Variance Risk in Commodity Markets*

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Abstract

We analyze the variance risk of commodity markets. We construct synthetic variance swaps and find significantly negative realized variance swap payoffs in most markets. We find evidence of commonalities among the realized payoffs of commodity variance swaps. We also document comovements between the realized payoffs of commodity, equity and bond variance swaps. Similar results hold for expected variance swap payoffs. Furthermore, we show that both realized and expected commodity variance swap payoffs are distinct from the realized and expected commodity futures returns, indicating that variance risk is unspanned by commodity futures.

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I Introduction

Over the past few years, several commodity-related volatility instruments, such as oil and gold VIX, have been introduced. The proliferation of these products raises several questions. Chief among them include: how large is the compensation required by investors to bear variance risk in commodity markets? Are there commonalities among realized commodity variance swap payoffs? How do these payoffs relate to those of the bond and equity markets? What is the relationship between the return on a commodity futures and the variance swap payoff on the same commodity? These are some of the questions we seek to answer in this paper.

We analyze variance risk in 21 commodity markets. On average, we document significantly negative realized variance swap payoffs in most commodity markets. We find that the variance swap payoffs of commodity markets are related to those of the S&P 500 index. However, the commodity variance swaps offer additional payoffs beyond what an investor with a passive exposure to the equity index variance swap payoff would earn. We document that the realized commodity variance swap payoffs are generally unrelated to commodity futures returns. An implication of this result is that commodity variance risk is not spanned by commodity futures. Similar results arise for the expected variance swap payoffs, i.e. the variance risk premia.

Our paper adds to the research of Coval and Shumway (2001), Bakshi and Kapadia (2003a,b), Carr and Wu (2009), Driessen et al. (2009), Trolle and Schwartz (2010), Wang et al. (2011) and Choi et al. (2016), who study variance risk in a range of markets. Bakshi and Kapadia (2003a,b) use a delta-hedging approach and find significant payoffs in individual equity options. Carr and Wu (2009) and Driessen et al. (2009) construct synthetic variance swaps and find little evidence of significant variance swap payoffs in individual equities. The conflicting evidence reported in extant studies may be due to their fairly short sample periods and different methodologies, which make the results difficult to compare.

Our study also complements the contributions of Gorton et al. (2013), Daskalaki et al. (2014) and Szymanowska et al. (2014), among others, on commodity futures returns. We focus on the compensation that investors require for bearing variance (rather than futures return) risk in commodity markets. We show that commodity variance swap payoffs are largely unrelated to commodity futures returns, suggesting that variance risk cannot be hedged by trading in the corresponding commodity futures market.

Our results are relevant for risk management in commodity markets. The existence of economically important variance swap payoffs in commodity markets challenges the common practice of relying on implied variance to obtain unbiased forecasts of future variance. To obtain a more accurate prediction of future variance, one must specifically account for the role of the variance risk premium (Prokopczuk and Wese Simen, 2014; Kourtis et al., 2016). Failure to do so would result in biased forecasts and suboptimal risk management decisions.

This paper proceeds as follows. In Section II we introduce our methodology and describe the data set employed. In Section III we present and discuss our empirical results. Finally, Section IV concludes.

II Methodology and Data

A. Data

We obtain our futures and option data from the Commodity Research Bureau (CRB). Table A.1 of the online appendix introduces the 21 commodities included in our sample. These commodity markets cover a variety of sectors, including energy and wood commodities. Overall, our dataset spans the period from January 1984 to July 2011. However, the exact starting date varies from one market to another depending on data availability. Table A.2 of the online appendix specifies the starting date of the option data for each commodity market. The data set contains information on the strike price, maturity and settlement price of individual commodity derivatives.

The last column of Table A.1 reports the average annual trading volume and open interest of individual commodity options for the period from 2008 to 2011. This information is obtained directly from the corresponding exchange.[1] We notice a lot of variation in trading activity across commodity sectors. The energy and grain sectors appear to be the most liquid groups. Relatedly, we find some heterogeneity within sectors. The energy sector illustrates this point. We can see that the average yearly trading volume in crude oil is more than 33 millions. In contrast, the comparable statistic for the heating oil options is merely 810,740.

To mitigate the effect of micro-structure related issues such as infrequent trading and stale prices, we only retain options with time-to-maturity of at least 12 days. We further discard options with prices lower than five times the minimum tick size reported in Table A.1. Given that our data set comprises American options and that our estimation approach requires European option prices, we convert the American option prices into European prices by following the standard approach of Barone-Adesi and Whaley (1987).

Our empirical analysis focuses on variance swaps with a maturity of 60 days. This decision is motivated by the observation that, with the exception of energy markets, no other commodity exhibits a monthly expiration schedule (see Table A.1). Therefore, we retain only OTM options on the two nearest maturity futures contracts. For energy commodities, we retain OTM options on the second and third nearest futures contracts. The reason for selecting the second and third nearby futures contracts is that energy commodities have a monthly expiration schedule. Table A.2 of the online appendix provides an overview of the final data set of option prices. The last two columns report the average number of OTM call and put options per trading day. Across all commodities, there are on average 17 and 14 OTM call and put options with different strike prices per day, respectively. These numbers compare well with other studies such as those of Carr and Wu (2009) and Taylor et al. (2010).

[1]Ideally, one should report the average annual open interest and trading volume for the full sample period. Alas, the CRB does not provide such information. Fortunately, the exchanges recently started reporting volume and open interest data. We use the information for the period 2008–2011 as an indication of trading activity in commodity markets. This is the longest period over which this information is publicly available across all exchanges. Section III.*C.6* addresses the concerns related to the tradability of these instruments.

B. Methodology

Empirical studies on variance risk are usually anchored around one of the following three estimation approaches: parametric, semi-parametric or model-free. The parametric approach consists of specifying a data-generating process for the underlying. In this framework, variance risk is usually analyzed by exploiting information from the underlying asset and options prices. This approach is not only computationally intensive but also subject to specification errors since it depends on the modelling choice. Broadie et al. (2007) empirically examine the impact of model misspecification.

Bakshi and Kapadia (2003a) propose a semi-parametric framework based on the profitability of delta-hedged puts and calls. This approach builds on the insights of financial theory, which posits that option prices are affected by changes in implied volatility and the underlying's price. Since delta-neutral positions are insensitive to small movements of the underlying's price, their profitability may shed light on the compensation investors require for bearing volatility risk. Though intuitive, this approach is still vulnerable to the criticism that it relies on a specific hedging model.

The more recent model-free approach builds on variance swaps defined as swap contracts in which the floating leg corresponds to the realized variance of the underlying over a predetermined period. The idea is to study the realized variance swap payoffs, defined as the differences between the realized variance and the risk-neutral expectation of variance. No-arbitrage arguments imply that the variance swap rate, which is known at inception, must be equal to the risk-neutral expectation of variance over the life of the swap. The realized payoff to a variance swap contract (with a notional of 1) can be computed at expiration as follows:

$$VSP_{t+\tau} = RV_{t\to t+\tau} - SV_{t\to t+\tau} \quad (1)$$

$$VSP_{t+\tau} \equiv RV_{t\to t+\tau} - \mathbb{E}_t^Q(V_{t\to t+\tau}) \quad (2)$$

where $VSP_{t+\tau}$ is the annualized variance swap payoff computed at $t+\tau$. τ indicates the time-to-maturity, expressed in months, of the variance swap at inception.

$RV_{t\to t+\tau}$ denotes the annualized realized variance computed using all return data for the period starting at t and ending at $t+\tau$. SV_t is the annualized variance swap rate at time t, which is equal to the risk-neutral expectation of variance $\mathbb{E}_t^Q(V_{t\to t+\tau})$ for the period starting at t and ending at $t+\tau$.

Realized Variance We use the following estimator to compute the annualized realized variance:

$$RV_{t\to t+\tau} = \frac{12}{\tau}\sum_{i=t}^{t+\tau-1}\left(\log\frac{F_{i+1}}{F_i}\right)^2 \tag{3}$$

where F_i denotes the price of the futures contract observed at time i. It is worth pointing out that futures contracts have a finite life. Thus, if one directly implements the formula above, the returns computed after the rollover date will be based on different futures contracts.

In order to address this concern, we create a constant maturity futures contract. For each observation date i, we use the term-structure of futures contracts to linearly interpolate a futures contract expiring at $i+\tau$. We use this constant maturity futures contract as input to the realized variance estimator in Equation (3).

Variance Swap Rate Britten-Jones and Neuberger (2000) and Demeterfi et al. (1999) demonstrate how to construct a variance swap under the assumption that the underlying processes are pure diffusions, and Jiang and Tian (2005) and Carr and Wu (2009) show that the theory also holds approximately for jump diffusions. The variance swap rate can be computed as follows:

$$\mathbb{E}_t^Q(V_{t\to t+\tau}) = MFIV_t = 2e^{r_t\frac{\tau}{12}} \times \frac{12}{\tau}\left[\int_0^{U_{t,\tau}}\frac{P_{t,K,\tau}}{K^2}\,dK + \int_{U_{t,\tau}}^{+\infty}\frac{C_{t,K,\tau}}{K^2}\,dK\right] \tag{4}$$

where $MFIV_t$ is the model-free implied variance at time t. r_t is the annualized risk-free rate at time t. $P_{t,K,\tau}$ and $C_{t,K,\tau}$ denote the price at time t of European put and call options struck at K and with time-to-maturity τ, respectively. These option contracts are written on an underlying futures contract U that also has a time-to-maturity τ. Note that τ is expressed in months. $U_{t,\tau}$ denotes the price, at time t of that underlying asset with time-to-maturity τ.

Du and Kapadia (2012) show that, in the presence of jumps, the risk-neutral variance of Bakshi et al. (2003) is more robust than the estimator defined in Equation (4). Consequently, we also use the Bakshi et al. (2003) variance as an alternative measure for the risk-neutral quadratic variation. We present these results in Section III.*C.4*.

Our aim is to compute the fixed leg of the variance swap of maturity τ months. On a given day t, we obtain and sort all out-of-the-money (OTM) options by time to maturity. We identify the two maturities τ_1 and τ_2 that are closest to and cover a maturity of τ months. We retain options of maturities τ_1 and τ_2 only. For each of these maturities, we compute K_l and K_u:

$$K_l = U_{t,\tau_i} \exp^{-10\sigma_{t,\tau_i}\frac{\tau_i}{12}} \quad (5)$$

$$K_u = U_{t,\tau_i} \exp^{10\sigma_{t,\tau_i}\frac{\tau_i}{12}} \quad (6)$$

where K_l and K_u refer to the lower and higher strikes, respectively. U_{t,τ_i} is the price at time t of the underlying futures contract that has time-to-maturity equal to τ_i. σ_{t,τ_i} is the average, at time t, of the annualized implied volatility of all OTM options of maturity τ_i. Note that τ_i corresponds to either τ_1 or τ_2.

Next, we construct a grid of 1,000 equidistant implied volatilities for strikes between K_u and K_l. More specifically, we linearly interpolate available Black (1976) implied volatilities across moneyness.[2] For strikes higher (lower) than the highest (lowest) listed strike price but lower (higher) than K_u (K_l), we assume constant implied volatility (Jiang and Tian, 2005). We then convert the implied volatilities back into option prices using the Black (1976) option pricing formula. We evaluate the integrands at each of the 1,000 points and numerically approximate (trapezoidal rule) the integrals in Equation (4) to estimate the variance swap rate.[3] Finally, we

[2]Section III.*C.3* shows that working with a spline interpolation approach yields very similar results.

[3]Essentially, we truncate the integrals in Equation (4). A similar approach is also used in Jiang and Tian (2005) and Carr and Wu (2009). Our results are robust to the choice of truncation points. See Section III.*C.2* for further details.

linearly interpolate between the swap rates of maturities τ_1 and τ_2 months to obtain the τ-month variance swap rate.

III Empirical Results

We begin by analyzing the realized payoffs to commodity variance swaps. Next, we focus on the expected variance swap payoffs, i.e. the variance risk premia, of commodity markets.

Our main analyses relate to variance swaps of 60-day maturity. In order to avoid statistical issues related to overlapping observation biases, we sample the realized variance and the variance swap rates at the end of every other month. An upshot of this is that we use non-overlapping observations.

A. Realized Variance Swap Payoffs

A.1 Dissecting Realized Variance Swap Payoffs

Unconditional Analysis Figure 1 shows the realized and implied variance of some commodity markets. For ease of exposition, we align the time-series of realized and implied variance. The realized and implied variance are computed using the methodology presented in Section II.*B*. We observe a positive relationship between the two series. This result is consistent with the literature showing that implied variance positively predicts realized variance (Simon, 2002; Prokopczuk and Wese Simen, 2014). The plots also reveal that implied variance is generally higher than realized variance, suggesting a negative variance swap payoff.

Table 1 presents the results for all commodity markets. In particular, it shows the average of the fixed and floating legs of all commodity variance swaps. We can see that realized variance is typically lower than implied variance. This suggests that, on average, an investor who takes a long position in a variance swap realizes a negative payoff in most commodity markets (18 out of 21 markets). The column labelled "$RV - MFIV$" sheds light on the magnitude of these losses. For instance, it shows that, on average, a long-only investor realizes a negative payoff of $-8.985\,\%$

in the natural gas market. To ascertain that these average variance swap payoffs are statistically significant, we turn our attention to Table 2. The Newey–West corrected t-statistics (with 3 lags) reported under the header "Unconditional" indicate that these payoffs are generally statistically significant.

Subsample Analysis As discussed in Boons et al. (2012), the CFMA introduced in December 2000 allows investors to trade directly in commodity derivatives, whereas prior to the Act, they would gain commodity exposure mainly via the stock price of commodity-related companies. This makes it interesting to formally contrast the results related to the earlier and more recent sample periods. We thus split our sample into two distinct periods: the first period stops at the end of the year 2000 and the second subsample starts from 2001 onward.

The entries reported under the header "Pre CFMA" and "Post CFMA" in Table 2 confirm that the average commodity variance swap payoff is generally statistically significant in each of the two subsamples. Comparing the two subsamples, we observe that the variance swap payoff generally becomes more negative in the more recent period. We formally test the null hypothesis that the average variance swap payoff observed in the first subsample is equal to the average variance swap payoff of the second period. We perform this test for each commodity market and report the p-value of the test statistic in the last column of Table 2. Inspecting the results, we notice that the p-values are typically greater than 5 %, implying that we cannot reject the null hypothesis at the 5 % significance level in most cases.

A.2 Commonality Analysis

One may wonder: why are commodity variance swap payoffs significantly negative in most markets? A possible explanation is that the variance of commodity returns rises during bad times, when marginal utility is high. In other words, the variance swap may yield large positive payoffs during bad states of the economy, making it a very good hedging instrument. If this is the case, we would expect that (i) there is some commonality among commodity variance swap payoffs and (ii) the commodity variance swap payoffs are significantly and positively related to equity variance swap payoffs, which themselves are positive during bad economic times.

Comovement among Commodity Variance Payoffs We analyze the relationship between the realized variance swap payoff of a commodity and the average realized variance swap payoff of all other commodity markets. In order to do so, we estimate the following regression for each commodity:

$$VSP_{i,t} = \alpha + \beta AVG_{i,t} + \epsilon_{i,t} \tag{7}$$

where $VSP_{i,t}$ is the realized variance swap payoff of commodity i at time t. $AVG_{i,t}$ is the average realized variance swap payoff (at time t) of all commodities excluding commodity i. By excluding the realized variance swap payoff of the commodity market i, we rule out any mechanical link between the dependent and independent variables.

Table 3 reveals that the slope estimates are generally positive and statistically significant at the 5 % level. This suggests that there is some evidence of commonality in the commodity variance swap payoffs. Looking at the intercepts, we notice that their sign, size and statistical significance are often similar to the entries in Table 2. An upshot of this result is that the AVG factor alone cannot completely explain the variance swap payoff of individual commodities. The modest explanatory power of the regression model for most markets further confirms that the AVG factor does not explain most of the variation in individual commodity variance swap payoffs.

An implicit assumption of the regression model above is that the intercept and the exposure to the AVG factor are constant throughout the sample period. It is interesting to check whether allowing for a different intercept as well as sensitivity to the AVG factor in the more recent subsample significantly improves the model fit. To shed light on this, we estimate a model that allows the intercept and slope parameters to be different during the more recent subsample:

$$VSP_{i,t} = \alpha + \alpha_1 D_t + (\beta + \beta_1 D_t) AVG_{i,t} + \epsilon_{i,t} \tag{8}$$

where D_t is the CFMA dummy that takes the value 1 from 2001 onward. All other variables are defined as before.

Column R^2_{UR} reports the explanatory power of this model. We perform an F-test to compare the two models. The last column of Table 3 reports the p-value associated with the F-test. In most cases, the results suggest that the larger model is not significantly better than the simpler model.

Comovement with Realized Commodity Futures Returns We now shed light on the relationship between the realized variance swap payoff of a given commodity and the realized futures return of that same commodity by estimating:

$$VSP_{i,t} = \alpha + \beta RET_{i,t} + \epsilon_{i,t} \tag{9}$$

where $RET_{i,t}$ is the 60-day realized return on the (60-day constant maturity) futures of commodity i. The constant maturity futures is computed as in Section II.B. Note that, linearly interpolating a constant maturity futures contract of 60-day is consistent with the approach used to construct the variance swap rate where a linear interpolation was also used.

Table 4 shows that the slope parameters are often not statistically significant (at the 5 % significance level). This result indicates that variance risk is not spanned by a position in a single futures contract. An upshot of this analysis is that term structure models of commodity futures and options must allow for unspanned stochastic variance in the spirit of Trolle and Schwartz (2009).

Similar to the preceding analyses, we also estimate a model that allows for different intercept and slope parameters in the more recent sample. As the last column of Table 4 shows, there is little evidence to suggest that this model provides a significantly better fit to the data than the simpler model.

Comovement with Bond and Equity Returns In order to shed light on the comovement between commodity variance swap payoffs on the one hand and bond and equity returns on the other, we estimate the following regression model:

$$VSP_{i,t} = \alpha + \beta_E RET_{E,t} + \beta_B RET_{B,t} + \epsilon_{i,t} \qquad (10)$$

where $RET_{E,t}$ and $RET_{B,t}$ denote the 60-day equity (S&P 500 index) and bond (30-Year Treasury) returns.

Table 5 shows that the payoffs of commodity variance swaps typically have no significant exposure to equity and bond returns. This is evidenced by slope estimates that are generally statistically insignificant. Furthermore, the intercept estimates remain very similar to those in Table 2. We thus conclude that the commodity variance swap payoffs cannot be explained by the bond and equity returns. We also consider the possibility that the intercept and the exposure to bond and equity returns may change during the more recent subsample. The p-values of the corresponding F-test shown in the last column of Table 5 reveal that there is very little to distinguish between the two models. This result differs from that observed for the commodity futures risk premium. Silvennoinen and Thorp (2013) document increased comovements between commodity and equity returns after the CFMA period. Our results suggest that such financialization effect is limited to the commodity futures returns and does not extend to the commodity variance swap payoffs. This conclusion is consistent with the notion that commodity variance risk is unspanned by commodity futures.

Comovement with Bond and Equity Variance Swap Payoffs We now analyze the relationship between the realized variance swap payoffs of a given commodity and the bond and equity variance swap payoffs. To achieve this goal, we download the 30-Year Treasury and S&P 500 index options data from OptionMetrics. Equipped with this dataset, we then implement the methodology described in Section II to compute the realized payoffs of the bond and equity variance swaps.

Next, we regress the realized variance swap payoff of each commodity on a constant, the equity variance swap payoff and the bond variance swap payoff:

$$VSP_{i,t} = \alpha + \beta_E VSP_{E,t} + \beta_B VSP_{B,t} + \epsilon_{i,t}. \tag{11}$$

where $VSP_{E,t}$ and $VSP_{B,t}$ denote the 60-day equity and bond variance swap payoffs at time t, respectively.

Table 6 shows that several commodity variance swap payoffs have a significant exposure to the equity and bond variance swap payoffs. The mainly positive loading on the equity variance swap payoff is interesting because equity variance swaps yield very large payoffs during bad economic times, when realized variance typically spikes. Thus, the results imply that commodity variance swaps perform well during these times. This could explain the significantly negative average realized variance swap payoff observed for most commodities.

In most cases, the intercept estimates remain highly significant, indicating that commodity variance swap investors earn payoffs above and beyond those implied by simple passive exposure to the bond and equity variance swap payoffs. Continuing our analysis, we estimate a more elaborate model where we allow for the intercept and the sensitivities to the bond and equity variance swap payoffs to change during the post CFMA subsample. The last column of Table 6 shows that this model does not significantly improve the fit.

B. Expected Variance Swap Payoffs

The preceding analysis focuses on *realized* variance swap payoffs. Intuitively, the *realized* variance swap payoff can be decomposed into the variance risk premium, i.e. the *expected* variance swap payoff, and a shock. We now turn our attention to the variance risk premium.

B.1 Overview

We compute the variance risk premium (VRP) as the difference between the physical and risk-neutral expectations of variance:

$$VRP_t = \mathbb{E}_t^P(V_{t\to t+\tau}) - \mathbb{E}_t^Q(V_{t\to t+\tau}) \qquad (12)$$

Before discussing the results, it is important to stress that the analysis of the variance risk premium depends on the model used to form expectations of future realized variance, making the results somewhat model dependent (Bekaert and Hoerova, 2014). In order to obtain the variance risk premium, we regress the non-overlapping time-series of the variance swap payoff on (i) a constant, (ii) the lagged realized variance and (iii) the lagged model-free implied variance. These forecasting variables are also used, for example, in Drechsler and Yaron (2011). In estimating the model, we allow the intercept and slope parameters to change with the CFMA dummy variable:

$$VSP_{t+\tau} = \alpha + \alpha_1 D_t + (\beta + \beta_1 D_t)RV_t + (\gamma + \gamma_1 D_t)MFIV_t + \epsilon_{t+\tau} \qquad (13)$$

where RV_t and $MFIV_t$ are computed as in Equations (3)–(4). All other variables are as previously defined.

Given the limited size of the non-overlapping sample, we elect to use all sample observations to estimate the model above for each commodity market. Equipped with the parameter estimates (see Table A.3 of the online appendix), we generate the expected variance swap payoff, i.e. the variance risk premium. Since the model is estimated using all sample observations, the average values of the variance swap payoff and the variance risk premium are equal. This is also true for each subsample. Tables 7 and 8 present some statistics. We can see that the variance risk premium is less volatile than the corresponding variance swap payoff. Furthermore, the persistence of the variance risk premium is substantially higher than that of the variance swap payoff.

B.2 The Dynamics of Commodity Variance Risk Premia

Comovement with Commodity Risk Premia We analyze the relationship between the variance risk premium of a given commodity and the futures risk premium related to the same commodity. In order to proxy for the commodity futures risk premium, we first compute the 60-day returns on the 60-day constant maturity futures as described in Section II.*B*. We do this at the end of every other month. We then regress this bi-monthly time-series of 60-day commodity futures returns on a constant and the 60-day lagged values of the following forecasting variables: the US CPI inflation rate (INF), the growth rate of US industrial production (IP), the 3-month T-bill yield ($TBILL$), the term spread ($TSPD$), the default spread ($DFSPD$) and the commodity futures basis (BAS). To compute the basis, we first calculate the logarithm of the ratio of the price of the second nearby futures over that of the first nearby futures. We then divide this quantity by the difference between the time-to-maturity of the second and first nearby contracts (Szymanowska et al., 2014).

The selection of the forecasting variables is motivated by previous studies, e.g. Bessembinder and Chan (1992) and Gargano and Timmermann (2014). We obtain all macroeconomic data from the Federal Reserve of St Louis. We use all sample observations to estimate the return forecasting regression. In estimating the model, we again allow for the intercept and slope parameters to change with the CFMA dummy. We then use the estimated model parameters to generate the time-series of the expected commodity futures returns, which we refer to as the futures risk premia.

The off-diagonal elements of Table A.4 of the online appendix show the correlation between the bi-monthly time-series of the commodity risk premia. Overall, we observe comovements across commodity risk premia especially among related commodity markets. For instance, the correlation between the risk premium of soybeans and soybean meal (soybean oil) is 0.87 (0.76). We also observe important comovements across sectors. For instance, the risk premia of crude oil and gold share a correlation of 0.52. The entries reported on the main diagonal of the same table suggest that the risk premia are persistent as evidenced by the positive autocorrelation estimates. Of all commodity markets, the lowest and highest first order autocorrelation estimates are observed for the soybeans (0.134) and cocoa (0.530) markets, respectively.

We next regress the commodity variance risk premium on a constant and the futures risk premium of the same market. The slope parameters presented in Table 9 are mainly insignificant, leading us to conclude that the variance risk premium is generally unrelated to the futures risk premium. Because the futures risk premia are first estimated and then used in the regression as an explanatory variable, one may worry that our analysis may be vulnerable to sampling error. However, Pagan (1984) studies this generated regressor problem and shows that the ordinary least squares standard errors are valid under the null hypothesis that the coefficient loading on the generated regressor is zero.

Comovement with Equity and Bond Risk Premia We now examine the relationship between commodity variance risk premia and the equity and bond risk premia. In order to estimate the equity risk premium, we first compute the 60-day returns of the S&P 500 index. We do this at the end of every other month. We then regress this time-series of returns on the 60-day lagged values of the following variables: the log dividend price ratio (DP), the T-bill ($TBILL$), the term spread ($TSPD$), the default spread ($DFSPD$) and the TED spread (TED). These variables are standard in the literature on return predictability (Goyal and Welch, 2003; Welch and Goyal, 2008). Equipped with the parameter estimates, we generate the time-series of the equity risk premium. We proceed in a similar way to obtain the bond risk premium, replacing the time-series of 60-day S&P 500 returns with that of 30-year Treasury bond returns.

We then regress the bi-monthly time-series of commodity variance risk premia on a constant and the equity and bond risk premia. The results are presented in Table 10. The slope estimates are generally insignificant and the intercept parameter remains highly significant, indicating that the equity and bond risk premia generally do not have a significant impact on commodity variance risk premia.

Comovement with Equity and Bond Variance Risk Premia Lastly, we analyze the commonalities between the commodity variance risk premia and the variance risk premia of the bond and equity markets. The estimation of the bond and equity variance risk premia is similar to that of the commodity risk premium. In particular, we use the time-series of bi-monthly variance swap payoffs, the 60-day lagged realized and implied variance to estimate the model in Equation (13). We do this separately for the equity and bond markets. Equipped with the estimated parameters, we generate the 60-day equity and bond variance risk premia. We then regress the bi-monthly time-series of commodity variance risk premia on a constant and the matched time-series of equity and bond variance risk premia.

Table 11 reveals a significant relationship between commodity variance risk premia and the contemporaneous bond variance risk premium. This is true for most markets. A look at the intercepts shows that they are generally statistically significant. This reveals that, exposures to the bond and equity variance risk premia alone cannot explain the commodity variance risk premia. This result broadly echoes our conclusions based on the realized variance swap payoffs.

C. Robustness Analysis

In this section, we establish the robustness of our findings. To begin with, we show that our main findings hold also when commodities are aggregated into portfolios. Next, we show that our findings are robust to the computation of the variance swap rate. Relatedly, we show that our constructed implied volatility indices correlate very well with publicly available volatility indices. Finally, we show that our main findings are robust to liquidity-based explanations.

C.1 Commodity Sectors

A potential concern could be that the variance swaps of individual commodities might be noisy. This makes it interesting to repeat our analyses by focusing on sectors (rather than individual commodity markets) computed as the equal-weighted average of all markets that belong to the same sector. We also compute a diversified portfolio that is essentially the equal-weighted average across all 21 commodity markets.

The bottom entries of Tables 1–11 confirm that our main findings hold when we analyze commodity sectors. In particular, there is a negative average realized variance swap payoff in all commodity sectors, most of which are statistically significant. These realized variance swap payoffs cannot be simply explained by the exposure of commodity variance swaps to realized commodity futures returns. The realized payoffs of commodity sectors often exhibit a significantly positive sensitivity to the equity and bond markets. However, these exposures are generally not enough to satisfactorily explain the realized payoffs of most commodity sectors.

C.2 Truncation Points

We investigate the sensitivity of our variance swap estimates to the truncation points. We work with tighter truncation points, K_l and K_u, defined as follows:

$$K_l = U_{t,\tau_i} \exp^{-8\sigma_{t,\tau_i}\frac{\tau_i}{12}} \tag{14}$$

$$K_u = U_{t,\tau_i} \exp^{8\sigma_{t,\tau_i}\frac{\tau_i}{12}} \tag{15}$$

where all variables are as previously explained.

Repeating our analysis of the realized variance swap payoffs, we obtain results that are very similar to our benchmark estimates (see Table A.5 of the online appendix).

C.3 Interpolation Technique

We evaluate the robustness of our results to the interpolation technique. To this end, we follow the procedure outlined in Section II with one difference: we use a cubic spline (rather than linear) interpolation technique to obtain a fine grid of implied volatilities. Table A.6 of the online appendix presents estimates of realized payoffs to variance swaps that are similar to those obtained using the linear interpolation technique.

C.4 The Role of Jumps

We now examine the robustness of our results to jumps, which could affect the variance swap rates. Du and Kapadia (2012) show that the risk-neutral variance of Bakshi et al. (2003) is more robust in the presence of jumps. Thus, we use the Bakshi et al. (2003) variance as an alternative measure for the risk-neutral quadratic variation. While there are some exceptions, e.g. silver and oats, Table A.7 presents average realized variance swap payoffs that are generally consistent with our benchmark estimates.

C.5 Synthetic v.s. Public Volatility Indices

We compare our synthetic swap rates to publicly available volatility indices. Since our methodology broadly mirrors that of the exchange, we expect the synthetic and publicly available variance swap rates to be highly correlated. Although there are volatility indices for the corn, soybeans and wheat markets, these indices were only recently introduced. Hence, we focus only on the crude oil and gold markets. There are, however, three issues that need to be highlighted. First, the crude oil volatility index reported by the exchange is based on a 30 day horizon. In contrast, our synthetic variance swap rates are available for the 60 day horizon. To ensure a valid comparison, we create synthetic variance swaps of 30 days for the crude oil market.[4] These variance swaps are used solely for comparison purposes and are not discussed further in the paper. Second, the exchange lists the model-free implied volatility rather than variance. As a result, we square the volatility indices in order to make them comparable to our variance swap rates. Third, these volatility indices are computed from options on ETFs that track crude oil and gold, respectively. Thus, we expect some small differences between these indices and our series.

[4] As discussed before, the construction of monthly variance swaps is not possible for non-energy commodities. This is due to the fact that non-energy commodity options do not have monthly expiration cycles.

We compute the correlation between our synthetic variance swap rates and the CME series. As expected, we observe a high correlation between the two series. The correlation coefficients are equal to 98.10 % and 99.57 % for the crude oil and gold markets, respectively. Second, we analyze the mean difference and find that our synthetic variance swap rate is very close to its CME counterpart. For example, the synthetic swap rate of crude oil differs from that of the exchange by an average of 6 basis points. Together, these results confirm the robustness of our methodology.

C.6 Tradability of Commodity Variance Swaps

Studies on variance swap payoffs, including those of Carr and Wu (2009) and Driessen et al. (2009), are invariably criticized on the grounds that variance swap contracts may not be actively traded and this may significantly drive the results. We argue that this is unlikely to be true in our case for several reasons. First, the evidence of significantly negative variance swap payoffs is not specific to a limited number of commodity markets. Second, if the lack of liquidity has a significant impact on our results, one would expect to observe large differences in the magnitude and significance of the variance swap payoffs during the period following the CFMA, when commodities witnessed a surge in trading activity. However, as Tables 2 and 8 show, the average payoffs are not significantly different across the two subsamples, making our results difficult to reconcile with a liquidity-based argument.

One may also wonder about the impact of transaction costs on our variance swap payoffs estimates. It may be that our synthetic variance swap rates are the sum of the true variance swap rates and transaction costs. It is therefore possible that the realized variance swap payoffs estimates presented in Table 2 are biased downwards, i.e. more negative than they should really be, owing to the influence of transaction costs. This makes it interesting to account for transaction costs. Unfortunately, we do not have access to OTC data on commodity variance swaps to exactly quantify the cost of transacting in the variance swap market. As a result, we assume some values for the transaction costs and assess their implications for our main findings. Since the results depend on potentially simplistic assumptions, they should be interpreted cautiously.

We follow two approaches. First, we assume that transaction costs represent a proportion of 10 % of the synthetic variance swap rate. This implies that the true variance swap rate corresponds to 90 % of the synthetic variance swap rate. For example, if the synthetic variance swap rate is 10% the true variance swap rate is 9 %. Second, we allow for fixed transaction costs in the spirit of Duarte et al. (2007), by assuming that the true model-free implied volatility (not variance) is, in level terms, 2 % lower than the synthetic model-free implied volatility. This means that if the synthetic model-free implied volatility is 10 %, then the true implied volatility is 8 %, leading to a true variance swap rate of 0.64 %. This approach is generally more stringent than the proportional approach, thus yielding very conservative variance risk premia estimates. Our empirical analysis reveals that most commodities exhibit a significantly negative net average variance swap payoff (see Table A.8 of the online appendix).

IV Conclusion

This paper analyzes variance risk in 21 commodity markets. Using synthetically constructed variance swaps, we document that realized variance swap payoffs are significantly negative in most commodity markets. Our empirical evidence suggests that realized commodity variance swap payoffs comove with equity variance swap payoffs. However, the commodity variance swap payoffs are too large to be explained by a passive exposure to equity variance swaps.

We show that the commodity realized variance swap payoffs are distinct from the returns on traditional assets. In particular, we establish that bond and equity returns cannot explain the commodity variance swap payoffs satisfactorily. Moreover, regressing the realized commodity variance swap payoffs on realized commodity futures returns, we find that the two are distinct, suggesting that variance risk is unspanned by commodity futures. We also estimate the commodity variance risk premia. Analyzing the commonality between commodity variance risk premia and the risk premia on the commodity futures, stock and bond markets, we find that there is a weak relationship between these quantities.

In future work, it would be interesting to develop a theoretical framework to rationalize the stylized facts presented in this paper. Ideally, such model should shed light on why variance swap payoffs are highly significant for most individual commodities whereas they are not in individual equities (Carr and Wu, 2009; Driessen et al., 2009).

References

Bakshi, G. and Kapadia, N. (2003a). Delta-hedged gains and the negative market volatility risk premium. *Review of Financial Studies*, 16(2):527–566.

Bakshi, G. and Kapadia, N. (2003b). Volatility risk premiums embedded in individual equity options. *Journal of Derivatives*, 11(1):45–54.

Bakshi, G., Kapadia, N., and Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *Review of Financial Studies*, 16(1):101–143.

Barone-Adesi, G. and Whaley, R. (1987). Efficient analytic approximation of american option values. *Journal of Finance*, 42(2):301–320.

Bekaert, G. and Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics*, 183(2):181–192.

Bessembinder, H. and Chan, K. (1992). Time-varying risk premia and forecastable returns in futures markets. *Journal of Financial Economics*, 32(2):169–193.

Black, F. (1976). The pricing of commodity contracts. *Journal of Financial Economics*, 3(1):167–179.

Boons, M., De Roon, F., and Szymanowska, M. (2012). The stock market price of commodity risk. *Working Paper*.

Britten-Jones, M. and Neuberger, A. (2000). Option prices, implied price processes, and stochastic volatility. *Journal of Finance*, 55(2):839–866.

Broadie, M., Chernov, M., and Johannes, M. (2007). Model specification and risk premia: Evidence from futures options. *Journal of Finance*, 62(3):1453–1490.

Carr, P. and Wu, L. (2009). Variance risk premiums. *Review of Financial Studies*, 22(3):1311–1341.

Choi, H., Mueller, P., and Vedolin, A. (2016). Bond variance risk premiums.

Coval, J. and Shumway, T. (2001). Expected option returns. *Journal of Finance*, 56(3):983–1009.

Daskalaki, C., Kostakis, A., and Skiadopoulos, G. (2014). Are there common factors in commodity futures returns? *Journal of Banking and Finance*, 40:346–363.

Demeterfi, K., Derman, E., Kamal, M., and Zou, J. (1999). A guide to volatility and variance swaps. *Journal of Derivatives*, 6(4):9–32.

Drechsler, I. and Yaron, A. (2011). What's vol got to do with it. *Review of Financial Studies*, 24(1):1–45.

Driessen, J., Maenhout, P., and Vilkov, G. (2009). The price of correlation risk: Evidence from equity options. *Journal of Finance*, 64(3):1377–1406.

Du, J. and Kapadia, N. (2012). The tail in the volatility index. *Working Paper*.

Duarte, J., Longstaff, F. A., and Yu, F. (2007). Risk and return in fixed-income arbitrage: Nickels in front of a steamroller? *Review of Financial Studies*, 20(3):769–811.

Gargano, A. and Timmermann, A. (2014). Forecasting commodity price indexes using macroeconomic and financial predictors. *International Journal of Forecasting*, 30(3):825–843.

Gorton, G. B., Hayashi, F., and Rouwenhorst, K. G. (2013). The fundamentals of commodity futures returns. *Review of Finance*, 17(1):35–105.

Goyal, A. and Welch, I. (2003). Predicting the equity premium with dividend ratios. *Management Science*, 49(5):639–654.

Jiang, G. and Tian, Y. (2005). The model-free implied volatility and its information content. *Review of Financial Studies*, 18(4):1305–1342.

Kourtis, A., Markellos, R. N., and Symeonidis, L. (2016). An international comparison of implied, realized, and GARCH volatility forecasts. *Journal of Futures Markets*, 36(12):1164–1193.

Pagan, A. (1984). Econometric issues in the analysis of regressions with generated regressors. *International Economic Review*, pages 221–247.

Prokopczuk, M. and Wese Simen, C. (2014). The importance of the volatility risk premium for volatility forecasting. *Journal of Banking and Finance*, 40:303–320.

Silvennoinen, A. and Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money*, 24:42–65.

Simon, D. P. (2002). Implied volatility forecasts in the grains complex. *Journal of Futures Markets*, 22(10):959–981.

Szymanowska, M., De Roon, F., Nijman, T., and Van den Goorbergh, R. (2014). An anatomy of commodity futures risk premia. *Journal of Finance*, 69(1):453–482.

Taylor, S., Yadav, P., and Zhang, Y. (2010). The information content of implied volatilities and model-free volatility expectations: Evidence from options written on individual stocks. *Journal of Banking and Finance*, 34(4):871–881.

Trolle, A. and Schwartz, E. (2009). Unspanned stochastic volatility and the pricing of commodity derivatives. *Review of Financial Studies*, 22(11):4423–4461.

Trolle, A. and Schwartz, E. (2010). Variance risk premia in energy commodities. *Journal of Derivatives*, 17(3):15–32.

Wang, Z., Fausti, S., and Qasmi, B. (2011). Variance risk premiums and predictive power of alternative forward variances in the corn market. *Journal of Futures Markets*, 32(6):587–608.

Welch, I. and Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, 21(4):1455–1508.

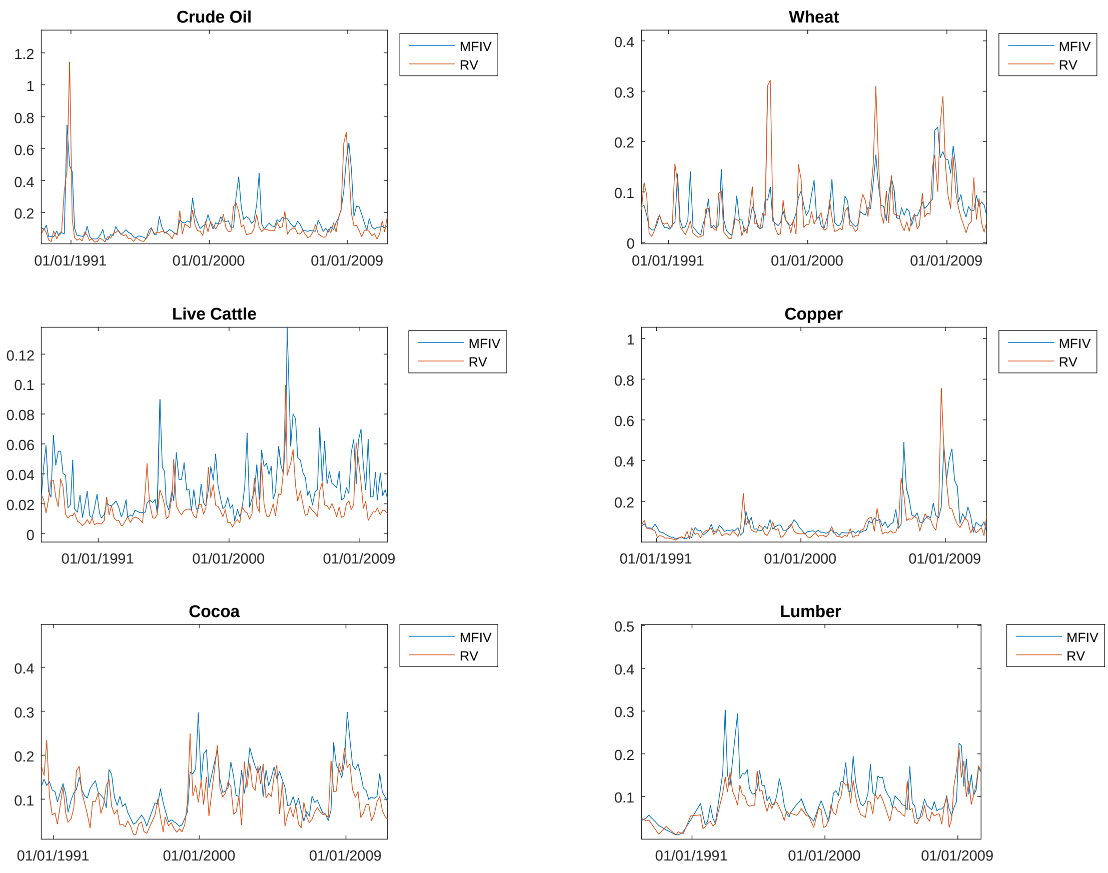

Figure 1: **Time Series of Realized Variance and Model-Free Implied Variance**

This figure displays the time series of (60-day) realized and model-free implied variances for crude oil, wheat, live cattle, copper, cocoa and lumber. The horizontal axis shows the dates. The vertical axis shows the annualized variance estimates (multiplied by 100). The blue and red lines depict the model-free implied and realized variances, respectively. The difference between realized and implied variances is the realized payoff to the corresponding variance swap. All observations are sampled at the end of every other month.

Table 1: **Variance Swap Payoffs**

This table presents the average 60-day realized variance (RV), the average 60-day implied variance ($MFIV$) and the average realized payoff ($RV - MFIV$) of the 60-day variance swap related to each commodity market. Std, Skew and Kurt indicate the standard deviation, skewness and kurtosis of the variance swap payoffs, respectively. $AR(1)$ indicates the first-order autocorrelation of the bi-monthly time-series of 60-day variance swap payoffs. All observations are sampled at the end of every other month.

Sector	**Commodity**	RV	$MFIV$	$RV - MFIV$	Std	$Skew$	$Kurt$	$AR(1)$
	Crude Oil	11.043%	13.834%	-2.791%	9.647%	2.384	22.089	-0.221
Energy	Heating Oil	9.874%	13.382%	-3.508%	7.774%	-0.640	9.444	0.148
	Natural Gas	19.351%	28.336%	-8.985%	13.908%	-2.112	12.185	0.197
	Corn	6.168%	7.745%	-1.577%	3.769%	0.210	9.332	0.141
	Cotton	5.923%	3.148%	2.775%	3.159%	0.291	6.078	0.056
	Soybeans	6.292%	6.617%	-0.324%	4.589%	1.922	10.812	0.229
Grains	Soybean Meal	7.162%	6.744%	0.418%	4.564%	2.651	15.055	0.071
	Soybean Oil	5.606%	6.222%	-0.616%	3.464%	2.064	13.123	0.148
	Sugar	11.109%	13.420%	-2.311%	6.249%	0.295	4.761	-0.003
	Wheat	7.790%	7.822%	-0.032%	3.991%	2.387	14.859	0.146
Livestock	Lean Hogs	7.610%	7.687%	-0.077%	3.758%	0.496	4.757	-0.040
	Live Cattle	1.883%	3.273%	-1.390%	1.672%	-0.993	7.538	-0.018
	Copper	7.642%	9.342%	-1.700%	8.093%	2.647	27.091	0.193
Metals	Gold	2.898%	3.763%	-0.864%	2.520%	0.050	10.440	0.209
	Silver	2.661%	2.952%	-0.292%	3.678%	-2.611	20.788	0.273
	Cocoa	9.398%	12.024%	-2.626%	4.427%	-0.020	5.525	-0.006
	Colombian Coffee	17.592%	16.618%	0.974%	21.092%	3.128	14.625	0.288
Tropical	Oats	6.948%	11.599%	-4.650%	7.146%	1.828	7.346	0.399
	Orange Juice	9.675%	11.240%	-1.566%	6.642%	0.499	7.201	-0.133
	Rough Rice	6.117%	8.224%	-2.107%	4.446%	0.895	7.945	0.060
Wood	Lumber	7.753%	10.147%	-2.393%	3.825%	-1.330	8.678	0.131
	Energy	12.939%	17.604%	-4.666%	7.781%	-0.512	8.502	-0.049
	Grains	7.273%	7.600%	-0.328%	2.869%	1.131	7.781	0.081
Portfolios	Livestock	3.488%	4.429%	-0.941%	1.913%	0.142	4.816	-0.018
	Metals	4.316%	5.179%	-0.864%	3.565%	0.099	9.616	0.185
	Tropical	9.009%	11.211%	-2.202%	4.201%	1.448	8.772	0.047
	Diversified	7.249%	8.831%	-1.582%	2.343%	0.736	7.886	0.188

Table 2: **Time Variation in Variance Swap Payoffs**

This table reports the mean 60-day realized payoff of variance swaps computed using (i) all sample observations (Unconditional), (ii) all observations before the year 2001 (Pre CFMA) and (iii) all observations from 2001 (Post CFMA). Newey–West corrected t-statistics with 3 lags are presented in parentheses. The last column shows the p-value testing the null hypothesis that the average 60-day realized variance swap payoffs of the two subsamples are equal. All observations are sampled at the end of every other month.

Sector	**Commodity**	**Unconditional**		**Pre CFMA**		**Post CFMA**		**p-val**
		Mean	$T-Stat$	**Mean**	$T-Stat$	**Mean**	$T-Stat$	
Energy	Crude Oil	-2.791%	(-3.802)	-1.494%	(-1.995)	-4.250%	(-3.498)	0.096
	Heating Oil	-3.508%	(-5.310)	-2.924%	(-3.099)	-4.139%	(-4.638)	0.370
	Natural Gas	-8.985%	(-5.950)	-5.950%	(-3.981)	-11.308%	(-5.044)	0.042
Grains	Corn	-1.577%	(-5.111)	-1.522%	(-5.627)	-1.641%	(-2.808)	0.856
	Cotton	2.775%	(8.692)	2.469%	(7.957)	3.268%	(4.938)	0.205
	Soybeans	-0.324%	(-0.723)	0.245%	(0.363)	-0.956%	(-1.771)	0.129
	Soybean Meal	0.418%	(1.160)	0.386%	(0.938)	0.452%	(0.754)	0.934
	Soybean Oil	-0.616%	(-1.872)	-0.503%	(-1.577)	-0.732%	(-1.260)	0.710
	Sugar	-2.311%	(-3.973)	-1.366%	(-1.806)	-3.270%	(-3.988)	0.084
	Wheat	-0.032%	(-0.082)	-0.200%	(-0.522)	0.154%	(0.219)	0.612
Livestock	Lean Hogs	-0.077%	(-0.191)	0.505%	(0.593)	-0.310%	(-0.707)	0.373
	Live Cattle	-1.390%	(-9.850)	-1.000%	(-6.002)	-1.936%	(-11.223)	0.001
Metals	Copper	-1.700%	(-2.188)	-0.991%	(-2.485)	-2.420%	(-1.623)	0.318
	Gold	-0.864%	(-3.215)	-0.393%	(-2.302)	-1.277%	(-2.815)	0.055
	Silver	-0.292%	(-0.704)	1.179%	(4.477)	-1.923%	(-3.224)	0.000
Tropical	Cocoa	-2.626%	(-6.506)	-2.476%	(-3.775)	-2.767%	(-5.589)	0.716
	Colombian Coffee	0.974%	(0.268)	6.996%	(1.315)	-6.618%	(-4.498)	0.019
	Oats	-4.650%	(-4.690)	-4.922%	(-3.635)	-4.451%	(-3.172)	0.757
	Orange Juice	-1.566%	(-2.733)	-1.326%	(-1.533)	-1.801%	(-2.443)	0.700
	Rough Rice	-2.107%	(-4.483)	-2.035%	(-2.886)	-2.163%	(-3.428)	0.884
Wood	Lumber	-2.393%	(-6.093)	-2.668%	(-4.130)	-2.104%	(-5.009)	0.424
Portfolios	Energy	-4.666%	(-6.785)	-2.977%	(-4.589)	-6.566%	(-6.005)	0.007
	Grains	-0.328%	(-1.392)	-0.093%	(-0.357)	-0.589%	(-1.490)	0.318
	Livestock	-0.941%	(-5.705)	-0.813%	(-3.703)	-1.118%	(-4.578)	0.344
	Metals	-0.864%	(-2.380)	0.034%	(0.176)	-1.873%	(-2.887)	0.002
	Tropical	-2.202%	(-5.704)	-1.461%	(-3.002)	-2.956%	(-5.494)	0.043
	Diversified	-1.582%	(-7.117)	-0.995%	(-5.537)	-2.353%	(-6.220)	0.000

Table 3: **Comovement across Commodity Variance Swap Payoffs**

This table presents the results of regressions of the 60-day realized variance swap payoff of a given commodity on a constant and the (equally-weighted) average variance swap payoff of all other commodities. We report the intercept α and the slope β estimates. Newey–West corrected t-statistics (with 3 lags) are in parentheses. R^2 is the explanatory power of the regression model. This model can be viewed as a restricted version of a more general model where the intercept and slope parameters are allowed to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). We report the explanatory power of this unrestricted model, i.e. R^2_{UR}, in the penultimate column. The last column shows the p-value of the F-test that the unrestricted and restricted models fit the data equally well. All observations are sampled at the end of every other month.

Sector	**Commodity**	α	$T-Stat$	β	$T-Stat$	R^2	R^2_{UR}	**p-val**
Energy	Crude Oil	-0.007	(-0.915)	1.355	(3.211)	10.473%	14.022%	0.069
	Heating Oil	-0.018	(-2.323)	1.120	(3.571)	11.605%	12.199%	0.647
	Natural Gas	-0.074	(-5.489)	1.121	(2.490)	3.453%	6.471%	0.177
Grains	Corn	-0.005	(-1.016)	0.685	(3.009)	18.831%	22.558%	0.048
	Cotton	0.030	(7.255)	0.121	(0.885)	0.605%	3.785%	0.187
	Soybeans	0.011	(1.793)	0.850	(5.065)	20.039%	20.621%	0.620
	Soybean Meal	0.011	(2.046)	0.398	(1.487)	4.764%	5.965%	0.444
	Soybean Oil	0.005	(0.872)	0.687	(2.840)	24.552%	31.805%	0.002
	Sugar	-0.013	(-2.051)	0.631	(2.459)	6.171%	6.958%	0.591
	Wheat	0.009	(1.410)	0.557	(2.485)	11.928%	16.816%	0.025
Livestock	Lean Hogs	-0.004	(-0.899)	-0.127	(-0.875)	0.832%	4.104%	0.261
	Live Cattle	-0.011	(-6.356)	0.175	(3.850)	6.977%	12.340%	0.020
Metals	Copper	0.007	(0.502)	1.486	(2.105)	18.662%	26.544%	0.002
	Gold	-0.004	(-1.315)	0.303	(2.951)	9.839%	10.614%	0.606
	Silver	0.002	(0.451)	0.314	(2.003)	4.504%	18.926%	0.000
Tropical	Cocoa	-0.015	(-3.290)	0.667	(3.828)	13.923%	16.029%	0.226
	Colombian Coffee	0.004	(0.125)	-0.366	(-0.301)	0.127%	13.429%	0.032
	Oats	-0.024	(-1.662)	1.279	(3.215)	20.442%	27.318%	0.019
	Orange Juice	-0.016	(-2.187)	-0.017	(-0.073)	0.004%	0.388%	0.805
	Rough Rice	-0.015	(-2.925)	0.347	(1.932)	3.827%	6.820%	0.203
Wood	Lumber	-0.020	(-3.978)	0.254	(2.357)	2.609%	4.238%	0.379
Portfolios	Energy	-0.036	(-5.879)	1.049	(3.878)	8.225%	11.965%	0.064
	Grains	0.003	(0.683)	0.284	(1.845)	8.607%	11.892%	0.091
	Livestock	-0.009	(-4.481)	0.030	(0.478)	0.173%	2.375%	0.227
	Metals	0.002	(0.504)	0.613	(2.937)	18.547%	24.792%	0.005
	Tropical	-0.014	(-3.662)	0.506	(5.070)	9.303%	10.423%	0.460

Table 4: **Comovement with Commodity Futures Returns**

This table presents the results of regressions of the 60-day realized variance swap payoff of a given commodity on a constant and the 60-day realized futures return of that same commodity. We report the intercept α and the slope β estimates. Newey–West corrected t-statistics (with 3 lags) are in parentheses. R^2 is the explanatory power of the regression model. This model can be viewed as a restricted version of a more general model where the intercept and slope parameters are allowed to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). We report the explanatory power of this unrestricted model, i.e. R^2_{UR}, in the penultimate column. The last column shows the p-value of the F-test that the unrestricted and restricted models fit the data equally well. All observations are sampled at the end of every other month.

Sector	**Commodity**	α	$T-Stat$	β	$T-Stat$	R^2	R^2_{UR}	**p-val**
Energy	Crude Oil	-0.025	(-3.761)	-0.238	(-1.920)	10.666%	15.101%	0.035
	Heating Oil	-0.036	(-4.791)	0.095	(0.746)	3.031%	16.827%	0.000
	Natural Gas	-0.090	(-5.860)	0.128	(1.716)	2.920%	5.862%	0.193
Grains	Corn	-0.016	(-4.799)	-0.006	(-0.094)	0.027%	0.165%	0.915
	Cotton	0.028	(8.917)	-0.061	(-1.688)	4.134%	5.900%	0.384
	Soybeans	-0.003	(-0.623)	-0.088	(-1.356)	3.756%	5.086%	0.402
	Soybean Meal	0.004	(1.171)	-0.033	(-0.612)	0.601%	2.568%	0.278
	Soybean Oil	-0.006	(-1.776)	-0.038	(-0.440)	1.085%	4.263%	0.132
	Sugar	-0.023	(-3.973)	0.004	(0.103)	0.009%	2.390%	0.222
	Wheat	-0.001	(-0.205)	0.079	(2.437)	4.485%	4.628%	0.908
Livestock	Lean Hogs	0.000	(-0.057)	-0.106	(-2.702)	11.378%	12.342%	0.645
	Live Cattle	-0.014	(-9.791)	-0.047	(-1.615)	2.586%	11.149%	0.002
Metals	Copper	-0.014	(-1.956)	-0.270	(-1.480)	14.726%	17.153%	0.165
	Gold	-0.008	(-3.415)	-0.033	(-0.776)	0.556%	3.164%	0.214
	Silver	-0.002	(-0.443)	-0.103	(-2.734)	8.089%	22.819%	0.000
Tropical	Cocoa	-0.026	(-6.435)	0.075	(1.443)	2.779%	4.523%	0.338
	Colombian Coffee	-0.030	(-1.458)	0.949	(4.455)	55.192%	64.279%	0.004
	Oats	-0.047	(-4.985)	-0.165	(-1.674)	6.888%	9.229%	0.352
	Orange Juice	-0.015	(-2.550)	0.170	(2.342)	9.027%	10.314%	0.447
	Rough Rice	-0.022	(-4.881)	0.115	(1.940)	10.766%	11.709%	0.585
Wood	Lumber	-0.024	(-6.049)	0.017	(0.482)	0.321%	2.363%	0.304
Portfolios	Energy	-0.047	(-6.716)	0.046	(0.443)	0.599%	10.325%	0.001
	Grains	-0.003	(-1.283)	-0.048	(-0.725)	1.500%	2.880%	0.397
	Livestock	-0.009	(-5.764)	-0.076	(-2.670)	6.382%	7.698%	0.369
	Metals	-0.007	(-2.211)	-0.199	(-2.032)	15.720%	19.301%	0.057
	Tropical	-0.022	(-5.869)	0.065	(0.785)	1.061%	11.564%	0.001
	Diversified	-0.015	(-7.117)	-0.151	(-1.971)	10.521%	21.256%	0.000

Table 5: **Comovement with Bond and Equity Returns**

This table presents the results of regressions of the 60-day realized variance swap payoff of a given commodity on a constant and the 60-day realized equity and bond excess returns. α is the intercept. β_E and β_B are the slope parameters linked to the equity and bond excess returns, respectively. Newey–West corrected t-statistics (with 3 lags) are in parentheses. R^2 is the explanatory power of the regression model. This model can be viewed as a restricted version of a more general model where the intercept and the slopes are allowed to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). We report the explanatory power of this unrestricted model, i.e. R^2_{UR}, in the penultimate column. The last column shows the p-value of the F-test that the unrestricted and restricted models fit the data equally well. All observations are sampled at the end of every other month.

Sector	**Commodity**	α	$T-Stat$	β_E	$T-Stat$	β_B	$T-Stat$	R^2	R^2_{UR}	**p-val**
Energy	Crude Oil	-0.036	(-4.722)	-0.330	(-1.737)	-0.202	(-1.227)	16.461%	26.087%	0.013
	Heating Oil	-0.041	(-6.666)	-0.188	(-1.549)	-0.129	(-1.127)	7.855%	13.237%	0.153
	Natural Gas	-0.098	(-6.101)	-0.333	(-1.548)	0.261	(1.313)	2.716%	4.496%	0.656
Grains	Corn	-0.017	(-4.070)	-0.070	(-0.814)	-0.167	(-1.866)	10.983%	11.912%	0.826
	Cotton	0.028	(6.697)	-0.089	(-1.401)	0.013	(0.235)	2.657%	6.509%	0.457
	Soybeans	-0.003	(-0.573)	0.001	(0.015)	-0.051	(-0.647)	0.533%	4.714%	0.294
	Soybean Meal	0.005	(1.168)	-0.028	(-0.256)	-0.071	(-0.737)	1.615%	2.279%	0.900
	Soybean Oil	-0.008	(-2.085)	-0.173	(-1.456)	-0.009	(-0.171)	11.581%	15.723%	0.256
	Sugar	-0.030	(-4.576)	-0.004	(-0.046)	-0.043	(-0.344)	0.261%	3.360%	0.430
	Wheat	-0.001	(-0.136)	-0.045	(-0.800)	-0.103	(-1.704)	4.023%	4.304%	0.969
Livestock	Lean Hogs	-0.002	(-0.399)	0.077	(1.319)	-0.052	(-0.816)	2.085%	6.268%	0.330
	Live Cattle	-0.016	(-10.939)	0.002	(0.099)	-0.028	(-0.915)	0.973%	10.452%	0.038
Metals	Copper	-0.019	(-2.139)	-0.484	(-2.104)	-0.125	(-0.835)	17.607%	21.069%	0.289
	Gold	-0.011	(-3.382)	-0.071	(-1.706)	-0.084	(-1.365)	11.176%	16.614%	0.157
	Silver	-0.010	(-1.916)	-0.005	(-0.106)	-0.049	(-0.894)	0.809%	14.505%	0.005
Tropical	Cocoa	-0.030	(-5.627)	0.076	(1.081)	-0.065	(-0.983)	1.666%	7.444%	0.168
	Colombian Coffee	-0.022	(-0.541)	0.915	(2.254)	0.115	(0.413)	19.626%	62.157%	0.001
	Oats	-0.041	(-3.275)	-0.149	(-0.790)	-0.057	(-0.429)	2.980%	6.075%	0.522
	Orange Juice	-0.018	(-2.852)	0.044	(0.391)	0.049	(0.544)	0.762%	5.336%	0.295
	Rough Rice	-0.023	(-4.354)	-0.019	(-0.366)	0.007	(0.146)	0.098%	1.024%	0.861
Wood	Lumber	-0.021	(-7.544)	-0.047	(-1.067)	-0.078	(-1.203)	5.508%	7.863%	0.582
Portfolios	Energy	-0.066	(-6.525)	-0.298	(-1.610)	-0.074	(-0.448)	9.066%	13.198%	0.453
	Grains	-0.005	(-1.206)	-0.094	(-1.181)	-0.150	(-1.666)	16.834%	17.740%	0.892
	Livestock	-0.009	(-3.882)	-0.001	(-0.018)	-0.018	(-0.442)	0.475%	8.847%	0.188
	Metals	-0.011	(-2.483)	-0.255	(-2.162)	-0.112	(-1.089)	27.943%	36.636%	0.064
	Tropical	-0.028	(-5.357)	0.063	(0.624)	-0.046	(-0.548)	1.380%	3.989%	0.679
	Diversified	-0.022	(-6.097)	-0.106	(-1.222)	-0.095	(-1.327)	17.110%	22.356%	0.297

Table 6: **Comovement with Bond and Equity Variance Swap Payoffs**

This table presents the results of regressions of the 60-day realized variance swap payoff of a given commodity on a constant and the 60-day realized variance swap payoffs of the bond and equity markets. α is the intercept. β_E and β_B are the sensitivity to the equity and bond variance swap payoffs, respectively. Newey–West corrected t-statistics (with 3 lags) are in parentheses. R^2 is the explanatory power of the regression model. This model can be viewed as a restricted version of a more general model where the intercept and the slopes are allowed to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). We report the explanatory power of this unrestricted model, i.e. R^2_{UR}, in the penultimate column. The last column shows the p-value of the F-test that the unrestricted and restricted models fit the data equally well. All observations are sampled at the end of every other month.

Sector	**Commodity**	α	$T-Stat$	β_E	$T-Stat$	β_B	$T-Stat$	R^2	R^2_{UR}	**p-val**
Energy	Crude Oil	-0.022	(-2.835)	0.542	(5.362)	0.286	(3.762)	28.419%	31.179%	0.378
	Heating Oil	-0.034	(-5.753)	0.268	(3.860)	0.162	(1.517)	9.870%	13.993%	0.299
	Natural Gas	-0.103	(-5.293)	0.317	(2.280)	0.041	(0.250)	1.753%	5.404%	0.396
Grains	Corn	-0.010	(-2.179)	0.292	(4.986)	0.049	(0.804)	17.924%	18.627%	0.883
	Cotton	0.025	(4.295)	-0.099	(-0.599)	0.014	(0.042)	0.520%	5.055%	0.383
	Soybeans	0.005	(0.780)	0.145	(2.853)	0.180	(4.699)	9.773%	12.114%	0.559
	Soybean Meal	0.007	(1.338)	0.271	(4.066)	-0.156	(-0.736)	9.002%	11.536%	0.534
	Soybean Oil	-0.003	(-0.556)	0.322	(3.424)	0.018	(0.740)	26.836%	32.520%	0.107
	Sugar	-0.021	(-2.914)	0.232	(3.913)	0.102	(1.666)	9.323%	11.673%	0.560
	Wheat	0.006	(0.988)	0.156	(4.694)	0.180	(4.058)	13.777%	14.315%	0.923
Livestock	Lean Hogs	-0.004	(-0.980)	-0.017	(-0.549)	-0.133	(-2.933)	5.420%	8.189%	0.547
	Live Cattle	-0.014	(-7.535)	0.044	(1.859)	0.054	(2.802)	7.262%	14.542%	0.093
Metals	Copper	0.005	(0.743)	0.947	(5.025)	0.431	(3.080)	52.295%	54.618%	0.270
	Gold	-0.006	(-2.718)	0.038	(0.584)	0.184	(3.964)	22.766%	23.885%	0.784
	Silver	-0.002	(-0.492)	0.005	(0.061)	0.180	(3.935)	7.777%	17.317%	0.036
Tropical	Cocoa	-0.023	(-4.169)	-0.005	(-0.094)	0.173	(4.218)	5.058%	8.863%	0.384
	Colombian Coffee	-0.066	(-2.695)	-1.464	(-2.017)	-1.680	(-1.180)	5.800%	28.892%	0.076
	Oats	-0.035	(-2.728)	0.482	(5.157)	-0.068	(-1.136)	14.715%	15.349%	0.923
	Orange Juice	-0.018	(-2.250)	-0.089	(-0.732)	-0.022	(-0.329)	0.855%	16.330%	0.008
	Rough Rice	-0.024	(-4.394)	0.060	(1.584)	-0.025	(-0.509)	0.790%	3.879%	0.502
Wood	Lumber	-0.020	(-7.080)	0.120	(4.054)	-0.006	(-0.139)	5.210%	6.953%	0.710
Portfolios	Energy	-0.053	(-6.732)	0.375	(5.749)	0.163	(2.053)	13.921%	16.541%	0.489
	Grains	0.002	(0.652)	0.225	(4.643)	0.083	(1.340)	26.796%	29.224%	0.449
	Livestock	-0.010	(-3.759)	0.014	(0.657)	-0.041	(-1.328)	1.146%	4.959%	0.378
	Metals	-0.001	(-0.193)	0.330	(8.022)	0.267	(7.361)	51.371%	55.771%	0.059
	Tropical	-0.024	(-4.550)	0.076	(1.085)	0.027	(0.896)	1.923%	9.889%	0.084
	Diversified	-0.014	(-4.984)	0.205	(5.412)	0.097	(4.796)	37.904%	45.098%	0.022

Table 7: **Variance Risk Premia**

This table presents the average value of the 60-day expected realized variance ($\mathbb{E}^{\mathbb{P}}(V_{t\to t+\tau})$), implied variance ($MFIV$) and variance risk premium ($\mathbb{E}^{\mathbb{P}}(V_{t\to t+\tau}) - MFIV$). Std, Skew and Kurt indicate the standard deviation, skewness and kurtosis of the 60-day variance risk premium, respectively. $AR(1)$ indicates the first-order autocorrelation of the bi-monthly time-series of the variance risk premium. All observations are sampled at the end of every other month.

Sector	**Commodity**	$\mathbb{E}^{\mathbb{P}}(V_{t\to t+\tau})$	$MFIV$	$\mathbb{E}^{\mathbb{P}}(V_{t\to t+\tau}) - MFIV$	*Std*	*Skew*	$Kurt$	$AR(1)$
Energy	Crude Oil	11.043%	13.834%	-2.791%	3.468%	-3.179	16.943	0.402
	Heating Oil	9.874%	13.382%	-3.508%	5.449%	-2.610	12.241	0.577
	Natural Gas	19.351%	28.336%	-8.985%	10.497%	-2.394	11.083	0.519
Grains	Corn	6.168%	7.745%	-1.577%	1.765%	-0.978	7.802	0.156
	Cotton	5.923%	3.148%	2.775%	1.694%	-1.771	11.391	0.079
	Soybeans	6.292%	6.617%	-0.324%	0.969%	0.262	7.619	0.510
	Soybean Meal	7.162%	6.744%	0.418%	0.921%	1.255	5.003	0.655
	Soybean Oil	5.606%	6.222%	-0.616%	1.271%	-0.220	7.278	0.174
	Sugar	11.109%	13.420%	-2.311%	3.524%	-1.256	4.990	0.730
	Wheat	7.790%	7.822%	-0.032%	0.809%	-1.068	6.655	0.312
Livestock	Lean Hogs	7.610%	7.687%	-0.077%	1.760%	-1.414	18.391	-0.140
	Live Cattle	1.883%	3.273%	-1.390%	1.284%	-1.671	6.938	0.320
Metals	Copper	7.642%	9.342%	-1.700%	4.495%	-3.467	17.847	0.528
	Gold	2.898%	3.763%	-0.864%	1.428%	-3.639	19.596	0.731
	Silver	2.661%	2.952%	-0.292%	2.897%	-4.471	31.400	0.670
Tropical	Cocoa	9.398%	12.024%	-2.626%	2.051%	-1.240	5.601	0.535
	Colombian Coffee	17.592%	16.618%	0.974%	9.512%	-1.310	4.461	0.535
	Oats	6.948%	11.599%	-4.650%	3.355%	-0.606	2.966	0.419
	Orange Juice	9.675%	11.240%	-1.566%	3.801%	-1.122	4.891	0.323
	Rough Rice	6.117%	8.224%	-2.107%	2.755%	-0.975	3.741	0.549
Wood	Lumber	7.753%	10.147%	-2.393%	2.830%	-2.759	13.925	0.532
Portfolios	Energy	12.879%	17.604%	-4.725%	5.119%	-1.984	8.579	0.558
	Grains	7.263%	7.600%	-0.337%	0.907%	-0.846	3.542	0.631
	Livestock	3.494%	4.429%	-0.935%	1.209%	-1.410	7.950	0.196
	Metals	4.313%	5.179%	-0.867%	2.288%	-2.802	11.960	0.693
	Tropical	9.148%	11.211%	-2.063%	2.650%	-0.264	4.014	0.520
	Diversified	7.253%	8.831%	-1.578%	1.348%	-1.022	4.915	0.673

Table 8: **Time Variation in Variance Risk Premia**

This table presents the summary statistics of the 60-day commodity variance risk premia using (i) all sample observations (Unconditional), (ii) all observations before the year 2001 (Pre CFMA) and (iii) all observations from 2001 (Post CFMA). Newey–West corrected t-statistics (with 3 lags) are in parentheses. The last column shows the p-value of the null hypothesis that the difference between the average variance risk premia of the two subsamples is equal to zero. All observations are sampled at the end of every other month.

Sector	**Commodity**	**Unconditional**		**Pre CFMA**		**Post CFMA**		**p-val**
		Mean	$T-Stat$	**Mean**	$T-Stat$	**Mean**	$T-Stat$	
Energy	Crude Oil	-2.791%	(-6.788)	-1.494%	(-7.006)	-4.250%	(-6.371)	0.000
	Heating Oil	-3.508%	(-5.218)	-2.924%	(-2.613)	-4.139%	(-6.235)	0.200
	Natural Gas	-8.985%	(-6.510)	-5.950%	(-8.839)	-11.308%	(-5.127)	0.007
Grains	Corn	-1.577%	(-11.114)	-1.522%	(-16.983)	-1.641%	(-5.750)	0.699
	Cotton	2.775%	(16.355)	2.469%	(17.413)	3.268%	(9.768)	0.017
	Soybeans	-0.324%	(-2.655)	0.245%	(2.994)	-0.956%	(-8.206)	0.000
	Soybean Meal	0.418%	(3.237)	0.386%	(6.188)	0.452%	(1.761)	0.680
	Soybean Oil	-0.616%	(-5.175)	-0.503%	(-2.798)	-0.732%	(-4.866)	0.310
	Sugar	-2.311%	(-4.389)	-1.366%	(-2.038)	-3.270%	(-4.400)	0.002
	Wheat	-0.032%	(-0.344)	-0.200%	(-1.394)	0.154%	(1.566)	0.011
Livestock	Lean Hogs	-0.077%	(-0.425)	0.505%	(1.257)	-0.310%	(-1.876)	0.055
	Live Cattle	-1.390%	(-9.368)	-1.000%	(-6.268)	-1.936%	(-9.244)	0.000
Metals	Copper	-1.700%	(-2.852)	-0.991%	(-3.162)	-2.420%	(-2.146)	0.071
	Gold	-0.864%	(-4.000)	-0.393%	(-4.069)	-1.277%	(-3.495)	0.001
	Silver	-0.292%	(-0.723)	1.179%	(36.327)	-1.923%	(-3.013)	0.000
Tropical	Cocoa	-2.626%	(-9.358)	-2.476%	(-6.736)	-2.767%	(-6.716)	0.432
	Colombian Coffee	0.974%	(0.463)	6.996%	(5.902)	-6.618%	(-3.843)	0.000
	Oats	-4.650%	(-9.235)	-4.922%	(-15.637)	-4.451%	(-5.298)	0.509
	Orange Juice	-1.566%	(-3.685)	-1.326%	(-1.851)	-1.801%	(-3.928)	0.501
	Rough Rice	-2.107%	(-5.173)	-2.035%	(-3.377)	-2.163%	(-3.968)	0.814
Wood	Lumber	-2.393%	(-6.333)	-2.668%	(-3.907)	-2.104%	(-7.930)	0.279
Portfolios	Energy	-4.725%	(-7.442)	-3.089%	(-4.897)	-6.566%	(-6.922)	0.000
	Grains	-0.337%	(-2.719)	-0.078%	(-0.581)	-0.625%	(-3.275)	0.000
	Livestock	-0.935%	(-7.346)	-0.807%	(-4.382)	-1.111%	(-7.205)	0.136
	Metals	-0.867%	(-2.575)	0.028%	(0.212)	-1.873%	(-3.094)	0.000
	Tropical	-2.063%	(-5.571)	-1.182%	(-2.541)	-2.958%	(-6.007)	0.000
	Diversified	-1.578%	(-8.590)	-0.992%	(-6.135)	-2.346%	(-8.895)	0.000

Table 9: **Relationship with Commodity Risk Premia**

This table presents the results of regressions of the 60-day commodity variance risk premium on a constant and the 60-day commodity futures risk premium. We regress the bi-monthly time-series of the 60-day realized commodity futures returns on a constant and the lagged forecasting variables (see Section III.B.2). We then use the parameter estimates to generate the commodity futures risk premium, which we use as explanatory variable. α *is the intercept.* β_C *is the sensitivity to the commodity futures risk premium. Newey–West corrected t-statistics (with 3 lags) are in parentheses.* R^2 *is the explanatory power of the regression model. This model can be viewed as a restricted version of a more general model where the intercept and the slopes are allowed to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). We report the explanatory power of this unrestricted model, i.e.* R^2_{UR}*, in the penultimate column. The last column shows the p-value of the F-test that the unrestricted and restricted models fit the data equally well. All observations are sampled at the end of every other month.*

Sector	**Commodity**	α	$T-Stat$	β_C	$T-Stat$	R^2	R^2_{UR}	**p-val**
Energy	Crude Oil	-0.029	(-6.552)	0.050	(0.677)	0.560%	17.503%	0.000
	Heating Oil	-0.038	(-5.204)	0.207	(2.194)	4.075%	11.126%	0.020
	Natural Gas	-0.091	(-6.527)	0.169	(1.517)	1.168%	8.448%	0.040
Grains	Corn	-0.016	(-10.363)	0.042	(1.612)	1.978%	5.524%	0.192
	Cotton	0.028	(16.389)	0.003	(0.079)	0.015%	7.980%	0.037
	Soybeans	-0.003	(-2.638)	-0.027	(-1.415)	1.405%	39.751%	0.000
	Soybean Meal	0.004	(3.254)	-0.011	(-0.395)	0.296%	8.454%	0.012
	Soybean Oil	-0.006	(-5.096)	-0.001	(-0.050)	0.001%	4.624%	0.119
	Sugar	-0.023	(-4.450)	-0.063	(-1.021)	1.124%	7.707%	0.035
	Wheat	0.000	(-0.307)	-0.005	(-0.249)	0.058%	6.976%	0.027
Livestock	Lean Hogs	-0.001	(-0.420)	-0.002	(-0.081)	0.009%	5.063%	0.248
	Live Cattle	-0.014	(-9.310)	0.076	(1.459)	2.284%	16.473%	0.000
Metals	Copper	-0.016	(-3.081)	-0.174	(-1.332)	5.601%	16.573%	0.002
	Gold	-0.008	(-3.525)	-0.084	(-1.356)	2.119%	42.240%	0.000
	Silver	-0.001	(-0.144)	-0.190	(-1.934)	7.158%	50.295%	0.000
Tropical	Cocoa	-0.026	(-9.440)	-0.047	(-0.915)	0.834%	4.306%	0.235
	Colombian Coffee	-0.001	(-0.066)	0.465	(2.571)	15.275%	68.484%	0.000
	Oats	-0.046	(-10.367)	0.173	(1.551)	6.373%	6.695%	0.960
	Orange Juice	-0.016	(-3.919)	-0.124	(-1.252)	1.667%	2.996%	0.675
	Rough Rice	-0.021	(-5.384)	0.035	(0.838)	0.792%	5.795%	0.158
Wood	Lumber	-0.024	(-6.360)	-0.014	(-0.224)	0.091%	1.574%	0.634
Portfolios	Energy	-0.052	(-6.741)	0.136	(1.115)	2.693%	16.758%	0.004
	Grains	-0.003	(-2.216)	-0.050	(-2.669)	5.733%	16.124%	0.016
	Livestock	-0.010	(-5.548)	0.081	(1.796)	6.464%	13.138%	0.121
	Metals	-0.007	(-1.992)	-0.084	(-0.813)	2.861%	35.102%	0.000
	Tropical	-0.020	(-4.053)	0.051	(0.439)	0.513%	19.332%	0.001
	Diversified	-0.016	(-7.057)	-0.021	(-0.282)	0.215%	28.579%	0.000

Table 10: **Comovement with Bond and Equity Risk Premia**

This table presents the results of regressions of 60-day commodity variance risk premia on a constant and the 60-day equity and bond risk premia. α is the intercept. β_E and β_B are the sensitivity to the equity and bond risk premia, respectively. In order to estimate the bond and equity risk premia, we regress the time-series of the realized bond and equity returns on a constant and lagged forecasting variables. We then use the forecasting model to generate the risk premia. Newey–West corrected t-statistics (with 3 lags) are in parentheses. R^2 is the explanatory power of the regression model. This model can be viewed as a restricted version of a more general model where the intercept and the slopes are allowed to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). We report the explanatory power of this unrestricted model, i.e. R^2_{UR}, in the penultimate column. The last column shows the p-value of the F-test that the unrestricted and restricted models fit the data equally well. All observations are sampled at the end of every other month.

Sector	**Commodity**	α	$T-Stat$	β_E	$T-Stat$	β_B	R^2	R^2_{UR}	**p-val**	
	Crude Oil	-0.031	(-6.706)	-0.023	(-0.155)	0.230	(1.894)	4.052%	19.189%	0.002
Energy	Heating Oil	-0.043	(-8.128)	0.111	(0.820)	-0.068	(-0.648)	1.120%	8.666%	0.069
	Natural Gas	-0.104	(-6.599)	0.135	(0.340)	-0.250	(-1.016)	0.608%	3.817%	0.401
	Corn	-0.017	(-6.689)	0.015	(0.219)	-0.002	(-0.037)	0.073%	0.650%	0.917
	Cotton	0.029	(13.392)	-0.045	(-0.922)	0.006	(0.142)	0.667%	7.016%	0.222
	Soybeans	-0.007	(-5.383)	0.098	(2.378)	-0.052	(-1.232)	11.948%	38.783%	0.000
Grains	Soybean Meal	0.004	(1.820)	0.004	(0.091)	-0.043	(-0.891)	1.937%	5.090%	0.409
	Soybean Oil	-0.006	(-3.460)	-0.020	(-0.361)	0.029	(0.746)	0.762%	13.845%	0.007
	Sugar	-0.030	(-4.878)	0.089	(0.615)	-0.196	(-1.458)	3.016%	22.917%	0.000
	Wheat	-0.001	(-0.884)	-0.008	(-0.323)	-0.048	(-1.659)	4.805%	28.150%	0.000
Livestock	Lean Hogs	-0.002	(-0.853)	0.067	(1.372)	-0.089	(-1.264)	4.244%	20.667%	0.002
	Live Cattle	-0.016	(-9.252)	0.026	(0.749)	0.013	(0.341)	1.101%	21.228%	0.000
	Copper	-0.018	(-2.754)	-0.411	(-2.173)	0.092	(0.535)	8.551%	13.038%	0.212
Metals	Gold	-0.011	(-2.996)	0.080	(0.861)	-0.019	(-0.238)	3.350%	8.442%	0.211
	Silver	-0.011	(-1.520)	0.217	(1.031)	0.000	(-0.001)	6.285%	20.999%	0.002
	Cocoa	-0.027	(-6.978)	0.040	(0.528)	0.028	(0.283)	0.750%	13.565%	0.008
	Colombian Coffee	-0.043	(-2.771)	0.500	(2.590)	-0.020	(-0.053)	9.621%	26.680%	0.163
Tropical	Oats	-0.049	(-7.885)	0.142	(1.216)	-0.212	(-1.848)	4.001%	6.364%	0.613
	Orange Juice	-0.017	(-3.717)	-0.036	(-0.266)	0.162	(1.569)	2.724%	4.696%	0.648
	Rough Rice	-0.021	(-4.779)	0.197	(1.675)	0.076	(0.890)	11.827%	13.826%	0.595
Wood	Lumber	-0.021	(-9.896)	0.036	(0.730)	-0.091	(-1.970)	3.151%	3.995%	0.874
	Energy	-0.059	(-8.321)	0.075	(0.368)	-0.029	(-0.268)	0.286%	5.042%	0.224
	Grains	-0.005	(-3.581)	0.017	(0.455)	-0.037	(-1.072)	1.606%	20.606%	0.000
Portfolios	Livestock	-0.010	(-5.865)	0.038	(1.027)	-0.042	(-0.841)	2.117%	27.643%	0.000
	Metals	-0.013	(-2.573)	-0.036	(-0.256)	0.025	(0.223)	0.295%	10.787%	0.019
	Tropical	-0.029	(-7.320)	0.157	(1.604)	0.010	(0.129)	6.502%	12.245%	0.129
	Diversified	-0.021	(-10.090)	0.056	(0.924)	-0.025	(-0.579)	2.526%	15.029%	0.006

Table 11: **Comovement with Bond and Equity Variance Risk Premia**

This table presents the results of regressions of 60-day commodity variance risk premia on a constant and the 60-day equity and bond variance risk premia. α is the intercept. β_E and β_B are the sensitivity to the equity and bond variance risk premia, respectively. Newey–West corrected t-statistics (with 3 lags) are in parentheses. R^2 is the explanatory power of the regression model. This model can be viewed as a restricted version of a more general model where the intercept and the slopes are allowed to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). We report the explanatory power of this unrestricted model, i.e. R^2_{UR}, in the penultimate column. The last column shows the p-value of the F-test that the unrestricted and restricted models fit the data equally well. All observations are sampled at the end of every other month.

Sector	**Commodity**	α	$T-Stat$	β_E	$T-Stat$	β_B	$T-Stat$	R^2	R^2_{UR}	**p-val**
Energy	Crude Oil	-0.031	(-5.707)	0.135	(0.481)	0.054	(0.842)	1.278%	29.223%	0.000
	Heating Oil	-0.035	(-5.595)	0.446	(1.772)	0.109	(1.658)	7.888%	9.420%	0.725
	Natural Gas	-0.115	(-5.160)	-0.927	(-1.392)	0.439	(2.764)	4.300%	7.565%	0.436
Grains	Corn	-0.019	(-6.652)	-0.167	(-1.106)	-0.001	(-0.009)	1.580%	7.788%	0.173
	Cotton	0.024	(6.321)	0.168	(1.766)	-0.754	(-2.763)	4.671%	15.078%	0.056
	Soybeans	-0.007	(-3.763)	-0.267	(-3.513)	0.065	(4.605)	15.653%	35.931%	0.000
	Soybean Meal	0.002	(1.227)	0.078	(1.274)	-0.129	(-10.908)	41.889%	43.012%	0.679
	Soybean Oil	-0.010	(-4.960)	-0.196	(-1.716)	-0.009	(-0.259)	7.113%	19.203%	0.015
	Sugar	-0.012	(-2.032)	0.539	(1.385)	0.077	(1.204)	11.618%	14.132%	0.519
	Wheat	0.000	(-0.067)	0.169	(2.423)	-0.058	(-3.089)	16.768%	34.272%	0.000
Livestock	Lean Hogs	0.000	(-0.138)	-0.006	(-0.040)	0.024	(1.073)	0.570%	15.156%	0.010
	Live Cattle	-0.018	(-6.962)	-0.194	(-1.647)	0.055	(2.759)	6.793%	17.284%	0.025
Metals	Copper	-0.017	(-1.847)	-0.555	(-1.269)	0.551	(3.385)	29.934%	38.079%	0.021
	Gold	-0.004	(-1.939)	0.180	(1.101)	0.162	(2.849)	43.937%	62.132%	0.000
	Silver	-0.001	(-0.210)	-0.048	(-0.136)	0.302	(2.234)	26.141%	45.665%	0.000
Tropical	Cocoa	-0.021	(-4.842)	0.223	(0.732)	0.126	(2.492)	15.596%	22.756%	0.086
	Colombian Coffee	-0.087	(-2.515)	-1.989	(-1.461)	-1.854	(-0.831)	9.905%	31.527%	0.081
	Oats	-0.037	(-4.730)	0.533	(2.167)	0.109	(2.295)	13.873%	22.157%	0.089
	Orange Juice	-0.009	(-1.730)	0.540	(1.520)	0.064	(1.054)	9.908%	12.016%	0.649
	Rough Rice	-0.017	(-2.972)	0.241	(0.731)	0.007	(0.131)	2.291%	14.336%	0.020
Wood	Lumber	-0.019	(-7.187)	-0.007	(-0.053)	0.037	(1.293)	1.702%	7.419%	0.216
Portfolios	Energy	-0.060	(-7.032)	-0.115	(-0.483)	0.201	(2.491)	4.648%	12.037%	0.097
	Grains	-0.003	(-1.836)	0.020	(0.227)	0.012	(0.518)	1.122%	5.963%	0.268
	Livestock	-0.010	(-5.225)	-0.130	(-1.078)	0.040	(1.981)	3.593%	15.144%	0.018
	Metals	-0.007	(-1.873)	-0.138	(-1.079)	0.338	(11.051)	48.756%	50.726%	0.380
	Tropical	-0.023	(-4.386)	0.245	(1.045)	0.087	(2.366)	9.484%	19.396%	0.028
	Diversified	-0.018	(-7.994)	0.004	(0.055)	0.116	(6.573)	25.537%	36.983%	0.004

Appendix to

“Variance Risk in Commodity Markets”

Not Intended for Publication!

Will be Provided as Online Appendix

Table A.1: **Overview of Commodities**

This table lists all commodities considered. The first two columns report the sector and name of specific commodities. The third column displays the exchange where the futures and options contracts of the commodity are traded. The fourth and fifth columns report the available maturity months and minimum tick sizes of the underlying contracts as reported by the relevant exchange. The sixth column shows the contract size of each derivative contract. The last two columns display the average yearly option volume and open interest (based on the years 2008 and 2011). We extract this information from the volume reports published on the exchange's websites.

Sector	**Commodity**	**Exchange**	**Maturity Months**	**Tick Size**	**Contract Size**	**Volume**	**Open Interest**
	Crude Oil	NYMEX	January-December	\$0.01 per barrel	1,000 barrels	33,327,282	3,887,456
Energy	Heating Oil	NYMEX	January-December	\$0.0001 per gallon	42,000 gallons	810,740	113,081
	Natural Gas	NYMEX	January-December	\$0.001 per MMBtu	10,000 million British thermal units	1,723,926	390,290
	Corn	CBOT	January, March, May, July, September, November, December	\$0.0025 per bushel	5,000 bushels	21,152,877	1,244,585
	Cotton	ICE	March, May, July, October, December	\$0.0001 per pound	50,000 pounds net weight	2,970,919	247,978
	Soybeans	CBOT	January, March, May, July, August, September, November	\$0.0025 per bushel	5,000 bushels	10,652,804	529,014
Grains	Soybean Meal	CBOT	January, March, May, July, August, September, October, December	\$0.10 per short ton	100 short tons	935,924	65,307
	Soybean Oil	CBOT	January, March, May, July, August, September, October, December	\$0.0001 per pound	60,000 pounds	1,729,504	126,609
	Sugar	ICE	March, May, July, October, December	\$0.0001 per pound	112,000 pounds	8,035,823	987,586
	Wheat	CBOT	March, May, July, September, December	\$0.0025 per bushel	5,000 bushels	4,216,575	244,188
Livestock	Lean Hogs	CME	February, April, June, July, August, October, December	\$0.00025 per pound	40,000 pounds	721,943	90,237
	Live Cattle	CME	February, April, June, August, October, December	\$0.00025 per pound	40,000 pounds	1,920,990	206,825
	Copper	COMEX	February, April, June, August, October, December	\$0.0005 per pound	25,000 pounds	16,383	1,129
Metals	Gold	COMEX	March, May, July, September, December	\$0.10 per troy ounce	100 troy ounces	6,739,852	745,059
	Silver	COMEX	March, May, July, September, December	\$0.001 per troy ounce	5,000 troy ounces	1,632,986	127,957
	Cocoa	ICE	March, May, July, September, December	\$1.00 per metric ton	10 metric tons	417,447	46,082
	Colombian Coffee	ICE	March, May, July, September, December	\$0.0005per pound	37,500 pounds	2,295,837	144,067
Tropical	Oats	CBOT	March, May, July, September, December	\$0.0025 per bushel	5,000 bushels	20,678	3,576
	Orange Juice	ICE	January, March, May, July, September, November	\$0.0005 per pound	15,000 pounds	218,331	28,038
	Rough Rice	CBOT	January, March, May, July, September, November	\$0.005 per hundred weight	2,000 hundred weights	29,474	2,783
Wood	Lumber	CME	January, March, May, July, September, November	\$0.10 per mbf	110,000 nominal board feet	11,859	727

Table A.2: **Description of Options Data**

This table summarizes information about the OTM options data. The first two columns report the sector and name of specific commodities. Columns "Start" and "End" indicate the starting and ending years of the sample, respectively. "Days" reports the number of observation days of the raw option dataset. The last two columns show the average number of OTM calls and puts with different strike prices on each trading day, respectively.

Sector	**Commodity**	**Start**	**End**	**Days**	**Calls**	**Puts**
Energy	Crude Oil	1989	2011	5,640	27	22
	Heating Oil	1989	2011	5,660	29	24
	Natural Gas	1992	2011	4,740	51	27
Grains	Corn	1989	2011	5,691	19	13
	Cotton	1990	2007	4,449	20	15
	Soybeans	1989	2011	5,692	20	14
	Soybean Meal	1989	2011	5,686	8	5
	Soybean Oil	1989	2011	5,651	13	11
	Sugar	1990	2011	5,372	26	17
	Wheat	1989	2011	5,692	18	13
Livestock	Lean Hogs	1985	2011	6,612	7	12
	Live Cattle	1984	2011	6,630	9	11
Metals	Copper	1989	2011	5,461	12	14
	Gold	1989	2011	5,704	16	13
	Silver	1989	2011	5,673	24	32
Tropical	Cocoa	1990	2011	5,384	10	6
	Colombian Coffee	1990	2011	5,390	5	19
	Oats	1990	2011	5,344	7	5
	Orange Juice	1990	2011	5,370	8	4
	Rough Rice	1992	2011	4,832	9	6
Wood	Lumber	1987	2010	5,680	10	7

Table A.3: **Predictability of Variance Swap Payoffs**

This table presents the results of regressions of the 60-day commodity variance swap payoff on a constant, the lagged 60-day realized variance and the lagged 60-day implied variance. We allow the intercept and slope parameters to change with the CFMA dummy that takes value 1 from 2001 (Post CFMA). Newey–West corrected t-statistics (with 3 lags) are in parentheses. R^2 *is the explanatory power of the regression model. All observations are sampled at the end of every other month.*

Sector	**Commodity**	α	$T-Stat$	α_1	$T-Stat$	β	$T-Stat$	β_1	$T-Stat$	γ	$T-Stat$	γ_1	$T-Stat$	R^2
Energy	Crude Oil	-0.007	(-0.398)	0.026	(1.162)	-0.118	(-0.749)	0.785	(3.523)	0.026	(0.101)	-0.897	(-2.959)	12.923%
	Heating Oil	0.038	(3.926)	-0.002	(-0.092)	-0.065	(-3.777)	0.484	(2.003)	-0.550	(-12.067)	-0.276	(-1.191)	49.119%
	Natural Gas	0.002	(0.065)	0.111	(2.361)	-0.245	(-2.681)	0.238	(2.578)	-0.066	(-0.317)	-0.616	(-2.692)	56.975%
Grains	Corn	-0.005	(-1.083)	0.011	(0.994)	0.130	(1.906)	0.298	(1.517)	-0.290	(-2.651)	-0.279	(-1.443)	21.938%
	Cotton	0.010	(1.462)	0.038	(2.309)	0.408	(5.742)	0.037	(0.171)	-0.173	(-0.534)	-0.896	(-2.160)	28.756%
	Soybean	0.000	(0.033)	-0.005	(-0.302)	0.141	(1.700)	0.060	(0.483)	-0.089	(-0.268)	-0.146	(-0.407)	4.779%
	Soybean Meal	0.011	(1.205)	-0.030	(-1.556)	0.045	(0.784)	-0.039	(-0.347)	-0.185	(-0.930)	0.453	(1.467)	4.089%
	Soybean Oil	0.025	(4.780)	-0.023	(-2.011)	-0.051	(-0.509)	0.384	(2.316)	-0.562	(-4.303)	0.129	(0.623)	13.465%
	Sugar	0.037	(3.377)	-0.002	(-0.109)	0.129	(0.785)	-0.039	(-0.195)	-0.582	(-4.516)	0.087	(0.501)	31.761%
	Wheat	0.013	(1.999)	-0.017	(-1.005)	0.307	(1.914)	-0.232	(-0.799)	-0.547	(-3.360)	0.531	(1.290)	3.244%
Livestock	Lean Hogs	0.011	(1.017)	0.000	(-0.027)	-0.545	(-7.068)	0.838	(5.445)	0.475	(1.773)	-0.933	(-2.894)	22.278%
	Live Cattle	0.007	(3.447)	0.001	(0.315)	0.308	(3.254)	0.055	(0.280)	-0.828	(-14.249)	-0.005	(-0.036)	59.039%
Metals	Copper	0.028	(2.245)	0.009	(0.516)	0.333	(3.096)	0.218	(1.819)	-0.924	(-4.337)	0.006	(0.028)	30.841%
	Gold	0.005	(1.833)	0.004	(0.890)	-0.051	(-0.419)	0.314	(1.097)	-0.354	(-2.299)	-0.271	(-1.233)	32.105%
	Silver	0.014	(2.937)	0.002	(0.388)	-0.005	(-0.121)	0.071	(1.133)	-0.432	(-1.082)	-0.326	(-0.800)	62.014%
Tropical	Cocoa	0.009	(0.694)	0.020	(1.047)	0.239	(1.566)	-0.107	(-0.468)	-0.511	(-2.615)	-0.025	(-0.103)	21.459%
	Colombian Coffee	0.138	(0.933)	0.034	(0.226)	0.042	(0.079)	-0.106	(-0.194)	-0.552	(-0.802)	-0.544	(-0.782)	18.582%
	Oats	0.000	(-0.023)	0.060	(1.758)	0.022	(0.118)	0.219	(0.903)	-0.460	(-3.029)	-0.612	(-1.695)	18.568%
	Orange Juice	0.070	(4.487)	-0.049	(-2.436)	-0.160	(-1.205)	0.335	(1.528)	-0.608	(-6.536)	0.109	(0.636)	32.761%
	Rough Rice	0.028	(2.194)	0.007	(0.450)	0.333	(2.086)	-0.279	(-1.392)	-0.930	(-8.538)	0.275	(1.811)	38.406%
Wood	Lumber	0.015	(3.922)	0.004	(0.378)	0.469	(3.698)	-0.111	(-0.577)	-0.776	(-7.118)	0.121	(0.643)	54.737%

Table A.4: **Comovement of Commodity, Equity and Bond Risk Premia**

This table presents estimates of the correlation between the bi-monthly time-series of 60-day risk premiums. The elements on the main diagonal show the first-order autocorrelation coefficient of the risk premium associated with asset [name in column]. We use all sample observations to estimate the risk premiums. All observations are sampled at the end of every other month.

		Crude Oil	Heating Oil	Natural Gas	Corn	Cotton	Soybeans	Soybean Meal	Soybean Oil	Sugar	Wheat	Lean Hogs	Live Cattle	Copper	Gold	Silver	Cocoa	Colombian Coffee	Oats	Orange Juice	Rough Rice	Lumber	Energy	Grains	Livestock	Metals	Tropical	Diversified	Equity	Bond
Energy	Crude Oil	0.198																												
	Heating Oil	0.908	0.311																											
	Natural Gas	0.490	0.497	0.291																										
Grains	Corn	0.469	0.400	0.304	0.340																									
	Cotton	0.181	0.204	0.073	0.138	0.157																								
	Soybeans	0.461	0.417	0.253	0.629	0.396	0.134																							
	Soybean Meal	0.288	0.229	0.085	0.445	0.367	0.870	0.216																						
	Soybean Oil	0.591	0.593	0.335	0.581	0.253	0.760	0.520	0.405																					
	Sugar	0.308	0.260	-0.052	0.287	0.115	0.232	0.263	0.184	0.416																				
	Wheat	0.492	0.413	0.045	0.581	0.165	0.521	0.430	0.604	0.097	0.361																			
Livestock	Lean Hogs	-0.109	0.003	0.145	-0.033	-0.022	0.032	-0.003	-0.026	-0.106	-0.205	0.410																		
	Live Cattle	-0.010	-0.052	0.041	0.042	-0.058	-0.283	-0.323	-0.144	-0.128	0.143	0.034	0.240																	
Metals	Copper	0.757	0.687	0.425	0.504	0.245	0.478	0.308	0.615	0.304	0.550	-0.055	0.055	0.352																
	Gold	0.521	0.520	-0.039	0.498	0.238	0.541	0.456	0.589	0.365	0.645	-0.105	-0.015	0.444	0.460															
	Silver	0.564	0.497	0.061	0.569	0.366	0.599	0.500	0.582	0.452	0.655	-0.112	0.104	0.456	0.793	0.208														
Tropical	Cocoa	0.297	0.297	-0.153	0.187	0.205	0.316	0.283	0.339	0.253	0.368	-0.527	-0.276	0.237	0.523	0.350	0.530													
	Colombian Coffee	0.039	0.098	0.069	0.282	0.281	0.501	0.508	0.224	0.304	-0.045	0.082	-0.217	0.074	0.204	0.362	0.179	0.288												
	Oats	0.444	0.407	0.059	0.691	0.233	0.632	0.542	0.620	0.243	0.838	-0.178	0.035	0.464	0.669	0.711	0.329	0.319	0.209											
	Orange Juice	0.242	0.315	0.397	0.522	0.159	0.476	0.319	0.494	0.167	0.259	-0.054	-0.097	0.355	0.415	0.351	0.122	0.243	0.510	0.496										
	Rough Rice	0.352	0.399	0.229	0.469	0.334	0.463	0.274	0.588	-0.022	0.396	0.074	0.054	0.455	0.305	0.350	0.027	0.256	0.372	0.435	0.331									
Wood	Lumber	-0.011	-0.064	0.215	0.131	-0.121	0.059	-0.033	0.054	-0.023	-0.088	0.257	0.207	-0.038	-0.218	-0.047	-0.371	-0.126	-0.139	0.019	0.218	0.185								
Portfolios	Energy	0.748	0.852	0.640	0.351	0.298	0.452	0.312	0.581	0.353	0.252	-0.156	-0.156	0.667	0.415	0.439	0.411	0.267	0.339	0.416	0.481	-0.196	0.332							
	Grains	0.742	0.695	0.339	0.692	0.579	0.732	0.583	0.791	0.476	0.656	-0.119	0.019	0.770	0.707	0.806	0.340	0.364	0.670	0.508	0.601	-0.098	0.610	0.200						
	Livestock	0.064	0.124	0.122	0.072	-0.052	0.010	-0.107	0.026	-0.198	0.063	0.706	0.461	0.081	0.111	0.170	-0.406	-0.140	-0.113	-0.065	0.130	0.228	-0.114	0.039	0.249					
	Metals	0.776	0.732	0.303	0.662	0.341	0.674	0.568	0.767	0.485	0.711	-0.027	0.115	0.838	0.758	0.845	0.201	0.312	0.736	0.396	0.659	-0.067	0.538	0.848	0.165	0.309				
	Tropical	0.584	0.609	0.395	0.616	0.305	0.753	0.605	0.855	0.440	0.562	-0.185	-0.157	0.678	0.634	0.665	0.427	0.626	0.714	0.670	0.692	-0.176	0.612	0.790	-0.099	0.743	0.281			
	Diversified	0.859	0.845	0.467	0.607	0.444	0.681	0.531	0.811	0.491	0.612	-0.085	0.047	0.820	0.744	0.818	0.304	0.417	0.638	0.458	0.640	-0.111	0.762	0.882	0.077	0.921	0.790	0.218		
Other Markets	Equity	0.225	0.144	0.180	0.109	0.153	0.011	-0.028	0.085	0.138	0.071	-0.035	0.153	0.156	0.075	0.240	-0.150	0.491	0.167	0.035	0.323	-0.098	0.231	0.315	-0.032	0.377	0.273	0.356	0.751	
	Bond	0.069	-0.088	-0.092	0.015	-0.047	0.206	0.210	0.125	-0.040	0.082	0.088	-0.198	-0.009	0.094	0.206	-0.117	-0.089	0.115	-0.207	0.115	-0.111	0.032	0.226	0.032	0.246	0.150	0.204	0.282	0.567

Table A.5: **Truncation Points**

This table reports the average 60-day realized payoff of variance swaps using (i) all sample observations (Unconditional), (ii) all observations before the year 2001 (Pre CFMA) and (iii) all observations occurring from 2001 (Post CFMA). In constructing the variance swap rate, we consider different truncation points for the integral. Newey–West corrected t-statistics (with 3 lags) are in parentheses. The last column shows the p-value of the null hypothesis that the average realized payoffs of the two subsamples are equal. All observations are sampled at the end of every other month.

Sector	**Commodity**	**Unconditional**		**Pre CFMA**		**Post CFMA**		**p-val**
		Mean	$T-Stat$	**Mean**	$T-Stat$	**Mean**	$T-Stat$	
Energy	Crude Oil	-2.752%	(-3.685)	-1.424%	(-1.810)	-4.247%	(-3.496)	0.086
	Heating Oil	-3.458%	(-5.363)	-2.833%	(-3.155)	-4.132%	(-4.628)	0.329
	Natural Gas	-8.894%	(-5.885)	-5.764%	(-3.886)	-11.290%	(-5.044)	0.036
Grains	Corn	-1.571%	(-5.089)	-1.520%	(-5.621)	-1.629%	(-2.787)	0.867
	Cotton	2.774%	(8.691)	2.468%	(7.956)	3.267%	(4.938)	0.205
	Soybeans	-0.320%	(-0.714)	0.247%	(0.365)	-0.949%	(-1.759)	0.131
	Soybean Meal	0.422%	(1.171)	0.390%	(0.948)	0.457%	(0.761)	0.933
	Soybean Oil	-0.608%	(-1.851)	-0.498%	(-1.562)	-0.722%	(-1.244)	0.717
	Sugar	-2.299%	(-3.963)	-1.362%	(-1.802)	-3.251%	(-3.979)	0.086
	Wheat	-0.020%	(-0.050)	-0.198%	(-0.519)	0.179%	(0.252)	0.589
Livestock	Lean Hogs	-0.066%	(-0.164)	0.526%	(0.616)	-0.303%	(-0.694)	0.364
	Live Cattle	-1.388%	(-9.845)	-0.999%	(-6.000)	-1.933%	(-11.196)	0.001
Metals	Copper	-1.678%	(-2.167)	-0.982%	(-2.463)	-2.384%	(-1.605)	0.325
	Gold	-0.864%	(-3.212)	-0.392%	(-2.296)	-1.276%	(-2.814)	0.055
	Silver	-0.283%	(-0.690)	1.180%	(4.479)	-1.906%	(-3.240)	0.000
Tropical	Cocoa	-2.619%	(-6.493)	-2.470%	(-3.771)	-2.759%	(-5.572)	0.717
	Colombian Coffee	1.026%	(0.282)	7.058%	(1.324)	-6.581%	(-4.487)	0.019
	Oats	-4.627%	(-4.673)	-4.899%	(-3.619)	-4.427%	(-3.161)	0.756
	Orange Juice	-1.547%	(-2.708)	-1.300%	(-1.509)	-1.791%	(-2.431)	0.690
	Rough Rice	-2.086%	(-4.448)	-2.022%	(-2.868)	-2.136%	(-3.397)	0.897
Wood	Lumber	-2.373%	(-6.122)	-2.640%	(-4.158)	-2.092%	(-4.988)	0.433

Table A.6: **Spline Interpolation**

This table reports the average 60-day realized payoff of variance swaps using (i) all sample observations (Unconditional), (ii) all observations before the year 2001 (Pre CFMA) and (iii) all observations occurring from 2001 (Post CFMA). In constructing the grid of interpolated implied volatilities, we consider a spline interpolation method. Newey–West corrected t-statistics (with 3 lags) are in parentheses. The last column shows the p-value of the null hypothesis that the average realized payoffs of the two subsamples are equal. All observations are sampled at the end of every other month.

Sector	**Commodity**	**Unconditional**		**Pre CFMA**		**Post CFMA**		**p-val**
		Mean	$T-Stat$	**Mean**	$T-Stat$	**Mean**	$T-Stat$	
Energy	Crude Oil	-2.775%	(-3.771)	-1.484%	(-1.981)	-4.228%	(-3.464)	0.098
	Heating Oil	-3.632%	(-5.354)	-3.148%	(-3.155)	-4.153%	(-4.671)	0.464
	Natural Gas	-9.091%	(-5.839)	-6.062%	(-4.116)	-11.410%	(-4.861)	0.046
Grains	Corn	-1.567%	(-5.110)	-1.499%	(-5.635)	-1.644%	(-2.826)	0.825
	Cotton	2.767%	(8.653)	2.456%	(7.924)	3.268%	(4.924)	0.199
	Soybeans	-0.320%	(-0.716)	0.252%	(0.376)	-0.955%	(-1.756)	0.127
	Soybean Meal	0.431%	(1.190)	0.397%	(0.956)	0.467%	(0.777)	0.930
	Soybean Oil	-0.598%	(-1.816)	-0.481%	(-1.503)	-0.720%	(-1.238)	0.699
	Sugar	-2.276%	(-3.911)	-1.327%	(-1.752)	-3.239%	(-3.954)	0.082
	Wheat	-0.032%	(-0.081)	-0.202%	(-0.526)	0.157%	(0.224)	0.606
Livestock	Lean Hogs	-0.066%	(-0.163)	0.508%	(0.596)	-0.296%	(-0.671)	0.380
	Live Cattle	-1.405%	(-9.918)	-1.010%	(-6.042)	-1.959%	(-11.394)	0.001
Metals	Copper	-1.697%	(-2.184)	-0.986%	(-2.474)	-2.419%	(-1.623)	0.317
	Gold	-0.862%	(-3.204)	-0.388%	(-2.278)	-1.276%	(-2.812)	0.054
	Silver	-0.278%	(-0.670)	1.200%	(4.542)	-1.918%	(-3.209)	0.000
Tropical	Cocoa	-2.622%	(-6.497)	-2.472%	(-3.770)	-2.763%	(-5.580)	0.715
	Colombian Coffee	1.034%	(0.285)	7.056%	(1.328)	-6.559%	(-4.478)	0.019
	Oats	-4.623%	(-4.681)	-4.898%	(-3.613)	-4.422%	(-3.172)	0.754
	Orange Juice	-1.545%	(-2.701)	-1.292%	(-1.496)	-1.793%	(-2.436)	0.685
	Rough Rice	-2.101%	(-4.465)	-2.027%	(-2.879)	-2.158%	(-3.410)	0.882
Wood	Lumber	-2.386%	(-6.070)	-2.664%	(-4.124)	-2.093%	(-4.973)	0.419

Table A.7: **The Role of Jumps**

This table reports the average 60-day realized payoff of variance swaps using (i) all sample observations (Unconditional), (ii) all observations before the year 2001 (Pre CFMA) and (iii) all observations occurring from 2001 (Post CFMA). In constructing the variance swap rate, we use the formula of Bakshi et al. (2003). Newey–West corrected t-statistics (with 3 lags) are in parentheses. The last column shows the p-value of the null hypothesis that the average realized payoffs of the two subsamples are equal. All observations are sampled at the end of every other month.

Sector	Commodity	Unconditional		Pre CFMA		Post CFMA		p-val
		Mean	$T-Stat$	**Mean**	$T-Stat$	**Mean**	$T-Stat$	
Energy	Crude Oil	-3.039%	(-4.049)	-1.578%	(-2.161)	-4.683%	(-3.758)	0.059
	Heating Oil	-3.488%	(-5.106)	-3.054%	(-2.970)	-3.956%	(-4.574)	0.513
	Natural Gas	-8.379%	(-6.392)	-5.964%	(-4.362)	-10.229%	(-5.253)	0.080
Grains	Corn	-1.476%	(-5.007)	-1.391%	(-5.363)	-1.572%	(-2.824)	0.777
	Cotton	2.775%	(8.739)	2.461%	(8.039)	3.279%	(4.981)	0.195
	Soybeans	-0.188%	(-0.423)	0.423%	(0.639)	-0.865%	(-1.609)	0.100
	Soybean Meal	0.495%	(1.396)	0.489%	(1.211)	0.501%	(0.849)	0.988
	Soybean Oil	-0.497%	(-1.527)	-0.368%	(-1.172)	-0.631%	(-1.095)	0.667
	Sugar	-3.044%	(-4.411)	-1.764%	(-1.914)	-4.343%	(-4.687)	0.028
	Wheat	0.070%	(0.181)	-0.086%	(-0.229)	0.244%	(0.349)	0.633
Livestock	Lean Hogs	-0.325%	(-0.780)	0.327%	(0.378)	-0.586%	(-1.296)	0.327
	Live Cattle	-1.457%	(-9.758)	-1.051%	(-5.915)	-2.024%	(-11.011)	0.001
Metals	Copper	-1.806%	(-2.290)	-1.049%	(-2.606)	-2.574%	(-1.704)	0.293
	Gold	-0.825%	(-3.140)	-0.376%	(-2.223)	-1.219%	(-2.744)	0.064
	Silver	5.488%	(6.983)	4.819%	(7.212)	6.231%	(4.273)	0.299
Tropical	Cocoa	-2.436%	(-6.091)	-2.093%	(-3.333)	-2.757%	(-5.461)	0.405
	Colombian Coffee	1.546%	(0.433)	7.266%	(1.369)	-5.666%	(-4.139)	0.025
	Oats	0.975%	(0.440)	-2.435%	(-2.043)	3.567%	(0.978)	0.076
	Orange Juice	-1.436%	(-2.568)	-1.199%	(-1.425)	-1.669%	(-2.300)	0.700
	Rough Rice	-1.979%	(-4.360)	-1.911%	(-2.778)	-2.032%	(-3.363)	0.890
Wood	Lumber	-2.463%	(-5.951)	-2.779%	(-4.055)	-2.131%	(-4.927)	0.382

Table A.8: **The Role of Transaction Costs**

This table presents summary statistics of 60-day commodity realized variance swap payoffs after accounting for transaction costs. We use two distinct approaches to capture transaction costs. "Fixed" (Panel A) assumes that the square root of the true variance swap rate is 2 % less than the square root of the synthetic variance swap rate. For example, if the square root of the synthetic variance swap rate is 10 %, then the square root of the true variance swap rate is 8 %. "Proportional" (Panel B) assumes that the true variance swap rate is 90 % of the synthetic variance swap rate. For example, if the synthetic variance swap rate is 10 %, the true variance swap rate is 9 %. The last column shows the p-value of the null hypothesis that the average realized payoffs of the two subsamples are equal. All observations are sampled at the end of every other month.

Panel A: Fixed

Sector	**Commodity**	**Unconditional**		**Pre CFMA**		**Post CFMA**		**p-val**
		Mean	$T-Stat$	**Mean**	$T-Stat$	**Mean**	$T-Stat$	
Energy	Crude Oil	-1.425%	(-1.951)	-0.286%	(-0.366)	-2.706%	(-2.249)	0.141
	Heating Oil	-2.159%	(-3.450)	-1.741%	(-1.987)	-2.611%	(-2.973)	0.506
	Natural Gas	-6.986%	(-4.824)	-4.180%	(-2.899)	-9.134%	(-4.234)	0.053
Grains	Corn	-0.552%	(-1.764)	-0.666%	(-2.555)	-0.423%	(-0.704)	0.708
	Cotton	3.405%	(10.162)	2.992%	(9.229)	4.071%	(6.030)	0.084
	Soybeans	0.620%	(1.381)	1.068%	(1.569)	0.122%	(0.223)	0.232
	Soybean Meal	1.374%	(3.668)	1.213%	(2.900)	1.545%	(2.463)	0.680
	Soybean Oil	0.317%	(0.953)	0.331%	(1.077)	0.303%	(0.507)	0.963
	Sugar	-0.942%	(-1.730)	-0.142%	(-0.199)	-1.754%	(-2.269)	0.130
	Wheat	1.002%	(2.490)	0.646%	(1.719)	1.397%	(1.928)	0.282
Livestock	Lean Hogs	0.960%	(2.341)	1.498%	(1.703)	0.744%	(1.693)	0.407
	Live Cattle	-0.733%	(-6.002)	-0.418%	(-2.844)	-1.173%	(-7.557)	0.003
Metals	Copper	-0.592%	(-0.788)	-0.064%	(-0.163)	-1.129%	(-0.778)	0.447
	Gold	-0.176%	(-0.715)	0.156%	(0.910)	-0.466%	(-1.110)	0.155
	Silver	0.224%	(0.616)	1.399%	(5.223)	-1.079%	(-1.990)	0.000
Tropical	Cocoa	-1.309%	(-3.373)	-1.244%	(-1.959)	-1.371%	(-2.885)	0.871
	Colombian Coffee	2.520%	(0.700)	8.366%	(1.570)	-4.851%	(-3.416)	0.022
	Oats	-3.349%	(-3.415)	-3.657%	(-2.727)	-3.123%	(-2.253)	0.722
	Orange Juice	-0.314%	(-0.567)	-0.086%	(-0.103)	-0.538%	(-0.752)	0.707
	Rough Rice	-1.037%	(-2.335)	-1.059%	(-1.562)	-1.021%	(-1.730)	0.964
Wood	Lumber	-1.201%	(-3.300)	-1.541%	(-2.668)	-0.844%	(-2.034)	0.298

Panel B: Proportional

Sector	**Commodity**	**Unconditional**		**Pre CFMA**		**Post CFMA**		**p-val**
		Mean	$T-Stat$	**Mean**	$T-Stat$	**Mean**	$T-Stat$	
Energy	Crude Oil	-1.408%	(-1.886)	-0.384%	(-0.453)	-2.559%	(-2.122)	0.183
	Heating Oil	-2.170%	(-3.670)	-1.842%	(-2.308)	-2.524%	(-2.910)	0.586
	Natural Gas	-6.151%	(-4.609)	-3.712%	(-2.661)	-8.018%	(-4.059)	0.075
Grains	Corn	-0.803%	(-2.520)	-0.989%	(-3.829)	-0.590%	(-0.964)	0.535
	Cotton	3.090%	(9.262)	2.680%	(8.365)	3.749%	(5.548)	0.085
	Soybeans	0.337%	(0.751)	0.748%	(1.098)	-0.118%	(-0.213)	0.273
	Soybean Meal	1.092%	(2.855)	0.894%	(2.135)	1.303%	(2.019)	0.613
	Soybean Oil	0.006%	(0.019)	-0.005%	(-0.015)	0.018%	(0.029)	0.971
	Sugar	-0.969%	(-1.885)	-0.280%	(-0.412)	-1.668%	(-2.281)	0.179
	Wheat	0.750%	(1.822)	0.311%	(0.832)	1.237%	(1.669)	0.187
Livestock	Lean Hogs	0.692%	(1.654)	1.256%	(1.384)	0.466%	(1.048)	0.385
	Live Cattle	-1.063%	(-8.627)	-0.741%	(-4.975)	-1.514%	(-9.845)	0.003
Metals	Copper	-0.766%	(-1.048)	-0.379%	(-0.968)	-1.159%	(-0.821)	0.570
	Gold	-0.488%	(-2.044)	-0.161%	(-0.939)	-0.775%	(-1.907)	0.154
	Silver	0.004%	(0.010)	1.228%	(4.629)	-1.355%	(-2.593)	0.000
Tropical	Cocoa	-1.424%	(-3.756)	-1.413%	(-2.278)	-1.434%	(-3.081)	0.978
	Colombian Coffee	2.636%	(0.739)	8.311%	(1.558)	-4.520%	(-3.339)	0.026
	Oats	-3.491%	(-3.587)	-3.818%	(-2.867)	-3.249%	(-2.365)	0.702
	Orange Juice	-0.442%	(-0.817)	-0.218%	(-0.268)	-0.662%	(-0.946)	0.706
	Rough Rice	-1.285%	(-2.966)	-1.342%	(-2.007)	-1.240%	(-2.176)	0.903
Wood	Lumber	-1.379%	(-3.969)	-1.728%	(-3.231)	-1.012%	(-2.422)	0.267