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Conditional Return Correlations between Commodity Futures and Traditional Assets

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Abstract

The article studies the temporal variations in the conditional return correlations between commodity futures and traditional asset classes (global stock and fixed-income indices). We reveal that the conditional correlations between commodity futures and S&P500 returns fell over time, a sign that commodity futures have become better tools for strategic asset allocation. The correlations with equity returns 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, falls in return correlations between commodity futures and Treasury-bills go hand in hand with rises in short-term interest volatility, suggesting that adding commodity futures to Treasury-bill portfolios reduces risk further in volatile interest rate environments.

Keywords: Commodity Futures, Traditional Assets, Correlation, Volatility, DCC Model
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1. Introduction

Commodity futures have low return correlation with traditional asset classes and thus are useful tools for strategic asset allocation (Jensen *et al.* 2000, Erb and Harvey 2006). They are also a good hedge against inflation (Bodie and Rosansky 1980, Bodie 1983). They present positive skewness in their return distribution (Gorton and Rouwenhorst 2006), offer leverage, high liquidity, low transaction costs, and complete transparency (relative to commodity trading advisors). Finally, recent research showed that tactical trading generated abnormal returns in commodity futures markets in the past (Jensen *et al.* 2002, Wang and Yu 2004, Basu *et al.* 2006, Erb and Harvey 2006, Miffre and Rallis 2007, Vrugt *et al.*, 2007, Fuertes *et al.*, 2008).[1] For all these reasons, commodity futures have recently attracted much attention among both institutional investors and academics.

It is well known that the strategic decision to include commodity futures in a well-diversified portfolio is not based solely 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. With this in mind, the paper evaluates the conditional correlation between commodity futures returns and those of traditional securities. We reveal that correlations between commodity futures and S&P500 returns fell over time. This suggests that the risk reduction obtained by adding long positions in commodity futures to an equity portfolio has increased over the period analyzed. Ultimately, this implies that commodity futures have become, over time, better portfolio diversifiers and thus better instruments for strategic asset allocation. Correlations between most commodity futures and equity returns also tend to fall in turbulent periods; namely, when market risk increases. This is good news to institutional investors with long positions in equities and commodity futures as it is precisely when market volatility is high that the benefits of diversification are most appreciated.

The paper also analyzes the temporal variations in the conditional correlations between commodity futures and fixed-income securities and relates them to the conditional volatility of short- and long-term fixed-income indices. The evidence from the stock market can be extended to short-term interest rate securities: as with international stocks, conditional correlations tend to fall in periods of high volatility in short-term interest rates. This conclusion, however, does not seem to apply to long-term global fixed-income securities for which the conditional correlation tends to increase with the volatility of global fixed-income markets. This suggests that, unlike global equity and US Treasury-bills, adding commodity futures to a long-term fixed-income global portfolio will not reduce risk further in periods of high interest rate volatility.

The decrease in return correlations between some commodity and equity (or Treasury-bill) returns 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 cut 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 or a sudden rise in inflation, for example, increases the volatility of equity markets. Simultaneously, it also 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.

The paper proceeds as follows. Section 2 presents the GARCH-DCC model used to estimate the conditional correlations and volatilities. Section 3 introduces the dataset. Section 4 studies the temporal variation in the conditional return correlations between 1. commodity futures and 2. global stock and bond indices. Finally, section 5 concludes.

1 - It is worth noting however that Marshall et al. (2008) question the ability of technical trading rules (such as filter, moving average, support and resistance, channel breakouts, etc.) to generate superior performance in commodity futures markets.

2 - Note that, 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

2. Methodology

By far the most successful volatility forecasting model is the 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

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

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

subject to $\gamma_i > 0, \alpha_i, \beta_i \geq 0, \alpha_i + \beta_i < 1$. α and β coefficients 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 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. $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is the time varying correlation matrix, with $Q_t = \left(q_{ij,t}\right)$ as described by $Q_t = (1 - a - b)\bar{Q} + a\left(\Xi_{t-1}\Xi_{t-1}'\right) + bQ_{t-1}$

$\bar{Q}$ 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

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} .$$

As with the GARCH(1,1) model, coefficients of the DCC(1,1) model are estimated by the maximum likelihood procedure using the algorithm of BFGS. The log likelihood function, under the assumption of conditional multivariate normality, is

$$L(\vartheta) = -\frac{1}{2}\left[TN\ln(2\pi) + \sum_{t=1}^{T}\left(\ln|H_t| + \Xi_t' H_t^{-1} \Xi_t\right)\right]$$

with $H_t = E_{t-1}\left(\Xi_t \Xi_t'\right)$ being the $N \times N$ conditional variance/covariance matrix.

We can use the framework presented above to analyze the conditional correlations between commodity futures returns and the returns of traditional asset classes. 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 would suggest 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 would indicate that correlations between commodity futures and equity returns fall in periods of high volatility in equity markets. Ultimately, this result would imply that the usefulness of commodity futures as a diversification tool increases in periods of above average market volatility.

3. Data

The data, from Datastream International, comprise returns of twenty-five commodities and thirteen 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. On this criterion, seven equity asset classes (four from the US and three 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 six 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 twenty-five commodities. We consider eleven agricultural futures (cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar, and wheat), five energy futures (crude oil, heating oil, lumber, natural gas, and unleaded gas), four livestock futures (feeder cattle, frozen pork bellies, lean hogs, and live cattle) and five 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 contract is used. Futures returns are then computed as the log difference in the settlement prices.

The frequency of the data is weekly.[3] To avoid the weekend 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 are used. The dataset spans the period December 12, 1980 to December 27, 2006 for most series, totaling 1,356 return observations. For series with relatively fewer observations, starting dates are shown in table 1.

Table 1 also shows summary statistics for the twenty-five commodity futures returns and the excess returns on the traditional asset classes.[4] The results indicate that the average annualized returns of commodity futures range from -9.44% (corn) to 16.6% (wheat) with an average of -1.30%. Higher volatility in commodity futures markets does not necessarily translate into higher average returns. For example, lumber and unleaded gas futures have average returns of -9% a year and above average standard deviations (28.65% and 35.26% respectively). The reward-to-risk ratios suggest that only a few commodities offer better risk-return trade-offs than stocks and bonds over the period considered. This confirms the general belief that commodity futures are poor stand-alone investments. Table 1 also shows the skewness, excess kurtosis, and Jarque-Bera test of normality. It is clear from this table that the return distribution of commodity futures departs from normality, with strong evidence of positive excess kurtosis at the 1% level.

Table 2 shows unconditional return 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. At 2.87% on average, the return correlations with other equity indices are equally low. Those with bonds are even lower (at 0.34% 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.

4. Empirical Results

This section first studies the conditional correlations between commodity futures and S&P500 returns (section 4.1) and then concludes with an analysis of the dynamics in the co-movements between commodity futures and bond and stock returns other than the S&P500 index (section 4.2).

3 - Should high frequency commodity futures returns be used instead, discontinuous inter- and intra-day periodicities that may exist in the data should be accounted for so as to avoid inferior forecasts of future return volatility (Taylor 2004).

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 this cost is not incurred in commodity futures markets, table 1 reports summary statistics for raw returns of commodity futures (as is standard in the literature, margins are ignored).

4.1. Conditional Correlation and Conditional S&P500 Volatility

Table 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 table 3) is of the same magnitude as the average unconditional correlation (at 0.0139 in table 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) of 25 commodities at the 5% (10%) level. The remaining coefficients are positive and significant for four commodities (coffee, crude oil, unleaded gas, and live cattle) or insignificant for heating oil. The decrease in correlation, measured as $\Delta\rho$ [5] in table 3, is significant in economic terms too. From 1981-2006, conditional correlations decreased by 5.81% on average. The decrease in correlation is particularly severe for precious metals, such as silver ($\Delta\rho$ = -28.38%), gold ($\Delta\rho$ = -18.8%), and platinum ($\Delta\rho$ = -17.72%). This result suggests that segmentation between the S&P500 index and commodity futures markets has increased over time. 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 decrease in correlation over time, as we observed in table 3, could in turn be explained by the results of table 4; namely, by the fact that correlations decrease in period of high market volatility.

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

Take, for example, figure 1, 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 correlation plunges, when the S&P500 volatility experiences a spike (for example, in October 1987, February 1991, and October 2002). On the other hand, when S&P500 volatility decreases, conditional correlation tends to be above average as in 1985 or in 2005-2006. As a result, the correlation between the two series in figure 1 is as low as -0.1751. This implies that gold futures contracts possess diversification benefits in times of increased market stress. Figure 1 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 table 3, that the correlation between S&P500 and gold futures returns fell over the period analyzed.

Across the twenty-five commodity futures, the average β_T coefficient in equation (1) is -0.2026 (table 4). Namely, a 1% rise in market risk leads, on average, to a 0.20% fall in correlation. This ultimately indicates that higher volatility in the S&P500 index implies, other things being equal, a higher allocation to commodity futures. Investors, by allocating higher portfolio weights to 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*-ratio = -16.20), platinum (β_T = -1.5638, *t*-ratio = -5.66) and silver (β_T = -1.5979, *t*-ratio = -4.28). Some agricultural commodities (cocoa, corn, orange juice, soybean meal) tend to do well, relatively speaking, when equity market volatility rises too. It follows that these futures contracts are the best candidates for inclusion in equity portfolios in periods of market turbulence. Gold's low β_T coefficient is accompanied by a negative, albeit insignificant, unconditional

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.

and conditional correlations with, and a comparative volatility to, the S&P500 index (tables 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.

The negative β_T coefficients in table 4 suggest that some commodity futures, such as precious metals, are similar to bonds, in that, like bonds, they reduce the volatility of an equity portfolio in periods of above average market volatility (Hunter and Simon 2005). Flight-to-quality is a possible economic rationale for the observed result. Put differently, institutional investors may view commodity futures (such as precious metals) as refuge securities in periods of high volatility in the S&P500 market. Our results are indeed consistent with the notion that, when market risk rises, institutional investors sell their shares to put a stop to losses in the value of their equity portfolios 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 to 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, table 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 table 1, panel E). Similarly, a rise in unexpected inflation is good 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. Furthermore, since commodities are inputs for most firms, an increase in commodity prices will tend to increase costs and increase uncertainty. Thus, higher commodity prices are favorable (unfavorable) for long positions in commodity futures (equities) and may create higher stock market volatility. This also would explain the observed inverse relationship between correlation and stock market volatility.

4.2. Return Correlations between Commodity Futures and Non-S&P500 Indices

Institutional investors do not hold just S&P500 stocks and commodity futures. To a large extent, their asset mix includes value and growth stocks, small, medium, and large capitalization stocks, US Treasury-bonds and Treasury-bills, and international assets. A thorough analysis of the temporal variations between commodity futures and a much broader range of assets is therefore warranted. With this in mind, tables 5 and 6 study the co-movements between commodity futures returns and the returns on bond and equity indices other than the S&P500 index. In each table we show the coefficient β_T on the conditional volatility of traditional asset markets from equation (1).

Table 5 focuses on equity indices other than the S&P500 index. By and large, the evidence from table 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 table 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. Other things being equal, a 1% rise in equity market volatility leads to a 15.9% fall in conditional correlation, a result that resembles that shown in table 4.

Table 6 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 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 terms to 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. Conversely, following the announcement of a tightening of monetary policy through rising short-term interest rates, Treasury-bill securities typically 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 a better hedge against interest rate risk.

The decrease in conditional correlations in volatile interest rate environments is particularly sharp for precious metals, energy, and 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, figure 2 plots the conditional return correlation between crude oil and 6-month Treasury-bills versus the conditional volatility of 6-month Treasury-bills. Clearly, and as in figure 1, 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%.

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 is positive on the whole at 3.351 (table 5). That is, when volatility in the US Treasury-bond market increases, correlation between Treasury-bond and commodity futures returns tends to rise. At the 5% level, β_T is positive for twelve (mainly agricultural) commodity futures and negative for eight. 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 are less felt in periods when long-term interest rates are highly volatile.

5. Conclusions

The aim of this paper is to study the way returns on commodity futures differ over time from those of traditional asset classes (as proxied by stock and bond indices around the world). We find that the conditional return correlations between 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 a better tool for strategic asset allocation. We also observe that for more than half of our cross section, the conditional correlations between commodity futures and equity returns fell in periods of market turbulence. We see this as good news to institutional investors with long positions in equities and commodity futures. Indeed, it is precisely when stock market volatility is high that benefits of diversification are most appreciated. We offer two hypotheses as possible explanations for this finding: i) that institutional investors treat commodity futures (such as precious metals) as refuge assets in periods of high market volatility and ii) that major events (hurricanes, a rise in unexpected inflation) do not affect the prices of commodity futures and equities in the same ways. 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 the short-term interest rate may rise. However, evidence from

long-term fixed-income securities differs from that from global equity indices and short-term interest rate instruments. In effect, there was no evidence in favor of the hypothesis that commodity futures diversify part of the risk arising from changing and highly volatile long-term interest rates around the world. This suggests that, unlike global equities or short-term US Treasury-bills, adding commodity futures to a US or global Treasury-bond portfolio may 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, 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.

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Table 1

Descriptive statistics of returns

The table reports the annualized mean and standard deviation of returns for twenty-five commodity futures (split into four styles) and thirteen 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		0.2960	-0.2990	0.2046	*	1.0557	*	72.44	*	Jan-81
Coffee	-0.0353		0.3668	-0.0963	0.4963	*	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		

Table 2

Unconditional return correlations between commodity futures contracts 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

Table 3

Summary statistics of conditional correlations: The case for the S&P500 index

"Trend" is the slope coefficient of a regression of conditional correlations ρ_t on a constant and a time trend. $\Delta\rho$ 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%

Table 4

The relation between conditional correlation and conditional market volatility: The case for the S&P500 index

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 the 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		Commodity Volatility		$\bar{R}^2$
	$\bar{\alpha}$	$t(\ )$	$\ _T$	$t(\ _T)$	$\ _C$	$t(\ _C)$	
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 bellies	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
Panel E: Commodity Average							
	0.0283		-0.2026		0.6802		0.1175

Table 5

Conditional correlation and conditional volatility in equity markets

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 the traditional asset class and commodity futures respectiv

$\overline{\iota_t}$ 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
Panel E: Commodity Average												
Average	0.101		0.173		-0.888		-0.219		-0.075		-0.048	
%ge positive at 5%		24%		44%		36%		40%		28%		28%
%ge negative at 5%		32%		32%		52%		32%		40%		36%

Table 6

Conditional correlation and conditional volatility in fixed income markets

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 the traditional asset class and commodity futures respectiv

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
Panel E: Commodity Average												
Average	-103.845		-48.950		3.351		3.924		1.014		0.066	
%ge positive at 5%		28%		20%		48%		72%		52%		28%
%ge negative at 5%		52%		64%		32%		8%		16%		20%

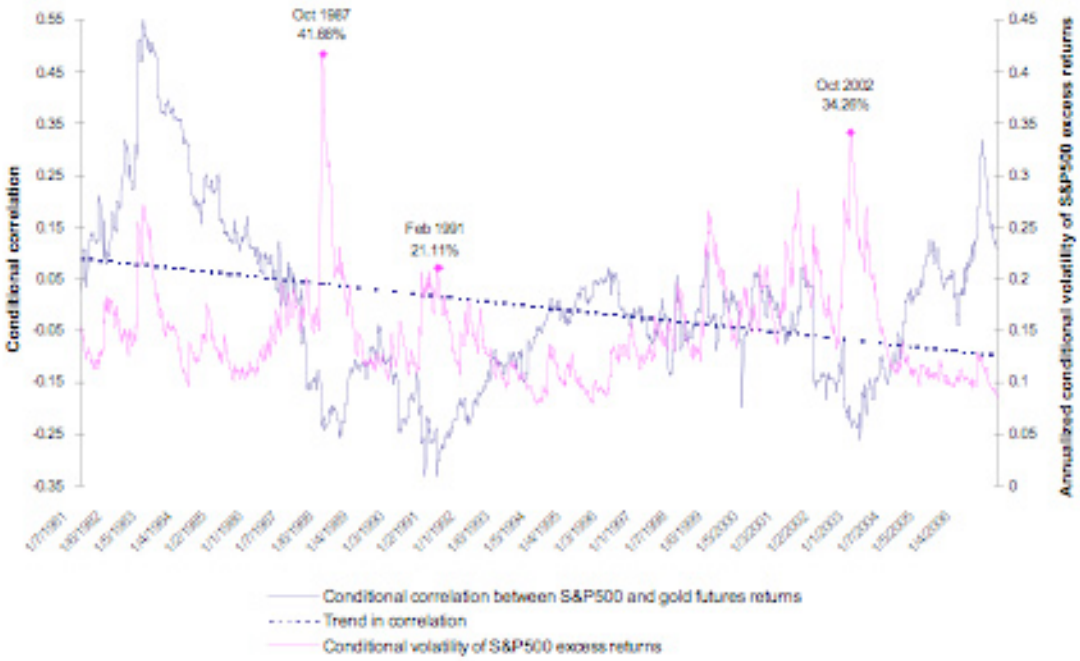

Figure 1 - The negative relation between conditional correlation and conditional S&P500 volatility: gold futures

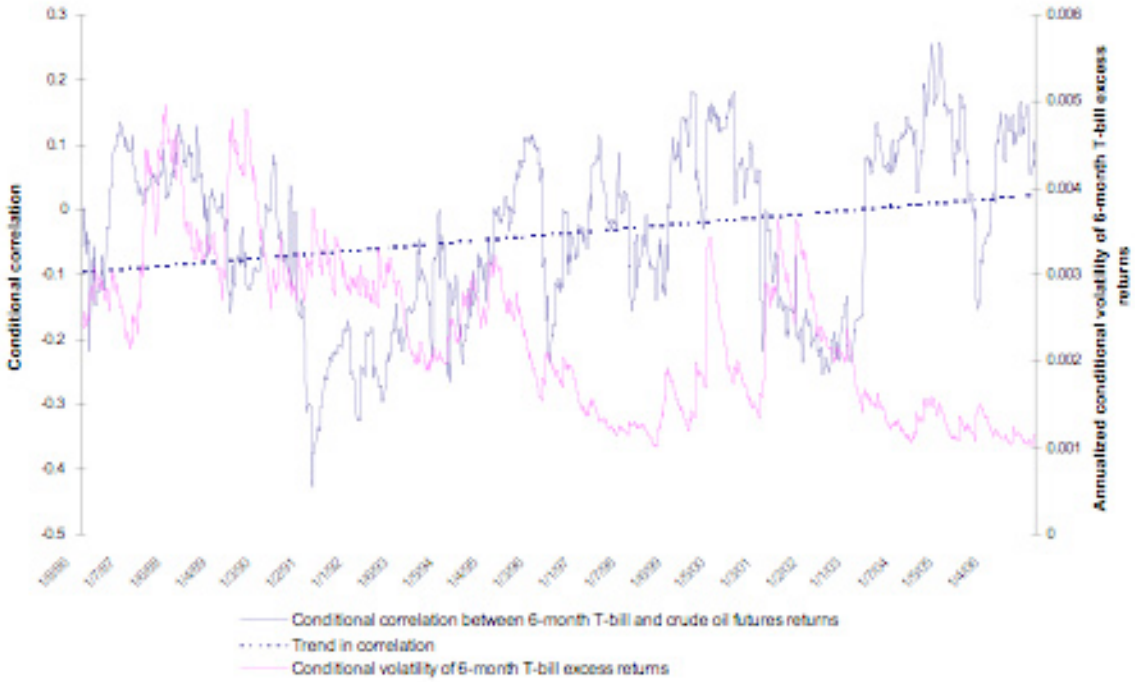

Figure 2 - The negative relation between conditional correlation and conditional 6-month Treasury-bill volatility: crude oil futures