39	
Fixed Income	0.0444	0.0783	0.5382	-0.8393	7.8378	3099.55	
Equity	0.0592	0.1823	0.3120	-0.2461	2.5606	330.81	

EXHIBIT 2
Unconditional Correlations between Commodity Futures and Traditional Asset Classes

Pearson correlation test is used to measure the significance of correlation. *, ** and *** indicate significance at the 1, 5 and 10% levels, respectively.

	Equity Indices							JPM Fixed Income Indices					
	S&P500	Russell 2000	Russell 1000 Value	Russell 1000 Growth	MSCI Europe	MSCI Asia Pacific	MSCI Latin America	US 6-mth T-Bill	US 12-mth T-Bill	US T-Bond	Global Asia	Global Africa	Global Europe
Panel A: Agricultural Commodities													
Cocoa	-0.0115	0.0092	-0.0085	-0.0159	0.0394	0.0083	-0.0335	0.0002	0.0000	-0.0182	-0.0157	-0.0018	-0.0199
Coffee	0.0425	0.0441	0.0485	0.0487	0.0925 *	0.0703 **	0.0703 **	-0.0006	-0.0013	-0.0147	-0.0136	-0.0405	-0.0071
Corn	0.0071	0.0343	0.0182	-0.0001	0.0148	0.0128	0.0345	0.0001	0.0004	-0.0005	0.0047	0.0227	-0.0017
Cotton	0.0064	0.0132	0.0065	0.0103	0.0238	0.0070	-0.0411	-0.0005	-0.0020	-0.0092	-0.0187	-0.0030	-0.0217
Oats	0.0055	0.0101	0.0474	-0.0441	-0.0059	0.0395	0.0430	0.0000	0.0004	0.0023	0.0254	0.0365	0.0330
Orange juice	0.0048	0.0128	0.0129	-0.0014	0.0023	0.0111	0.0233	0.0003	0.0011	0.0006	0.0042	0.0128	-0.0118
Soybean meal	0.0069	0.0647 **	0.0184	0.0009	0.0806 *	0.1186 *	0.1749 *	0.0004	0.0013	-0.0022	0.0112	0.0107	0.0619
Soybean oil	0.0098	0.0260	0.0126	0.0123	0.0203	0.0179	0.0442	0.0001	0.0009	0.0026	0.0080	0.0260	0.0136
Soybeans	0.0280	0.0436	0.0371	0.0237	0.0489	0.0509	0.0260	0.0001	0.0001	0.0036	0.0072	0.0056	-0.0154
Sugar	0.0207	0.0336	0.0262	0.0211	0.0333	0.0352	0.0443	0.0001	0.0005	0.0042	0.0092	0.0211	0.0016
Wheat	0.0214	0.0926 *	0.0270	0.0245	0.0399	0.0534 ***	0.1063 *	0.0000	0.0003	0.0020	0.0031	0.0308	0.0307
Panel B: Energy Commodities													
Crude oil	-0.0018	0.0656 **	0.0010	0.0005	0.0140	0.0483	0.0737 *	-0.0001	-0.0001	-0.0056	-0.0002	0.0347	0.0364
Heating oil	0.0132	0.0607 ***	0.0191	0.0115	0.0181	0.0509	0.0686 *	-0.0003	-0.0003	-0.0013	-0.0001	0.0251	0.0412
Lumber	0.0948 *	0.0991 *	0.0900 *	0.1054 *	0.0584 ***	0.0285	0.0937 *	-0.0004	-0.0016	-0.0139	0.0011	0.0149	0.0270
Natural gas	0.0058	0.0112	0.0095	0.0040	0.0049	-0.0038	-0.0292	-0.0001	-0.0004	-0.0019	-0.0092	-0.0092	-0.0184
Unleaded gas	-0.0206	-0.0021	-0.0105	-0.0272	0.0036	-0.0124	0.0178	-0.0003	-0.0012	-0.0083	0.0003	0.0231	0.0307
Panel C: Livestock Commodities													
Feeder cattle	0.0188	0.0215	0.0196	0.0200	0.0130	-0.0027	-0.0057	-0.0002	-0.0011	-0.0057	-0.0020	-0.0070	-0.0104
Frozen pork bellies	-0.0195	0.0161	-0.0118	-0.0238	-0.0153	0.0011	-0.0478	0.0001	-0.0001	0.0018	0.0068	0.0038	0.0327
Lean hogs	0.0205	0.0231	0.0263	0.0173	0.0073	-0.0298	-0.0317	0.0003	0.0005	0.0017	0.0059	0.0069	-0.0011
Live cattle	0.0253	0.0368	0.0298	0.0245	0.0217	0.0030	0.0192	-0.0002	-0.0010	-0.0049	-0.0032	-0.0089	0.0023
Panel D: Metal Commodities													
Copper	0.0603 ***	0.0819 *	0.0630 ***	0.0610 ***	0.0859 *	0.1007 *	0.1118 *	-0.0004	-0.0019	-0.0159	0.0006	0.0281	0.0308
Gold	-0.0117	0.0196	-0.0047	-0.0150	0.0415	0.0568 ***	0.0893 *	0.0006	0.0015	0.0056	0.0103	0.0096	0.0263
Palladium	0.0101	0.0161	0.0083	0.0168	0.0195	0.0508	0.0218	0.0000	-0.0001	0.0079	0.0016	-0.0045	0.0017
Platinum	0.0144	0.0543 ***	0.0012	0.0282	0.0390	0.0742 *	0.0882 *	0.0003	0.0002	-0.0028	0.0045	-0.0144	0.0084
Silver	-0.0042	0.0133	0.0056	-0.0118	0.0213	0.0739 *	0.0655 **	0.0003	0.0002	-0.0045	0.0028	0.0226	0.0268
Panel E: Average	0.0139	0.0361	0.0197	0.0117	0.0289	0.0346	0.0411	0.0000	-0.0001	-0.0031	0.0018	0.0098	0.0119

EXHIBIT 3
Conditional Correlations with the S&P500 Index

"Trend" is the slope coefficient of a regression of conditional correlations ρ_t on a constant and a time trend. *t*-ratio is the associated *t*-statistic. $\Delta\rho$ is the difference between the last and first fitted values of a regression of conditional correlations on a constant and a zero-mean time trend. *, ** and *** indicate significance at the 1, 5 and 10% levels, respectively.

	Average		Standard Deviation	Trend (*1,000)	*t*-ratio	$\Delta\rho$
Panel A: Agricultural Commodities						
Cocoa	0.0053		0.0717	-0.0901	-17.95	-12.20%
Coffee	0.0263		0.0476	0.0502	18.26	6.80%
Corn	0.0568	**	0.0715	-0.0944	-21.02	-12.79%
Cotton	0.0466	***	0.0732	-0.0822	-18.95	-11.14%
Oats	0.0422		0.0319	-0.0261	-9.82	-3.53%
Orange juice	0.0443		0.0304	-0.0106	-6.17	-1.44%
Soybean meal	0.0404		0.0656	-0.0685	-15.89	-9.28%
Soybean oil	0.0711	*	0.0496	-0.0195	-5.55	-2.65%
Soybeans	0.0727	*	0.0426	-0.0192	-6.99	-2.61%
Sugar	-0.0223		0.0829	-0.1132	-24.87	-15.34%
Wheat	0.0469	***	0.0253	-0.0075	-4.38	-1.02%
Panel B: Energy Commodities						
Crude oil	-0.0637	**	0.0688	0.0289	6.72	3.58%
Heating oil	-0.0201		0.0788	0.0042	0.91	0.57%
Lumber	0.1544	*	0.0513	-0.0071	-2.29	-0.96%
Natural gas	0.0128		0.0506	-0.0446	-10.76	-3.79%
Unleaded gas	-0.0209		0.1117	0.0246	2.69	2.83%
Panel C: Livestock Commodities						
Feeder cattle	0.0817	*	0.0637	-0.0164	-4.26	-2.22%
Frozen pork bellies	-0.0135		0.0572	-0.0476	-13.69	-6.45%
Lean hogs	0.0442		0.0225	-0.0034	-2.21	-0.47%
Live cattle	0.0686	*	0.0676	0.0321	7.70	4.36%
Panel D: Metal Commodities						
Copper	0.1353	*	0.0306	-0.0061	-1.93	-0.55%
Gold	-0.0025		0.1649	-0.1387	-11.16	-18.80%
Palladium	0.0689	*	0.0610	-0.0892	-21.39	-12.09%
Platinum	0.0864	*	0.0957	-0.1308	-19.90	-17.72%
Silver	0.0582	**	0.1263	-0.2095	-25.25	-28.38%
Panel E: Commodity Average						
	0.0408		0.0657	-0.0434	-8.33	-5.81%

EXHIBIT 4
Correlation and S&P500 Volatility

The results are derived by estimating the regression $\rho_{TC,t} = \alpha + \beta_T \sqrt{h_{T,t}} + \beta_C \sqrt{h_{C,t}} + \varepsilon_t$, where T and C stand for traditional asset class (here, S&P500) and commodity futures, respectively, $\rho_{TC,t}$ is the conditional return correlation between traditional asset and commodity futures, $\sqrt{h_t}$ is a conditional volatility and ε_t is an error term. $\bar{R}^2$ is the adjusted coefficient of determination statistic.

	Intercept		S&P500 Volatility: h_{Tt}		Commodity Volatility: h_{Ct}		$\bar{R}^2$
	α	$t(\alpha)$	β_T	$t(\beta_T)$	β_C	$t(\beta_C)$	
Panel A: Agricultural Commodities							
Cocoa	0.0233	2.17	-2.7574	-10.19	0.9934	4.21	0.0742
Coffee	0.0611	10.17	-0.8156	-3.93	-0.3604	-4.61	0.0295
Corn	0.1488	16.51	-3.5572	-10.13	-0.6531	-2.83	0.1162
Cotton	0.0382	5.29	0.8648	2.80	-0.3129	-1.80	0.0056
Oats	0.0491	6.12	-0.3668	-1.69	0.0189	0.11	0.0024
Orange juice	0.0571	8.14	-0.7486	-6.36	0.0770	0.46	0.0275
Soybean meal	0.1259	18.90	-3.2038	-11.74	-0.6178	-3.66	0.1148
Soybean oil	0.0712	7.40	0.5555	2.14	-0.3738	-1.42	0.0068
Soybeans	0.0618	8.40	0.3433	1.77	0.1389	0.63	0.0022
Sugar	-0.2374	-31.09	2.5068	10.30	3.4169	22.22	0.3445
Wheat	0.0444	7.39	0.5999	4.67	-0.3252	-1.91	0.0298
Panel B: Energy Commodities							
Crude oil	-0.1169	-14.92	3.5155	12.01	-0.4550	-2.56	0.1076
Heating oil	0.0277	2.28	0.2214	0.54	-1.2285	-4.54	0.0734
Lumber	0.1932	35.97	1.0764	5.77	-1.5692	-15.67	0.1497
Natural gas	0.0568	4.82	1.1497	3.85	-1.0460	-5.49	0.0783
Unleaded gas	0.0941	4.53	-1.1233	-2.19	-1.8849	-4.86	0.0652
Panel C: Livestock Commodities							
Feeder cattle	-0.0156	-2.43	4.7341	18.24	-0.0511	-0.20	0.2627
Frozen pork bellie	0.0264	2.96	-1.3186	-3.94	-0.2650	-1.92	0.0237
Lean hogs	0.0422	11.81	0.4392	3.88	-0.2305	-1.88	0.0160
Live cattle	-0.0468	-7.10	4.5670	19.61	1.0431	3.78	0.2164
Panel D: Metal Commodities							
Copper	0.1899	34.92	-1.9415	-11.50	-0.4938	-3.73	0.1637
Gold	-0.1043	-9.09	-6.9796	-16.20	11.1970	31.64	0.4425
Palladium	0.0135	1.62	0.3352	1.53	1.1676	6.89	0.0611
Platinum	-0.0023	-0.24	-1.5638	-5.66	3.8455	16.03	0.2415
Silver	-0.0931	-7.18	-1.5979	-4.28	4.9728	18.40	0.2814

EXHIBIT 5
The Negative Relation between Correlation and S&P500 Volatility: The Case of Gold Futures

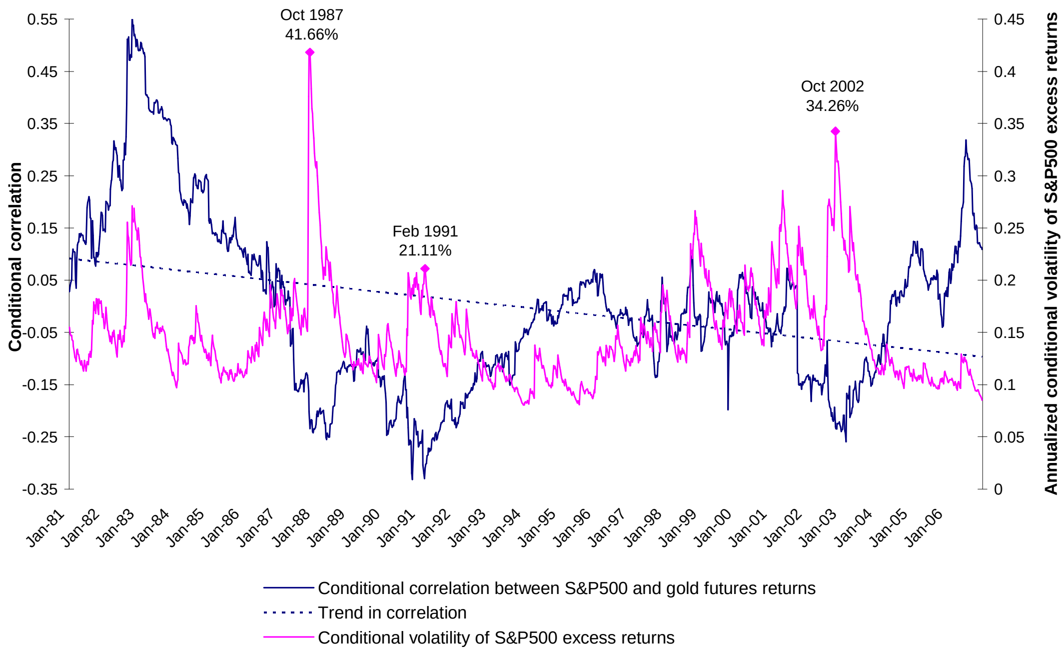

EXHIBIT 6
The Positive Relation between Correlation and S&P500 Volatility: The Case of Feeder Cattle Futures

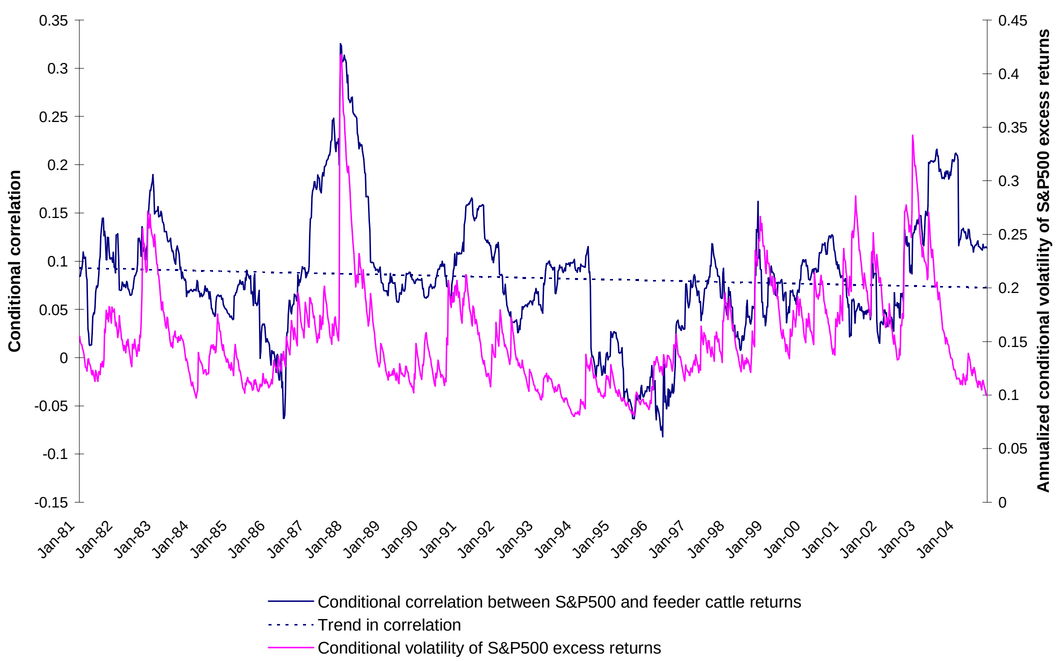

EXHIBIT 7
Correlation and Volatility in Global Equity Markets

β_T is the slope coefficient of the regression $\rho_{TC,t} = \alpha + \beta_T \sqrt{h_{T,t}} + \beta_C \sqrt{h_{C,t}} + \varepsilon_t$, where *T* and *C* stand for traditional asset class and commodity futures, respectively, $\sqrt{h_t}$ is a conditional volatility and ε_t is an error term. $t(\beta_T)$ is the associated *t*-statistics.

	Russell 2000		Russell 1000 Value		Russell 1000 Growth		MSCI Europe		MSCI Asia Pacific		MSCI Latin America	
	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$
Panel A: Agricultural Commodities												
Cocoa	-0.876	-4.28	-5.273	-6.91	-4.788	-12.62	-1.592	-2.91	5.513	7.24	-0.609	-6.65
Coffee	-0.666	-1.67	2.662	3.85	0.788	1.58	1.264	2.40	0.618	2.01	-0.738	-2.69
Corn	-5.949	-13.52	-5.807	-6.96	-8.982	-18.08	-4.188	-5.47	1.210	1.32	0.524	1.61
Cotton	-0.193	-0.43	3.905	4.84	2.080	2.95	0.365	4.31	3.322	4.46	-0.282	-1.54
Oats	-1.472	-7.18	-6.422	-11.44	-5.582	-10.62	-6.545	-14.89	0.538	0.69	-1.353	-3.80
Orange juice	-1.537	-7.90	-4.387	-10.42	-2.054	-3.88	0.003	0.02	-0.148	-0.48	0.264	1.44
Soybean meal	-0.269	-13.44	-2.182	-2.25	-3.379	-4.97	-1.013	-1.49	5.384	5.74	0.127	0.33
Soybean oil	-0.049	-1.58	5.120	5.57	-0.804	-4.20	2.618	3.68	-1.044	-1.14	-1.646	-3.12
Soybeans	-1.565	-2.56	-1.742	-1.69	-3.187	-4.43	-0.564	-0.79	-0.636	-4.22	0.139	0.28
Sugar	0.340	0.52	2.479	4.56	6.093	8.83	2.713	4.92	0.399	0.93	2.301	4.09
Wheat	-1.620	-2.69	4.207	4.54	-1.516	-3.00	-3.581	-7.65	-1.880	-3.16	-1.072	-2.64
Panel B: Energy Commodities												
Crude oil	5.406	9.82	0.406	0.51	2.149	8.78	2.092	3.09	-1.092	-3.33	0.639	2.32
Heating oil	3.022	8.13	2.930	3.04	8.946	17.53	0.364	0.48	-2.324	-6.15	0.553	5.55
Lumber	0.782	1.00	6.662	12.25	0.855	1.99	1.391	10.13	8.747	13.57	-1.408	-3.25
Natural gas	3.339	3.94	4.146	6.86	0.171	0.33	0.009	0.17	0.179	1.24	0.934	2.64
Unleaded gas	3.149	6.80	-1.920	-1.67	1.356	5.52	0.056	0.13	-1.022	-4.42	1.176	6.62
Panel C: Livestock Commodities												
Feeder cattle	0.525	5.49	8.592	12.21	4.443	7.72	6.949	10.40	3.947	6.16	-1.216	-2.70
Frozen pork bellies	-0.634	-1.00	-7.283	-9.44	-9.037	-18.45	-3.998	-7.08	-2.613	-4.20	-0.316	-0.88
Lean hogs	0.229	1.04	0.967	1.09	-5.933	-11.79	1.865	3.42	-6.017	-6.66	0.245	0.47
Live cattle	0.416	4.10	7.190	9.92	2.315	5.44	3.046	6.91	5.485	5.11	0.007	0.02
Panel D: Metal Commodities												
Copper	0.141	0.93	1.247	5.51	1.419	6.26	6.943	8.61	0.037	0.07	-0.623	-3.18
Gold	-0.688	-1.44	-5.160	-14.94	-3.206	-5.97	-9.859	-14.12	-7.433	-7.48	1.302	2.95
Palladium	-0.139	-1.30	-0.525	-1.87	-1.165	-2.39	-0.122	-0.71	-4.160	-10.35	-0.386	-1.30
Platinum	-0.401	-2.10	-0.557	-0.90	-2.342	-4.71	-0.883	-2.76	0.588	1.68	0.904	3.02
Silver	1.232	1.82	-4.937	-7.94	-0.831	-0.90	-2.816	-10.22	-9.458	-13.95	-0.655	-2.43

EXHIBIT 8
Correlation and Volatility in Global Fixed Income Markets

β_T is the slope coefficient of the regression $\rho_{TC,t} = \alpha + \beta_T \sqrt{h_{T,t}} + \beta_C \sqrt{h_{C,t}} + \varepsilon_t$, where T and C stand for traditional asset class and commodity futures, respectively, $\sqrt{h_t}$ is a conditional volatility and ε_t is an error term. $t(\beta_T)$ is the associated t-statistics.

	JPM US 6-month Tbill		JPM US 12-month Tbill		JPM US T-Bond		JPM Global Asia		JPM Global Africa		JPM Global Europe	
	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$
Panel A: Agricultural Commodities												
Cocoa	175.397	10.33	25.916	2.16	-14.721	-18.10	1.229	1.24	1.697	9.91	1.103	2.73
Coffee	52.316	3.42	-36.912	-2.74	4.271	1.47	5.495	9.63	-1.564	-8.36	-0.054	-0.29
Corn	-37.235	-5.31	-108.514	-6.75	18.027	6.29	8.712	11.91	4.522	10.90	1.109	6.03
Cotton	166.378	23.27	50.074	4.32	-5.189	-2.98	4.179	4.54	1.350	2.91	-1.070	-3.25
Oats	-11.390	-1.19	-35.491	-2.33	5.046	1.52	5.087	8.27	3.623	7.99	-0.818	-3.69
Orange juice	193.758	5.69	84.502	5.31	7.193	4.42	-6.833	-6.44	0.543	0.78	0.364	1.01
Soybean meal	-93.661	-3.21	-33.898	-2.40	16.448	2.44	5.257	8.21	0.081	0.19	0.432	2.00
Soybean oil	-355.093	-12.64	-167.991	-13.16	13.627	7.59	5.071	4.84	1.147	2.60	-0.948	-3.84
Soybeans	-212.447	-12.56	-123.840	-10.44	7.431	4.55	6.403	7.65	1.551	2.91	-0.145	-0.55
Sugar	-225.514	-7.64	-91.356	-6.76	12.937	8.16	7.341	6.13	1.732	3.96	0.897	1.79
Wheat	-51.443	-2.13	-23.015	-1.68	12.912	4.72	6.508	8.07	4.430	10.92	2.105	6.10
Panel B: Energy Commodities												
Crude oil	-328.949	-11.27	-194.957	-11.51	3.799	6.41	0.129	0.12	0.383	1.46	-0.636	-1.85
Heating oil	-414.695	-15.88	-43.826	-10.85	18.940	4.28	1.390	1.71	-0.696	-1.73	-0.581	-1.85
Lumber	459.323	18.40	175.230	11.94	2.108	0.77	4.122	4.44	2.898	7.45	1.459	4.49
Natural gas	33.067	1.15	-26.718	-1.64	-16.203	-4.01	9.670	11.58	3.473	11.80	0.647	3.44
Unleaded gas	-267.986	-10.65	-27.508	-10.28	1.810	2.26	2.655	3.18	2.647	5.44	0.023	0.05
Panel C: Livestock Commodities												
Feeder cattle	-53.830	-1.41	-20.037	-3.75	-2.339	-3.53	6.131	3.99	-1.880	-4.23	-1.231	-3.81
Frozen pork bellies	3.910	0.12	-3.331	-0.22	17.360	6.98	6.608	9.95	1.646	9.27	-0.099	-0.76
Lean hogs	23.123	1.53	-25.570	-1.85	-12.092	-3.07	9.743	10.10	-0.155	-0.34	0.358	1.28
Live cattle	30.248	3.62	-118.118	-7.08	-24.594	-5.00	4.006	3.00	-0.994	-1.84	0.613	1.75
Panel D: Metal Commodities												
Copper	239.338	9.28	30.315	2.86	-21.227	-6.09	4.571	4.97	1.837	3.55	0.299	2.46
Gold	-643.030	-10.53	-154.064	-20.66	37.729	9.06	-0.730	-1.25	-2.315	-4.66	-0.685	-1.54
Palladium	-179.580	-7.13	-66.298	-10.97	-0.508	-3.33	-2.624	-8.85	-0.900	-3.08	-2.118	-4.96
Platinum	-381.202	-25.31	-105.056	-16.61	1.123	1.08	3.970	3.14	-0.231	-0.59	0.384	1.05
Silver	-716.939	-34.34	-183.301	-16.37	-0.114	-0.05	0.024	0.02	0.520	1.61	0.239	0.96

EXHIBIT 9
The Negative Relation between Correlation and T-Bill Volatility: The Case of Crude Oil Futures

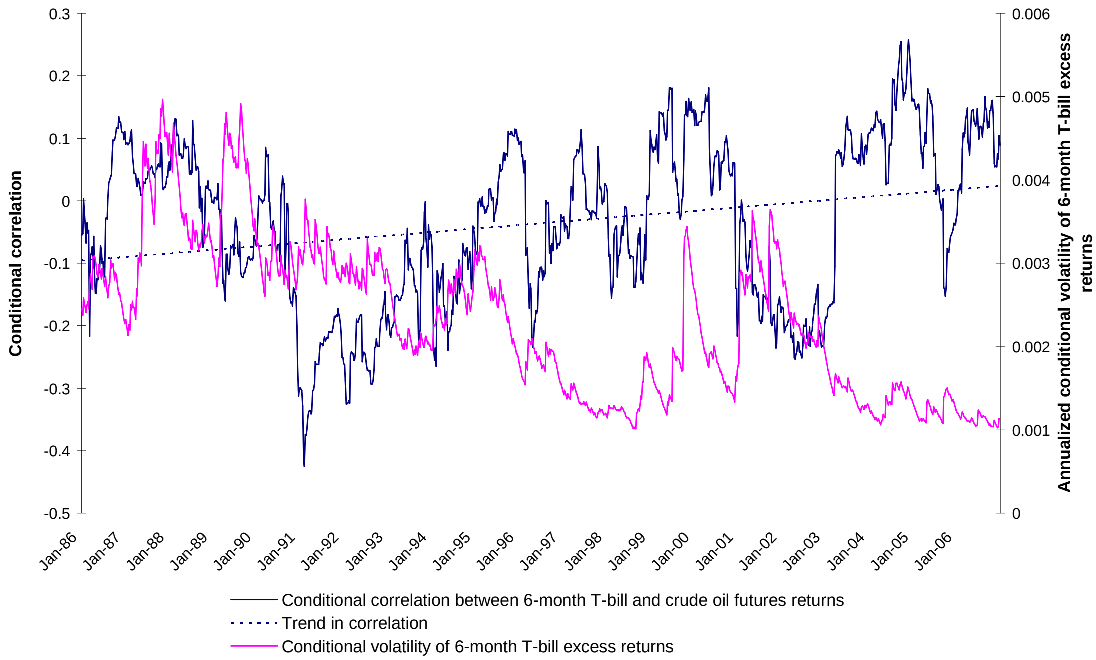

EXHIBIT 10
Conditional Correlation and Volatility at the Daily Frequency

The results are derived by estimating the regression $\rho_{TC,t} = \alpha + \beta_T \sqrt{h_{T,t}} + \beta_C \sqrt{h_{C,t}} + \varepsilon_t$, where T and C stand for traditional asset class (here, S&P500 or US Treasury-bond index) and commodity futures, respectively, $\rho_{TC,t}$ is the daily conditional return correlation between traditional asset and commodity futures, $\sqrt{h_t}$ is a daily conditional volatility and ε_t is an error term.

	S&P500 Volatility		T-Bond Volatility	
	β_T	$t(\beta_T)$	β_T	$t(\beta_T)$
Panel A: Agricultural Commodities				
Cocoa	-1.2339	-12.52	-0.9755	-0.80
Coffee	-0.2666	-4.52	10.0897	17.90
Corn	-0.2384	-2.00	7.3002	17.92
Cotton	-0.2037	-2.33	-9.2780	-16.28
Oats	-1.0979	-11.21	9.7741	5.40
Orange juice	-1.5335	-20.35	-2.6438	-3.99
Soybean meal	-0.7681	-5.37	4.2965	2.95
Soybean oil	2.0046	8.61	21.8594	21.54
Soybeans	-0.0568	-16.68	4.8750	13.44
Sugar	1.0159	7.43	-11.9866	-8.62
Wheat	2.5814	18.73	0.7079	3.10
Panel B: Energy Commodities				
Crude oil	4.7005	26.44	5.2083	3.36
Heating oil	3.1901	15.67	4.5907	2.57
Lumber	1.4065	12.37	-6.9142	-3.95
Natural gas	1.3935	8.62	3.2997	2.08
Unleaded gas	1.8882	9.46	1.9463	1.11
Panel C: Livestock Commodities				
Feeder cattle	1.3627	20.42	-7.9941	-8.86
Frozen pork bellies	-1.5947	-6.09	-10.4763	-19.00
Lean hogs	2.8221	10.69	0.5175	0.71
Live cattle	-0.4741	-3.58	0.8861	1.08
Panel D: Metal Commodities				
Copper	5.3103	18.12	-28.5310	-16.72
Gold	-1.9997	-7.89	36.2133	22.43
Palladium	-3.9833	-8.14	-41.7744	-15.95
Platinum	-5.2152	-17.55	-16.9844	-6.17
Silver	-4.6250	-11.04	0.0460	0.01

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ENDNOTES

[1] To name only a few authors, Greer [1978]; Bodie and Rosansky [1980]; Bodie [1983]; Locke and Venkatesh [1997]; Jensen *et al.* [2000, 2002]; Basu *et al.* [2006]; Erb and Harvey [2006]; Gorton and Rouwenhorst [2006]; Miffre and Rallis [2007]; Fuertes *et al.* [2009].

[2] Even in turbulent times, conditional return correlations remain, for the most part, positive. We do not claim therefore that commodity futures prices rise in periods of market stress. Instead, we hypothesize that in times of high volatility the stop-loss orders of traditional asset managers and the subsequent re-allocation of resources towards commodity futures put more downward pressure on the prices of traditional assets than on the prices of commodity futures.

[3] As a robustness check, we also use daily data to study the relation between conditional correlation and conditional S&P500 volatility.

[4] The 3-month Treasury-bill rate is subtracted to measure excess returns. This is to account for the opportunity cost of buying stocks and bonds. Since such cost is not incurred in commodity futures markets, Exhibit 1 reports summary statistics for raw returns of commodity futures (as is standard in the literature, margins are ignored).

[5] Conditional correlations are regressed on a constant and a zero-mean time trend. For each commodity, $\Delta\rho$, the difference between the last and first fitted values, measures the amount by which the correlations have decreased or increased over the period analyzed.

[6] Since the explanatory power of the model is, at times, low and the constant in (1) is often significant, conditional volatilities may not be the only drivers of conditional correlations. Note also that regressing the conditional correlation on solely a constant and the conditional S&P500 volatility does not change the inference on the signs and significance of β_T.

[7] If instead of assuming equal weighting, we weigh the commodities with negative β_T coefficients based on their relative average open interests over the sample studied, the average β_T coefficient equals -3.04.

[8] For the 10 commodities with positive β_T at the 5% level in Exhibit 4, the average β_T coefficient in (1) is 1.6084, suggesting that a 1% rise in market risk leads on average to a 1.61% rise in correlation. If instead of assuming equal weighting as above, we

weigh the commodities with positive β_T coefficients based on their relative average open interests over the sample studied, the average positive β_T coefficient equals 1.8765.

[9] We are thankful to the referee for pointing this out.