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The Determinants of Extreme Commodity Prices

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The determinants of extreme commodity prices[1]

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Abstract

Fat-tailed commodity price innovations are well-documented in the literature and long recognized as disruptive for consumers and producers, yet little is known about what factors drive such extreme events. Utilizing a wide range of factors from the economics and finance literature and quantile regression techniques, we shed light on this issue. Our models explain more variation in extreme than in median price innovations. Common global financial and demand factors account for a greater proportion of extreme daily spot price variations than do commodity-specific factors such as basis and open interest. Financialization of commodity markets, via significant and increasing co-variation of extreme spot price innovations with US equity market and trade-weighted US dollar returns, appears to be a major driver of extreme events in the 2000-2009 period.

Keywords: commodities price returns, extreme dependence, quantile regressions

JEL Classifications: G13, G15, E31

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1 Introduction

Fat tails in the distributions of financial asset returns, in particular those of commodity prices, is a well-known phenomenon, dating back to the seminal contribution of Mandelbrot (1963). However, despite renewed interest in measuring and explaining extreme events in financial markets, it is unknown how successful a set of determinants drawn from the the asset pricing literature and theories of commodity price formation might be in explaining variation of such prices in the extremes, or through what channels, statistically speaking, the effect of such determinants might operate. This paper seeks to provide a first answer to these long-standing questions.

We model extreme price innovations using quantile regressions, developed by Koenker and Bassett (1978)[2]. Quantile regressions are particularly well-suited to the problem at hand, as coefficients of determinants may vary by quantile of the dependent variable, are robust to outliers in the dependent variable, and quantile regression models are more efficient than OLS when the error term is non-normal (Buchinsky (1998)). We complement our main quantile regression model results with results for the conditional mean obtained from standard linear regression models estimated using OLS with Newey-West standard errors. This paper is the first of which we are aware that applies quantile regressions to commodities, using a variety of determinants drawn from the economics and finance literature.

In particular, we consider two broad categories of factors for explaining extreme price innovations: global (G) and commodity-specific (S). Within the list of global factors, we include (i) global risk variables, such as the VIX, the risk-free interest rate, and the yield spread; (ii) market variables, such as the return on the Dow Jones US equity index, the return of the trade-weighted US dollar index, and the growth rate of the spot price of gold; and (iii) the growth rate of the Baltic Dry index as a proxy for global demand. The inclusion of common global factors, and in particular global financial factors, takes inspiration from theories of integrated commodity markets, in particular those in the spirit of ICAPM models developed by Merton (1973), that regard commodity markets and global financial markets as being fundamentally integrated. Within the list of commodity-specific factors, we include (i) a return momentum factor from the asset pricing literature; (ii) variables for the commodity basis familiar from storage-based models of commodity price formation in the tradition of Deaton and Laroque (1992) and earlier empirical studies by e.g. Fama and French (1987) and Bailey and Chan (1993); and (iii) open interest variables based on the recent theory of Hong and Yogo (2012). Theories of segmented commodity markets, which suggest that commodity prices are driven by commodity-specific or local factors, build in large part on earlier theories of backwardation advanced by Keynes (1930) and Hicks (1939).

While much of the literature, especially in finance, has focused on explaining the returns of commodity futures contracts, we deliberately concentrate on explaining extreme innovations of

[2]The quantile regression approach has been used in many areas of applied economics, econometrics and the financial literature. Applications in the field of finance include work on Value-at-Risk (Chernozhukov and Umantsev (2001)), option pricing (Morillo (2000)), analysis of the cross section of stock market returns (Barnes and Hughes (2002)), and analysis of hedge fund strategies (Meligkotsidou et al. (2009))

commodity spot prices. In particular, the dependent variable of our models for each commodity is the growth rate, computed as the log difference, of the daily spot price during the period from 1986-2009 for each of the eleven commodities crude oil, heating oil, copper, platinum, silver, cocoa, coffee, corn, cotton, soybeans, and wheat. We focus on spot prices because they are the prices most directly relevant to commodity produces and consumers, the parties for whom fat-tails in commodity price innovations are most disruptive, and because they serve as the underlying prices for the associated futures contracts used to hedge and speculate on commodity spot price movements.

We find that our models explain significantly more variation in the extremes of spot price growth distributions than at the conditional median. Further, we find that common global (G) factors are routinely more statistically significant and explain more variation in extreme prices than do the commodity-specific (S) factors in our study. Among the global factors we consider, the global risk variables are routinely significant in the extreme tails, but not at the conditional mean in linear regression models. The global market variables, however, explain significant variation in the extreme tails as well as at the conditional mean of the spot price growth distribution. Our global demand proxy, the growth rate of the Baltic Dry index, is only modestly significant in the extreme tails in our quantile regression exercises, and usually insignificant in our linear regression exercises.

We supplement our baseline results by implementing decomposition tests to measure the incremental explanatory power of global (G) and commodity-specific (S) factors based on goodness-of-fit tests for quantile regressions developed by Koenker and Machado (1999). The results of these tests for commodity spot price growth support our conclusion that global factors explain a greater share of variation in extreme commodity price innovations for most commodities, with the notable exceptions of the commodities heating oil and coffee, for which the commodity-specific factors clearly play a greater role. Extreme price innovations for the case of agricultural commodities appear to be modestly more difficult to account for on average using our set of determinants than do extreme price innovations for energies and metals.

To better understand the mechanisms through which our determinants might affect extreme price innovations, we rerun all of our main exercises after filtering commodity spot price growth using an asymmetric GARCH(1,1) model due to Zakoïan (1994), following the practice of Poon et al. (2004), to remove clustering of extreme values caused by volatility persistence. This allows us to test whether some patterns in the ability of our set of determinants to explain extreme spot price moves is driven by their effect on the conditional volatility of (log) price innovations.

We find that some, but not all, of the co-variation of extreme price innovations with our determinants is due to their effect on the conditional volatility. Within our group of global (G) determinants, the global risk variables act primarily through their effect on the conditional volatility, as their significance in the models of filtered price innovations is greatly diminished. However, the global market variables, consisting of the Dow Jones return, the trade-weighted

US dollar return, and the return on gold, remain highly significant in many cases in the models of filtered price innovations. Coupled with the fact that these variables are often significant in the linear regression models, we can infer that their effect occurs through both the conditional mean as as well as conditional higher moments, such as skewness and kurtosis. On the whole, our results suggest that modeling conditional volatility is clearly necessary, but not sufficient, for capturing the effect of our determinants on extreme spot price growth.

In our quantile regression models, we find that the effect of many variables in the lower and upper extreme quantiles is statistically significant but opposite in sign. In such cases, when the pattern of signs consists of negative coefficients in the left tail and positive coefficients in the right tail, we label this as the "stretching effect" on conditional spot price growth: higher values of the determinant are associated with more negative extreme negative price innovations and more positive extreme positive price innovations. Alternatively, when the sign pattern is reversed, we label this a "contraction effect". Several determinants, in particular the global risk variables, exhibit such sign patterns for most commodities, and support our conclusion that an important and intuitive channel for the effect of global risk variables on extreme commodity prices is through their effect on the conditional volatility of price innovations. The global market variables, on the other hand, do not in general exhibit a stretching or contraction effect in our models, as their coefficients tend to be of the same sign (although with different magnitudes) across different quantiles.

Despite the fact that common global (G) factors play a more important role in explaining extreme commodity spot price growth, we find that the commodity-specific (S) factors play a lesser, but nonetheless important, role as well. In particular, commodity basis variables have the most explanatory power for one-day ahead extreme spot price growth. The maturity of the futures contract used to compute the basis and open interest matters: the basis computed using data from short maturity (one to three months until expiry) futures contracts is associated with positive mean and extreme price growth for most commodities, whereas to the extent that the basis computed using long maturity (greater than three months to expiry) futures contracts is significant, the sign pattern is typically that of a stretching or contraction effect as described above. Open interest variables are less significant on average than basis variables, but also tend to exhibit a contraction or stretching effect when significant. Although global (G) factors dominate commodity-specific (S) factors on average for agricultural commodities, moreover, their relative dominance is less for those commodities than it is in the cases of crude oil and metals.

Finally, in light of our finding that global factors explain more variation in extreme commodity spot prices, we split our sample into two sub-periods, the first from 1986-1999 and the second from 2000-2009, to test whether the coefficients of our determinants changed significantly from the pre- to the post-millennial period. This exercise is motivated by recent evidence by Tang and Xiong (2011) that commodity markets have become increasingly influenced by developments in financial markets, and that co-movement between equity markets and commodity futures markets has increased in the post-millennial period. We find that commodity price changes have become more sensitive to changes in global (G) factors, while we do not observe comparable trends in the sensitivity of commodity prices to variations in commodity-specific (S) factors. Moreover, consistent with the financialization theory of Tang and Xiong (2011), we find that the co-movement of extreme spot prices with equity returns has increased in the post-millennial period. Somewhat more surprisingly, however, we find that the co-movement of extreme spot price innovations with returns on the trade-weighted US dollar index has increased in the post-millennial period to a greater extent than in the case of equity returns. This places the US dollar's movement with respect to other major world currencies as the primary driver of extreme commodity prices in our study.

The above findings have key policy implications. First, commodity producers and consumers affected by extreme price moves should care about hedging equity and foreign exchange market risk, especially during periods of high US equity market and US exchange rate volatility. Second, future modeling efforts on behalf of these parties that build on our results should, especially in the case of global factors but also in the case of commodity basis, focus on the modeling of conditional higher moments, such as skewness and kurtosis, in addition to the conditional mean and volatility as has been the focus of most previous literature.

The paper proceeds as follows. Section 2 introduces the quantile regression approach and tests we implement in the paper. Section 3 describes the data and discusses construction of key determinants. The summary statistics are presented in Section 4. Our results from both quantile and OLS regressions are discussed in Section 5. Section 6 tests the financialization hyptothesis for the case of extreme spot price innovations by documenting how the coefficients of determinants in our models have changed between the 1986-1999 and 2000-2009 periods, respectively. Section 7 concludes.

2 The QR method and tests

In this paper we rely on the quantile regression (QR) method developed by Koenker and Bassett (1978), which proves well-suited for our analysis. The basic assumptions and structure of the quantile regression model are discussed in detail in Koenker and Bassett (1978), and Buchinsky (1998) among others and hence we present only a short summary here.

We consider the usual quantile regression objective function, which can be written as:

$$\hat{V}(q) = \min_{\Gamma_j(q)} \sum_t \rho_q(Y_{jt} - [\alpha_j(q) + X'_{jt}\Gamma_j(q)]), \tag{1}$$

where $\rho_q(u) = (q - I(u < 0))u$, and $I(\cdot)$ is the usual indicator function and q refers to qth quantile. In our analysis, the dependent variable $Y_t \equiv \ln P_t - \ln P_{t-1}$, is defined as the log difference of the current US dollar price P_t of a commodity of interest. In our work, we differentiate between two groups of explanatory variables: global ($X_{t,G}$) and commodity-specific factors ($X_{t,S}$), and we partition the vector, X_t, as $X_t \equiv (X_{t,G}, X_{t,S})$, and the vector of coefficients, Γ, as $\Gamma \equiv (\Gamma_G, \Gamma_S)$.

It can be shown that the solution of the problem (1) is the conditional quantile. By using the definition for $\rho_q(u)$, we can re-write the objective function in (1) as follows:

$$\hat{V}(q) = \min_{\Gamma_j(q)}\Big(\sum_{t:Y_{jt}>X'_{jt}\Gamma_j(q)} q|Y_{jt}-[\alpha_j(q)+X'_{jt}\Gamma_j(q)]|+\sum_{t:Y_{jt}<X'_{jt}\Gamma_j(q)}(1-q)|Y_{jt}-[\alpha_j(q)+X'_{jt}\Gamma_j(q)]|\Big), \tag{2}$$

as the objective function of the quantile regression model is the weighted sum of absolute errors. As shown in Buchinsky (1998), this optimization problem can be represented either as linear programming problem or as a GMM problem. The former implies that the quantile regression estimates are obtained in a finite number of simplex iterations and that estimates are robust to outliers. The GMM representation implies that under certain regularity conditions (see details in Buchinsky (1998)), the quantile regression estimate is consistent and asympotically normal:

$$\sqrt{n}(\hat{\Gamma}_j(q) - \Gamma_j(q)) \xrightarrow{d} N(0, \Omega_q) \tag{3}$$

There are several approaches to inference for quantile regressions. We use the most commonly used in the literature, which is based on the matrix bootstrap (see for details Buchinsky (1998)). This approach is based on random draws of bootstrap pairs $(Y_{i,jt}, X'_{i,jt})$, $i = 1, ...B$ from the original observations with replacement. For each resampling the estimator $\hat{\Gamma}^{BS}_{i,jt}$ is recomputed. Repeating this procedure B times results in a sample of B vectors whose sample covariance matrix is an estimator of the covariance matrix of the original estimator, Ω_q. The estimates based on the bootstrap method are robust to dependence between regressors and regression errors. This procedure can be implemented by using the software program Stata. We estimate the coefficient vector for the extreme lower and upper quantiles, $q = 0.05$, $q = 0.10$, $q = 0.90$ and $q = 0.95$, those we compare with the values obtained for the conditional median, $q = 0.50$, and the conditional mean from classic OLS estimation.

2.1 Tests of linear restrictions for quantile regressions

Since one of the goals of this paper is to evaluate the extent to which our set of determinants can explain variation in the growth of spot commodity prices, we implement a number of tests to assess the incremental explanatory power obtained by each of our two groups of factors (global vs. commodity-specific). We use a goodness-of-fit criterion for quantile regressions, called $R^1(q)$, and defined as follows:

$$R^1(q) = 1 - \hat{V}(q)/\tilde{V}(q), \tag{4}$$

where $\hat{V}(q)$ and $\tilde{V}(q)$ denote the values of the minimized objective function for the unrestricted and restricted models respectively at the same quantile. We implement five tests, by evaluating:

the explanatory power of our full set of determinants versus a constant, the incremental explanatory power of our G factors versus a constant, the incremental explanatory power of our full set of determinants versus the restriction of the model with $\Gamma_G = 0$, the incremental explanatory power of our S factors versus a constant, and the incremental explanatory power of our full set of determinants versus the restriction $\Gamma_S = 0$, respectively.

The inference processes required to perform such tests in the context of the $R^1(q)$ goodness-of-fit measure are described in detail in Koenker and Machado (1999) and hence we present only a short summary here. Let $\tilde{\Gamma}(q)$ denote the subset of parameters of the linear quantile regression model we are restricting to zero, so that the null hypothesis of the test is written as

$$H_0 : \tilde{\Gamma}(q) = 0 \tag{5}$$

for the quantile of interest, where $\dim(\tilde{\Gamma}(q)) = k$ is the number of restrictions. Let $\hat{V}(q)$ and $\tilde{V}(q)$ be as defined above. Then, under the null hypothesis just stated, the $L_T(q)$ test statistic is given by

$$L_T(q) = \frac{2(\tilde{V}(q) - \hat{V}(q))}{q(1-q)s(q)} \overset{a}{\sim} \chi_k^2 \tag{6}$$

and the $\Lambda_T(q)$ test statistic is given by

$$\Lambda_T(q) = \frac{2T\sigma(q)}{q(1-q)s(q)} \log(\tilde{V}(q)/\hat{V}(q)) \overset{a}{\sim} \chi_k^2 \tag{7}$$

We focus on implementing tests of incremental explanatory power based on their $L_T(q)$ and $\Lambda_T(q)$ statistics, where T refers to the sample size and q refers to the quantile of interest. We report the incremental $R^1(q)$ statistics for each test along with the statistical significance of the associated $L_T(q)$ statistics[3] in Section 5.2.5.

3 Data and variable definitions

Commodity spot price data We use daily end-of-day commodity spot prices during the period from 1986-2009. All price data was sourced from the Global Financial Data (GFD) database, for the individual commodities crude oil, heating oil, copper, platinum, silver, cocoa, coffee, corn, cotton, soybeans, and wheat.

3.1 Global (G) factors

Global financial and monetary variables Our set of financial and monetary variables draws from the asset-pricing theories, according to which the commodity markets are fully integrated

[3] Results for the $\Lambda_T(q)$ statistics are highly similar, and available from the authors upon request

(Merton (1973)). We group our financial and monetary variables into two sub-categories: global risk variables and global market variables.

As global risk variables, we include the (log) VIX index, the yield spread, and the short rate. We focus on the log VIX index and the yield spread because these variables capture common contributors to variability across commodity, bond and stock markets (Campbell (1987), Bessembinder and Chan (2004)). The reasoning is as follows. If the presence of risk-premiums in stock and bond markets represent rewards to investors for exposure to a economy-wide macroeconomic risks, which are also common to commodity markets, then we should expect a strong connection between variation in commodity spot prices and measures of risk in stock and bond markets. We include the (log) VIX, which is a model-free measure of S&P 500 option-implied volatility, as a measure of equity market risk. As a measure of risk-premiums in bond markets, and following Hong and Yogo (2012), we use the yield spread, constructed as the difference between Moody's Aaa corporate bond yield and the short rate, which in our case is proxied by the Federal Funds effective rate[4]. Inclusion of these variables allows us to control for the two dimensions of uncertainty linked to the state of US corporate balance sheets: the equity side (VIX), and the debt-side (yield spread).

As a third global risk variable, we include the short rate, proxied by the Federal Funds effective interest rate. Although we feel that the short rate is best categorized as a global risk variable, due to the fact that it directly affects the Sharpe ratio of most risky investment strategies, variations in the short rate can affect commodity prices through a number of channels. On one hand, movements in the interest rate are perceived by markets as an indicator of the overall economic outlook. Increases in the interest rate can be associated with a tightening of monetary policy, and may be considered as a signal of a higher-than-expected inflation figure. Expectations of a higher inflation rate may prompt investors to assign a larger weight in their portfolios to commodities. Other things equal, this creates additional demand for commodities, thus pushing their prices up. On the other hand, from the perspective of the theory of storage, the interest rate is one of the components of the commodity basis. Inclusion of the interest rate into our analysis allows us to separate the storage-related effects of interest rate changes from the commodity basis-related effects of interest rate changes. As a result, the coefficient in front of the US interest rate picks up any association between the dependent variable and the interest rate, including the simple storage-related effect. For this reason, the elasticity of commodity spot price changes with respect to the interest rate can be either positive or negative. The relative strengths of these two effects are, *a priori*, unclear, and in such cases the net effect of the interest rate is an empirical matter.

[4]Note that most of the related literature on the question at hand defines the short rate as the monthly average yield on one month T-Bill. We could not use T-bill yield series due to the unavailability of the series during the early part of our sample at the daily frequency. We however plot and calculate correlation between yield on one month T-bill and Federal Funds effective rate for the period 2001-2009 and report means, standard deviations and medians of both series. Statistical analysis (available from the authors) shows that these series are highly correlated and follow similar pattern, confirming the use of Federal Funds effective rate as alternative measure of the short rate.

Our second category of global financial and monetary variables consists of global market variables: the Dow Jones equity market return, the trade-weighted US dollar return, and the return on the spot price of gold. To control for the co-movement of commodity prices with financial market returns, we include the rate of return on the Dow Jones Industrial Average Index. [5] The Dow Jones Index represents a market proxy, and is one candidate sometimes used when computing the excess market return for inclusion in a CAPM regression. We expect to find a positive association between Dow Jones index returns and commodity price changes, under the assumption that positive innovations in the Dow Jones index are signals, among other things, of the market's belief that innovations in future business profits and aggregate demand will be favorable, and that this will be reflected in higher demand for commodities.

The exchange rate against the US dollar is often cited as another factor influencing commodity prices (IMF (2008), Roache (2008)), given that all major transactions are settled in US dollars. Some have argued that the weak dollar was the main culprit behind the 1974-75 and 2007-08 oil and food crises. The idea is that a weak dollar relative to other currencies tends to reduce the relative price of commodities for holders of other currencies, increasing demand and thus commodity prices. To control for these "numéraire currency effects", we include the Trade Weighted US dollar index[6]. When this index increases, the value of the dollar against foreign currencies increases, which we expect should reduce demand and prices of commodities.

In addition to US equity market and US dollar returns, we include the rate of return on gold as our third market variable, given the traditional role of gold as a safe-haven and store of value, as well its status as a highly liquid commodity often documented as having a negative beta in traditional CAPM-style regressions (Berk and DeMarzo (2007)).

Global demand As a measure of global real economic activity, we use the growth rate of the Baltic Dry Index (BDI)[7]. World economic activity is far the most important determinant of demand for transport services, so that shipping indices are efficient indicators of economic growth and production, which drive demand for commodities and affect their prices. By using the Baltic Dry index, we follow a similar approach to Killian (2009)[8], who constructed the shipping index to account for aggregate demand for commodities caused by increases in economic activity in his study of determinants of oil price shocks.

[5]The Dow Jones Industrial Index is an index which tracks the stock market activity of thirty large, publicly owned companies based in the United States

[6]The Trade Weighted US dollar Index is a measure of the value of the US Dollar relative to other world currencies. Its numerical value is determined as a weighted average of the price of various currencies relative to the dollar.

[7]BDI tracks worldwide international shipping prices of various dry cargoes. The index measures the price of shipping the major raw materials by sea, as dry bulk primarily consists of materials that are raw material inputs into production of intermediate or finished goods.

[8]Our statistical analysis (available from the authors upon request) shows that the Baltic Dry Index is highly correlated with the shipping index constructed by Killian (2009). It is important to note that Killian's shipping index data is at monthly frequency. To analyze correlation between Baltic Dry index and Killina's shipping index, we take Baltic Dry Index at monthly frequency from Bloomberg

3.2 Commodity-specific (S) factors

Momentum We construct a one-month, or 21-trading day geometric average of commodity spot price growth, which we use to control for momentum in the time series of spot price growth for each individual commodity. Inclusion of this variable is motivated by the idea of gradual diffusion of information in financial markets - if positive (or negative) information transmission about an asset is not instantaneous for all market participants, then past price rises due to the gradual incorporation of positive information can be positively correlated with the current price rise. This idea of gradual transmission of information has been used previously in macroeconomics (Mankiw and Reis (2002)), international finance (Gourinchas and Tornell (2004)) and financial economics (Hong and Stein (1999)).

Commodity basis As a measure of supply-demand imbalances and the state of inventories, we use commodity basis, which is motivated by the storage models of Kaldor (1939), Working (1948), Williams and Wright (1989) and Deaton and Laroque (1992). To calculate basis, we need futures prices, which we source from Reuters. We verified that the spot and futures prices for each commodity examined in the paper are based on data from the same exchange, in particular the CBOT (corn, soybeans, wheat), the NY Mercantile Exchange (crude oil, heating oil, copper, platinum, silver), and the Inter-continental exchange (cocoa, coffee, cotton). All futures contracts have a well-defined expiration date.

We construct the commodity basis in the same way as Hong and Yogo (2012). In particular, first we sort the universe of commodity futures into two levels of maturity. We define short-maturity contracts as those with more than 30 calendar days but no more than 90 calendar days to maturity. We exclude futures contracts with 30 calendar days of less to maturity, which are typically illiquid because futures traders do not want to take physical delivery of the underlying. Long-maturity contracts are those with more than 90 calendar days to maturity. We then construct the commodity basis for each commodity i with time until maturity $T-t$ as[9]:

$$Basis_{i,t} \equiv B_{i,t} = \left(\frac{F_{i,t,T}}{S_{i,t}}\right)^{\frac{365}{T-t}} - 1 \tag{8}$$

where T is the delivery date of the contract. We then compute the median of basis within each commodity, corresponding to all commodities of our sample and two levels of maturity. Following Hong and Yogo (2012), we use the median instead of the mean, because the median is less sensitive to outliers in the basis for individual futures contracts. It is worth noting that since Hong and Yogo (2012) construct portfolios, they employ a highly aggregated measure of basis. In contrast, in our analysis, we distinguish between the effects of short-maturity and long-maturity basis in

[9]Notice we use daily data, while Hong and Yogo (2012) use monthly futures and commodity spot prices data to construct basis. So to construct the maturity, measured in years or fractions thereof, we take the number of calendar days remaining until the expiration date of each contract, and divide this number by the number of calendar days per year, 365.

the models for each individual commodity. Finally, given that the contemporaneous basis, $B_{i,t}$, includes the effects of inventory shocks, as explanatory variables we use the lagged values of our basis variables, which capture variation in the initial supply-and-demand conditions prior to commodity price shocks.

Open interest We also adapt open interest, or the amount of futures contracts outstanding, as another commodity-specific factor in our analysis. This is motivated by the observation that high anticipated economic activity leads to higher hedging demand and thus higher open interest. Open interest can be a good signal of future economic activity and, consequently, future movements in commodity prices (Hong and Yogo (2012)).

Following Hong and Yogo (2012), we first compute the dollar value open interest for each commodity as the spot price times the quantity of futures contracts outstanding, and then use the geometric moving average of the growth of this variable in our empirical models with a one-day lag. Unlike Hong and Yogo (2012), however, and following our handling of the basis variables described above, we distinguish between the effects of open interest for the short maturity futures contracts outstanding and the long maturity futures contracts outstanding. We focus on growth rates rather than (log) levels of our open interest variables due to the fact that they have a stochastic trend.[10] All data on open interest quantities is sourced from Datastream-Reuters.[11]

4 Summary Statistics

This section reports summary statistics on commodity spot price growth and on the determinants of the commodities considered in this paper. In the tradition of Mandelbrot (1963), we begin by calculating the tail indices of the spot price growth distributions.

4.1 Tail indices by commodity

We use the well-known Hill estimator to compute the tail index η. Table 1 reports the Hill index for both left and right tails of unfiltered and filtered spot price growth data series. The model used to implement the filter is an asymmetric version of the GARCH (1,1) model that is shown in the appendix 8.2.

[10]Just as Hong and Yogo (2012) take the 12-month geometric moving average of open interest value growth in their low frequency study with monthly data, in order to smooth this variable, we find that the 21-trading day moving average delivers somewhat better results than the lagged open interest value growth variable itself in our study.

[11]Note that for any given date, the set of short and long maturity futures contracts used to for the short and long maturity basis variables is the same as the set used to compute the short and long maturity basis variables, respectively. We evaluated Bloomberg as an alternative data source for daily open interest and futures contract price data, but found that Bloomberg does not report open interest by contract, and furthermore has spottier coverage than does Datastream-Reuters, hence our use of the latter for the constructing of both basis and open interest variables in this study.

	Unfiltered				Residuals from AGARCH			
	Left tail		Right tail		Left tail		Right tail	
	$\hat{\eta}$	s.e.	$\hat{\eta}$	s.e.	$\hat{\eta}$	s.e.	$\hat{\eta}$	s.e.
Crude oil	0.2728	0.0475	0.2215	0.0443	0.2488	0.0433	0.2292	0.0468
Heating oil	0.3543	0.0540	0.4352	0.0870	0.2329	0.0355	0.3750	0.2165
Copper	0.2659	0.0396	0.2955	0.0303	0.2887	0.0430	0.2345	0.0287
Platinum	0.3393	0.0260	0.2732	0.0546	0.3029	0.0251	0.2725	0.0545
Silver	0.3256	0.0338	0.2600	0.0520	0.2713	0.0281	0.1498	0.0319
Cocoa	0.2516	0.0359	0.2268	0.0324	0.2235	0.0319	0.1944	0.0293
Coffee	0.3399	0.0296	0.3686	0.0737	0.3669	0.0432	0.2817	0.0563
Corn	0.1678	0.0336	0.2157	0.0311	0.1581	0.0316	0.2358	0.0373
Cotton	0.2007	0.0290	0.2156	0.0415	0.2925	0.0422	0.2092	0.0446
Soybeans	0.2626	0.0426	0.1223	0.0245	0.1800	0.0292	0.2042	0.0426
Wheat	0.3260	0.0652	0.3014	0.0329	0.2748	0.0550	0.2119	0.0252

Table 1: Tail indices, $\hat{\eta}$, for spot price growth of selected daily commodities during the period 1986-2009

The tail index was estimated using the Hill estimator and the threshold selection for the unfiltered series is based on the bootstrap method of Daníelsson and de Vries (1997), implemented with 3 bootstrap iterations of 500 resamples each. For calculating the tail index for the filtered price growth series for a given commodity and tail, the same number of tail points was used as for the unfiltered series.

All the tail indices reported in Table 1 are statistically significant. At conventional levels of significance, the tail indices remain the same or fall in all cases for the filtered versus unfiltered commodity returns, although the point estimates are slightly greater in a few cases for the filtered returns. Thus, volatility persistence is a contributing factor to extreme price movements. For all commodities the restriction $\hat{\eta} < 0.5$ is comfortably satisfied, implying finite variance for the spot price growth distributions of all commodities. Finite variance of data series under investigation justifies our use of GARCH-style filtering techniques in the remainder of the paper.

4.2 Other statistics

Table 4 reports summary statistics for daily commodity spot price change during the period 1985-2009. Panels A and B of the table reports the sample means, standard deviations, autocorrelations and correlations with key commodity of each category of commodities we consider[12] for unfiltered and filtered spot price growth respectively. Table 5 reports some summary statistics for the global and commodity-specific factors. There are several important observations worth making based on these tables.

First, the yield spread has a near-zero correlation with the growth rate of the Baltic Dry index, and a modest positive correlation with the log VIX. The latter finding is consistent with the fact that both the log VIX and the yield spread provide equity-based and debt-based measures,

[12] Results for the correlation with all remaining commodities are available upon request

respectively, of the risk on US corporate balance sheets. Second, short maturity basis and long maturity basis are highly correlated, with correlation coefficient around 0.5 or over in all cases, with the exception of cocoa, for which the correlation is 0.27. Third, there is no consistent pattern across commodities in the correlation between either the basis variables or the commodity open interest (OI) variables and the growth rate of the Baltic Dry index. In fact, the magnitude of all of these bivariate correlations is under 0.10. This is somewhat at odds with the finding of Hong and Yogo (2012), who report a correlation of 0.36 between the (highly aggregated) commodity open interest index they construct and the Chicago Fed National Activity Index. Given that the idiosyncratic component of our daily frequency individual commodity series is likely to be much more important than is the case for their monthly aggregated series, however, this finding is not surprising.

Finally, as in Hong and Yogo (2012), the OI variables have a very low correlation (not reported) with the commodity basis for many commodities, with the exceptions of crude oil, cocoa, cotton, and soybeans, for which the sign of the correlation in any case does not have a consistent pattern. The correlation between level of inventories (proxied by basis) and OI depends on the relative sensitivities of risk-averse investors and the inventory holders, implying an ambiguous sign for this correlation. See Gorton et al. (2007) for a theoretical model of commodity futures which generates an ambiguous sign for the correlation between inventories and the amount of open interest in the futures market

5 Empirical results

We now discuss the baseline regression results of commodity spot price growth on our set of explanatory variables. Detailed results for the upper and lower quantiles of estimates are summarized in Tables 6 - 12, including corresponding p-values, which were obtained using the bootstrap method, so that t-statistics (and corresponding p-values) are robust. As the aim is to quantify the effects of various control factors on the extreme upper quantiles and compare with their effects in the extreme lower quantiles, we limit our discussion to the impact of covariates in the 5th, 10th and 90th, 95th quantiles. Quantiles further out in the tails than 0.05 and 0.95 are not as precisely estimated and, in this paper, not considered. Given that the previous literature has focused primarily on the conditional mean of the commodity price return distribution, which is usually much closer to the conditional median, we also report results for the conditional median quantile for comparison. As before, we group our set of explanatory variables into two categories: global and commodity-specific.

5.1 OLS results

Before we proceed with discussion of our quantile regression results, we first present estimates from OLS regressions with Newey-West standard errors. As results reported in Tables 6 - 27 show, only a small group of variables is usually significant for most commodities. Variables which are well known to be important determinants of commodity price changes indeed have significant explanatory power over mean spot price changes. Specifically, the trade-weighted US dollar index as well as returns on the gold spot price are the most robustly significant explanatory variables across all commodities. The Dow Jones index return is the next significant variable in explaining changes in the mean spot price of commodities. Global risk variables - the log VIX, yield spread, and the short rate - along with variations in demand, are significant only for a few commodities, suggesting that the explanatory power of those variables for mean spot price growth is rather weak. Among the commodity-specific determinants, the short-maturity basis is consistently positive and highly significant in sign for most commodities in our study. The long-maturity basis is often significant, and generally negative in sign, with the open interest variables less often significant, and of varied sign. At the daily frequency for individual commodities, therefore, we tend to find, in contrast to Hong and Yogo's (2012) findings, that commodity basis variables have stronger explanatory power for next-period commodity spot price growth than do open interest variables. Also, we find that the maturity of the underlying futures contracts used to compute basis matters a great deal: the coefficients for the short- and long-maturity basis variables typically have opposite signs. Since the short- and long-maturity basis variables have high positive correlations for most commodities, our results indicate that these two variables clearly contain distinct information with respect to subsequent mean spot price growth, which deserves future theoretical attention. The above results nonwithstanding, the inability of many variables to explain mean spot price changes do not imply that these variables fail to be useful in explaining other parts of the commodity price growth distribution, in particular the extreme left and right tails. To explore the latter issue in detail, we next turn to discussion of our quantile regression results.

5.2 Quantile regression results

5.2.1 Quantiles and the higher moments of commodity price growth distribution

Before we proceed to the discussion of our quantile regression results, we provide more intuition for the quantile regression models, by showing that if an explanatory variable affects conditional volatility or conditional higher moments, such as skewness or kurtosis, in the commodity spot price growth distribution, then we would expect to find the largest impact of such a variable in the tails of the distribution. To see this, we follow Cenesizoglu and Timmermann (2008) and write the conditional quantile of the spot price growth distribution (in our case at time t) as

$$Q_q(Y_t|\mathcal{F}_t) = \mu_t + \sigma_t F_\epsilon^{-1}(q), q \in (0,1). \tag{9}$$

Here $\mathcal{F}_t$ contains information known at time t, and F_ϵ^{-1} is the inverse distribution function of the standardized, mean-zero and unit-variance error ϵ. Further, we can use a Cornish-Fisher expansion to approximate F_ϵ^{-1}, as:

$$F_\epsilon^{-1}(q) = z_q + \frac{1}{6}(z_q^2 - 1)s + \frac{1}{24}(z_q^3 - 3z_q)\kappa - \frac{1}{36}(2z_q^3 - 5z_q)s^2, \tag{10}$$

where z_q is the z-score (quantile function) for quantile q of a standard normal distribution, and s and κ are the conditional skewness and conditional kurtosis, respectively, of Y_t given the information set $\mathcal{F}_t$. As in Chernozhukov et al. (2010), we can rearrange the Cornish-Fisher approximation to the quantile function to further reduce the approximation error between the approximation and the true quantile function.

In relation to the above model, note that conditional effects of determinants on the spot price growth at time t can occur through a variety of channels. First, as in Hong and Yogo (2012), the effect of determinants on spot price growth could occur through the conditional mean, with $\mu_t = \alpha + X_t\Gamma$. If the effect of determinants on the conditional spot price growth occurs only through the conditional mean, we will have

$$\frac{\partial}{\partial X_t} Q_q(Y_t|\mathcal{F}_t) = \Gamma, \tag{11}$$

and the marginal effects of each determinant will be equal across different quantiles of the spot price growth distribution.

Alternatively, if the effect of determinants on spot price growth is due only to their effects on conditional volatility, of the form $\sigma_t = \alpha + X_t\Gamma$, then we will have

$$\frac{\partial}{\partial X_t} Q_q(Y_t|\mathcal{F}_t) = \Gamma F_\epsilon^{-1}(q), \tag{12}$$

where the quantile function $F_\epsilon^{-1}(q)$ of the normalized error distribution ϵ in this case does not depend on the vector of exogenous determinants X_t. For an error distribution for which $s = \kappa = 0$, such as the case of unit normal errors, the Cornish-Fisher expansion approximation for $F_\epsilon^{-1}(q)$ yields $\Gamma F_\epsilon^{-1}(q) = \Gamma z_q$. As z_q is an increasing function of q, this implies that, for variables in X_t whose corresponding element of Γ is positive, the magnitude of their quantile regression coefficient (the corresponding element of Γz_q) will be larger at extreme quantiles than at quantiles near median quantiles, negative in sign for quantiles $q < 0.50$, and positive in sign for quantiles $q > 0.50$, following the sign pattern of z_q itself. This is the pattern of signs (the "S" pattern) and magnitudes we use to identify the "stretching effect" on conditional spot price growth. Alternatively, for variables corresponding to negative elements of the vector Γ, the sign pattern will be opposite the pattern characteristic of the "stretching effect"; we label such patterns the "contraction effect". Note that the stretching effect provides evidence of a situation where the conditional effect of a the determinant in question on the volatility is positive, whereas the contraction effect provides evidence of a situation in which the conditional effect of the determinant on volatility is negative. These conclusions generalize to the situation when volatility commands a positive (constant) risk premium in the conditional mean, as in Merton (1980)).

Extending the above analysis, it might be the case that there exists conditional dependence of the skewness (s) or (excess) kurtosis (κ) of the distribution of Y_t on X_t, which is distinct from conditional dependence of the volatility σ_t on X_t. What the Cornish-Fisher expansion of the quantile function for Y_t above makes clear is that, for extreme upper quantiles, we will have z_q sufficiently large that $\frac{1}{24}(z_q^3 - 3z_q) > 0$, and the effect of the conditional kurtosis in particular on $F_\epsilon^{-1}(q)$ will be unambiguously positive in the Cornish-Fisher approximation. For extreme lower quantiles, with z_q large and negative, the above coefficient will be negative, and we have that the effect of the conditional kurtosis on $F_\epsilon^{-1}(q)$ will be unambiguously negative in the approximation. Thus, we see that the "stretching effects" mentioned above could just as well arise due to dependence on the determinants via the conditional kurtosis in extreme quantiles. Our results for the gjr-GARCH(1,1) filtered spot price growth allows us to assess the likely importance of such effects acting through the conditional skewness and kurtosis in particular.[13]

5.2.2 Baseline results: Global factors

The (log) VIX is a measure of equity market implied volatility, and is highly significant at multiple quantiles for most commodities. The novel result from our perspective is that an "S" sign pattern for the log VIX is observed, where the variable has a negative sign in the lower tails and a positive sign in the upper tails, indicating a "stretching" effect on the conditional distribution of commodity spot price changes. Consistent with our previous claims, the magnitude of the coefficient on the log VIX is generally higher in the tails than at the median.

The yield spread, which is an alternative measure of the risk on corporate balance sheets to the VIX, does not obtain levels of statistical significance comparable to those obtained by the log VIX, but does nonetheless display high levels of significance for the commodities copper, silver, corn, wheat, and to a lesser extent crude oil, coffee and soybeans. In cases where the effect of the yield spread is statistically significant (e.g. for wheat), the nature of the effect is consistently opposite that of the (log) VIX. This is a counter-intuitive result, but the conclusion is clear: equity-side and debt-side measures of corporate sector risk have consistently opposite effects on conditional spot price growth at extreme quantiles. This could, as discussed above, be due to their having opposite effects on conditional higher moments. This stylized fact deserves further scrutiny, as it is unclear why equity- and debt-based measures of corporate balance sheet risk should have opposite effects on extreme commodity price innovations.

The interest rate is most highly significant for the agricultural commodities, in particular corn, cotton, soybeans, and wheat, and has a contracting effect on the conditional distributions of these commodities, with positively signed coefficients in the lower quantiles and negatively signed coefficients in the upper quantiles.

[13] However, as the effect of skewness in the extremes is ambiguous and depends on both the quantile and the size of the skewness parameter, future work is needed to identify the channels through which our determinants affect extreme conditional quantiles via conditional higher moments.

The Dow Jones return coefficients are modestly significant but do not vary too much as a function of quantile; they are most significant across quantiles for copper, corn, and soybeans. Somewhat surprisingly, the Dow Jones return does not appear to be an important factor for crude oil or the two precious metals, platinum and silver.

Perhaps the single most robustly significant determinant across commodities and quantiles is the trade-weighted US dollar index, whose coefficients are uniformly negative, although higher in magnitude at extreme quantiles than at the conditional median. This finding indicates that numéraire currency effects are highly important for nearly all commodities, as expected, and especially important at extreme quantiles of price growth.

Most commodities, and in particular crude oil and the metals, move positively in tandem with the gold spot price, confirming the role of gold as a benchmark reference commodity and store of value.

Variations in demand captured by Baltic Dry index are sometimes significant, and when they are (e.g. in the upper tails of coffee, corn, soybeans, and wheat), the sign pattern across quantiles is consistent with a volatility contraction effect rather than a positive conditional mean effect as expected. It appears that global demand growth may lower conditional contemporaneous spot price volatility more visibly than any effect it may have on the conditional mean.

5.2.3 Baseline results: Commodity-specific factors

The momentum factor induces a contraction effect for crude oil and copper, a stretching effect for cocoa and coffee, and is generally insignificant for the other commodities. As the effect of higher price momentum on extreme quantiles is consistently opposite in sign for several important commodities, and the coefficient of the momentum variable appears to be larger in magnitude in the extremes than at the median, this raises the question of why commodity spot price momentum often has a significant negative, rather than positive, effect on extreme price innovations in extreme quantiles. Although we would expect higher momentum to be associated with a rightward shift in the distribution of conditional spot price growth, according to the theory of gradual diffusion of information, it may be the case that momentum effects act through conditional higher moments, for example by lowering conditional volatility, as well.

We test both long and short maturity versions of the basis and the open interest variables, respectively. We find that the long maturity basis variable induces a contraction effect on the tails of the copper spot price growth distribution, and has negative and significant coefficients in the upper tails of platinum, silver, coffee, corn, and soybeans. In contrast, the short maturity futures basis factor displays positive and highly significant coefficients in one or both extreme tails of the commodities copper, platinum, silver, coffee, corn, cotton, soybeans, and wheat. Thus, the effects of the lagged commodity basis on extreme price growth differ consistently in sign as a function of the maturity of the underlying futures contracts used to compute the basis.

The results on the short-maturity basis being positive when significant are consistent with the theory of storage, which says that if the basis is low and thus the level of inventories is low today, then the price is expected to fall in the following period (mean revert) once demand-supply imbalances correct. That is, a higher commodity basis predicts higher spot price growth. This is what we find in both our OLS and quantile regression models. Moreover, to the extent that increases in the basis signal an increase in inventory, which is linked to lower spot price volatility in storage models such as those of Deaton and Laroque (1992), the results on the long maturity basis, to the extent that they can be identified with a contraction effect, might be justified by the theory of storage as well. Our findings regarding the basis variables in our study call for further research, in order to explain (from the viewpoint of storage models or otherwise) why higher short maturity basis is positively related to subsequent extreme price innovations, whereas a contraction effect seems to be associated with the long maturity futures basis.

Despite the success of highly aggregated open interest measures in predicting subsequent monthly innovations of commodity prices in the recent work of Hong and Yogo (2012), we find that higher frequency open interest measures, for both long and short maturity futures contracts, exhibit modest statistical significance in our study, with the exceptions of the commodities platinum, soybeans, and wheat, and to a lesser extent crude oil and cotton. When the coefficients of the open interest variables are significant, moreover, they are often negative in sign for different quantiles, contrary to the findings of Hong and Yogo (2012) that higher levels of open interest predict higher subsequent returns on commodity futures (and positive subsequent spot price innovations). As we have endeavored to construct our open interest variables for the daily frequency following a procedure analogous to that of those authors for monthly data, we attribute our findings to a combination of our use of more disaggregated data and a higher observation frequency.

5.2.4 Filtered spot price growth results

As we have shown in the summary statistics section 4, volatility clustering is a contributing factor to fat tails in commodity prices. Thus, it is possible that any dependence between price changes and various determinants works through time-varying volatility. For this reason, when time-series of asset returns are characterized by time-varying volatility and leptokurticity, a GARCH filtering of asset returns is often appropriate. In this section we repeat our quantile regression exercise with filtered spot price changes. This achieves one main objective. It allows us to study if the ability of the factors to explain extreme price moves found by using raw spot prices are due to their association with changes in volatility or not. As consistent with the Cornish-Fisher expansion approximation of extreme conditional quantiles as functions of the conditional mean, volatility, skewness, and kurtosis, significance of a determinant in the models of filtered spot price growth allows us to infer that that determinant affects the conditional skewness and/or kurtosis, as the residuals used as dependent variables in those exercises are taken as the residuals from the gjr-GARCH(1,1) model applied to the unfiltered spot price growth.

The results are as follows. Among the global (G) determinants, we find that while the log VIX is often significant in the lower tails of filtered spot price growth, its significance is greatly diminished in the models of filtered as compared to unfiltered spot price growth for several key commodities, including crude oil, copper, platinum, silver, corn, and wheat. This finding is intuitive: the log VIX, itself a measure of implied US equity market volatility, appears to affect extreme commodity price movements principally through its effect on the conditional volatility of commodity spot price growth, rather than its effect on higher moments such as skewness and kurtosis. The US federal funds rate, like the log VIX, exhibits a substantially lower incidence of significance for the filtered price growth models, in particular for the commodities copper, corn, soybeans, and wheat. The yield spread, which is important across quantiles for copper, corn, and wheat in the unfiltered spot price growth models, exhibits substantially lower significance in the models of filtered price growth as well. Thus, we find clear evidence that global risk variables work principally through their effect on the conditional volatility of spot price growth.

As opposed to the three global determinants just mentioned, the Dow Jones market return, the trade-weighted dollar index return, and the gold spot price growth variables retain a substantial degree of significance in the models of filtered spot price growth. Thus, market variables appear to affect extreme commodity prices both via conditional volatility as well as through conditional higher moments, and their role in the latter channels appears to be quite important. The growth rate of the Baltic Dry index, our proxy for global demand, displays somewhat less significance for filtered spot price growth, although the same general pattern of positive coefficients in the lower quantiles and negative coefficients in the upper quantiles as observed in models of unfiltered spot price growth.

Among the commodity-specific (S) determinants, the momentum factor is sporadically significant for different commodities and quantiles, but has a positive sign for some (e.g. corn, wheat) and a negative sign for others (e.g. for silver and cocoa). Compared to the unfiltered price growth exercises, the high incidence of significance of the momentum variable for crude oil and copper is greatly diminished in the filtered price growth exercises for these commodities. The long maturity basis and short maturity basis variables are often signficant in the models of filtered spot price growth. Of these two variables, however, it is the short maturity basis variable that is most often significant across commodities and quantiles. Moreover, the sign of the coefficient of the short maturity basis variable is uniformly positive. Interestingly, the incidence of statistical significance of the long and short maturity basis variables is only slightly diminished in the filtered price growth exercise, and the sign patterns of the coefficients of these variables across quantiles is essentially the same at that observed in the unfiltered price growth exercises. This indicates that a substantial part of the effect of basis variables on subsequent spot price changes may be operating through conditional higher moments–in particular skewness and kurtosis–as per the Cornish-Fisher expansion logic discussed above. The open interest variables are significant for some commodities and quantiles, but the sign of the effect differs. For crude oil, for instance, we find that the short maturity OI variable is positive and highly significant at the conditional median and for the extreme upper quantiles studied, whereas for wheat, the short maturity OI variable is negative and significant at the conditional median and extreme upper quantiles of the filtered spot price growth distribution. This behavior is quite similar to the results found on the open interest variables in the unfiltered price growth exercises.

Overall, the results we obtain for the models of filtered spot price growth display several of the same patterns as the results we obtained from the models of the unfiltered dependent variable: among the global (G) determinants, it is the trade-weighted US dollar index that is the most robustly significant determinant, which enters with a consistently negative sign across quantiles as expected, and among the commodity-specific (S) determinants, it is the short maturity basis that is the most robustly significant factor, which enters with a consistently positive sign. It appears that these two factors in particular drive the third and higher moments of the commodity spot price growth distributions.

5.2.5 The explanatory power of determinants in quantile regressions

In this section we report results of the tests we implement to evaluate the incremental explanatory power of the G and S factors, respectively, at each quantile. We report only the incremental $R^1(q)$ statistics for each test, along with the statistical significance of the associated $L_T(q)$ statistic. As discussed in Section 2.1, we implement five tests: to assess the explanatory power of our full set of determinants versus a constant, the incremental explanatory power of our G factors versus a constant, the incremental explanatory power of our S factors versus a constant, and the incremental explanatory power of our full set of determinants versus the restrictions of the model with $\Gamma_G = 0$, and $\Gamma_S = 0$, respectively.

The results from the Koenker-Machado tests of incremental explanatory power are as follows. Table 28 displays the values of the $R^1(q)$ statistic for each pair of unrestricted and restricted quantile regressions, respectively. The significance level of the associated $L_T(q)$ test is indicated next to the $R^1(q)$ values by one, two or three stars, indicating significance at the 10%, 5%, and 1% levels, respectively. The sum of the incremental $R^1(q)$ statistics for the G vs. Baseline and the GS vs. G columns is (approximately) equal to the value of $R^1(q)$ in the GS vs. Baseline column for a given quantile, as is the sum of the incremental $R^1(q)$ statistics for the S vs. Baseline and the GS vs. S columns. As the G and S factors may be correlated, these decomposition results allow us to measure explicitly the incremental explanatory power of the S factors once the G factors have been controlled for, and vice versa.

For unfiltered commodity price growth, the global (G) factors explain more of the variation in extreme quantiles of price growth than do commodity-specific (S) factors for the majority of commodities. In particular, for six commodities, including crude oil, all three metals, and the major agricultural commodities corn and wheat, the G factors explain more variation in both tails, as well as at the conditional median. Heating oil and coffee represent the two major exceptions to the rule, as S factors explain more variation in both tails of these commodities. For the cases of cocoa, coffee, and soybeans, G factors explain more variation in the lower extreme quantiles, but S factors exhibit roughly equal importance in explaining variation in the upper tails. The values of the $R^1(q)$ statistic obtained for extreme upper and lower quantiles is noticeably greater than that obtained at the conditional median for all commodities and all five tests displayed. The majority of $L_T(q)$ statistics associated with the respective $R^1(q)$ values reported are significant at the 1% level.

For filtered commodity spot price growth, whose $R^1(q)$ statistics are displayed in Table 29, we observe a similar pattern of results as those obtained for the unfiltered commodity returns, except that the magnitudes of the $R^1(q)$ statistics is noticeably lower. This indicates that, as expected, an important part of the effect of our set of determinants on extreme commodity spot price growth occurs through effects acting through the conditional volatility. This is especially true for crude oil. Still, most $R^1(q)$ statistics displayed in Table 29 are non-zero and have associated $L_T(q)$ statistics that are significantly different from zero at the 1% level. This indicates that a non-trivial fraction of variation in extreme commodity price growth occurs through the conditional skewness and kurtosis as well. While modeling such dependence explicitly is beyond the scope of this paper, it should feature prominently on the agenda of researchers wishing to better understand the drivers of extreme commodity prices.

5.3 A recap of our results from quantile and OLS regressions

Our findings from the quantile and OLS regression exercises for filtered and raw spot price changes can be summarized as follows. We find, from performing tests based on the $R^1(q)$ statistic (or "pseudo R^2" statistic) of Koenker and Machado (1999), that our set of determinants are able to explain more variation in the growth of individual commodity spot prices in the tails than at the median. Our results suggest that common global (G) factors play an important role as drivers of extreme changes in commodity prices over the entire period from 1986-2009. In this sense, our findings provide further support for earlier theories such as those of Merton (1973) that take a view in favor of the integration of commodity markets with global financial markets.

Within the group of G factors, we find distinct patterns in the way that global risk variables and global market variables, respectively, co-vary with extreme commodity prices. In particular, the global risk variables tend to explain variation in extremes but not at the mean of commodity log price growth distributions. Conversely, global market variables tend to be statistically significant at both the tails and the mean. This suggests that the use of conventional OLS regressions in the analysis of extreme changes in commodity prices does not tell the whole story, as it would mask the importance of global risk variables in explaining changes in the tails. The importance of global risk factors in the tails is due to volatility spillover effects from financial to commodity markets.

Our findings with respect to asymmetric effects on the distribution of commodity price changes are similar to some other previous studies. In particular, Cenesizoglu and Timmermann (2008) find that a range of economic state variables can predict different quantiles of stock returns, and that several variables produce distinct effects on lower, central and upper quantiles. Their out-of-sample forecasts of the equity market return distribution suggest that the upper quantiles of the return distribution can be predicted by means of economic state variables, while the center of the return distribution is more difficult to predict.

Consistent with our story about global risk variables affecting the conditional volatility of changes in commodity prices, our next set of results suggests that global risk factors follow a systematic pattern: the log VIX (yield spread) displays negative (positive) values in the left tail and positive (negative) values in the right tail of commodity price growth distributions. Thus, an increase in the log VIX (yield spread) is accompanied by an increased (decreased) dispersion in commodity price changes. This sharpens our claim that the effects of global risk variables occur primarily through their effect on the conditional volatility of spot price changes. The effects of global market variables, in contrast, do not change sign as a function of quantile, implying that changes in extreme moves of commodity prices driven by shocks to global market variables are not purely volatility driven.

Finally, although common global (G) factors tend to explain more variation of commodity prices, the relative importance of commodity-specific (S) factors is greater for heating oil and agricultural commodities (most notably in the case of coffee) than for crude oil and metals. One potential explanation for this pattern is that crude oil and metals are the commodities in our sample with the highest exposure to macroeconomic shocks through the channel of pro-cyclical demand, so that shocks to common global (G) factors, which often convey information about the future state of global demand, play a relatively more important role in driving the prices of crude oil and metals than the prices of agricultural commodities on average.

6 The relative importance of determinants in the 2000-2009 vs. 1986-1999 periods

Related to our main result that the relative importance of global factors is greater than that of commodity-specific factors in explaining variation in commodity spot prices across most commodities, recent evidence also suggests that these global factors, and in particular financial market variables have recently come to play an increasingly important role in influencing movements in commodity prices (Tang and Xiong (2011)). This process of financialization of commodity markets began in the early 2000s, driven by the collapse of the equity market and considerable interest in alternative asset classes among investors. While Tang and Xiong (2011) have focused on testing the financialization hypothesis using a standard regression approach, we test it for the case of extreme spot prices.

To do this, we split our sample of daily spot price growth into two subperiods, the first ranging from 1986-1999 and the second ranging from 2000-2009. We run our quantile regression models in each sub-period, and then, given the point estimates and standard errors of the coefficients for each determinant in each sub-period, we perform t-tests on the difference of the coefficients against the null hypothesis that the difference is zero. In performing the t-tests, we use the student t-test statistic appropriate for two samples of unequal size and unequal variance, and calculate the degrees of freedom for the tests using the Welch-Satterthwaite equation. Results of those tests are reported in tables 2 and 3. The tables report the values of $\hat{\Gamma}_i^2(q) - \hat{\Gamma}_i^1(q)$, where $\hat{\Gamma}_i^j(q)$ denotes qth quantile estimate of determinant i in period $j = 1, 2$ with stars indicating the degree of statistical significance of the the unpaired t-test against the null hypothesis.

Our findings are as follows. Among the global risk variables, the effect of the log VIX on extreme commodity price growth is characterized by "dynamic stretching" and "dynamic contraction" effects for different commodities. By a dynamic stretching (contraction) effect, we mean that the change in the coefficient of the log VIX from period 1 to period 2 is negative (positive) in the extreme lower quantiles and positive (negative) in the extreme upper quantiles. In other words, dynamic stretching effect implies that if there was a stretching effect, it became more pronounced, and if there was a contraction effect in period 1, then it became less pronounced in the second period.

The log VIX exhibits a pronounced dynamic stretching effect for copper, and a partial one for heating oil, silver, cocoa, coffee, and wheat. The federal funds rate exerts a partial dynamic contraction effect on silver, soybeans, and wheat, and a dynamic stretching effect on coffee. The yield spread exerts a dynamic stretching effect on crude oil and coffee, and a dynamic contraction effect on silver, corn, and wheat. Overall, the evidence points to a dynamic change in the sensitivity of extreme commodity spot price growth to global risk variables after the turn of the millennium, although the form of such changes most likely take the form of changes in the sensitivity of second and higher moments to the global risk variables.

With respect to the global market variables, the Dow Jones return, the trade-weighted US dollar index return, and the growth of the gold spot price, we find strong evidence in favor of the financialization hypothesis. In particular, all statistically significant changes in the coefficient of the Dow Jones index return between periods are positive across multiple quantiles for several important commodities, including crude oil, copper, platinum, silver, cotton, and to a lesser extent soybeans. The magnitudes of the changes, such as 0.4325 for the 5th quantile of crude oil and 0.2738 for the 95th quantile of copper, are economically large compared to the point estimates for these coefficients in the pooled quantile regression results discussed above in the paper, and suggest that positive co-movement of extreme spot price growth with equity market returns is indeed primarily a recent phenomenon dating to the 2000-2009 period. Turning to the trade weighted dollar index return, we find that all statistically significant changes in the coefficient of this variable between periods are negative across multiple quantiles for several commodities, including crude oil, copper, platinum, silver, corn, cotton, soybeans, and wheat. The coefficients of the trade-weighted dollar index return, which are negative in our pooled quantile regressions, became significantly more negative during the 2000-2009 period, indicating an increased comovement of extreme spot prices with the US dollar in international markets: a given 1 percent daily depreciation of the dollar against other major currencies during the 2000-2009 period had a significantly greater positive effect on the spot prices of commodities on the same day. Furthermore, the magnitudes of the changes in the point estimates between periods are generally greater than the magnitudes of the changes in the point estimates of the Dow Jones index return for given commodities and quantiles, implying that the foreign exchange dimension of financialization of extreme commodity prices during the post-millennial period is potentially even more important than the equity dimension. With respect to the coefficient of the spot price growth of gold, all significant increases were positive, although marked increases in this coefficient only occurred for the commodities copper and silver, with little difference observed for the energy or agricultural commodities. The coefficient of the growth rate of the Baltic Dry index did not change substantially between periods for most commodities.

The above evidence presented in favor of the financialization hypothesis is useful to contextualize via comparison to the changes in the coefficients of the commodity-specific (S) factors we consider. While several of the S factor coefficients exhibit significant changes between periods for several quantiles and commodities, the sign of such significant changes are typically opposite for lower versus upper extreme quantiles for a given commodity. An example of this rule is the momentum factor for copper, whose sign change pattern between periods is consist with a dynamic contraction effect, or the long maturity basis factor for platinum, whose sign change pattern is consistent with a dynamic stretching effect. The main exceptions to this characterization of the dynamics of the S factor coefficients are the behavior of the short maturity basis factor coefficient for our two most idiosyncratic commodities, heating oil and coffee, for which the short maturity basis coefficient becomes significantly more positive in both lower and upper extremes during the 2000-2009 period. Since the short maturity basis coefficient is positive for virtually all commodities, and particularly for these two, in our pooled sample, it appears that extreme heating oil and coffee prices have become increasingly sensitive to short maturity variations in basis during the post-millennial period. Why this might be the case deserves further study. However, what is apparent from our analysis of the dynamics of the S factor coefficients is that, with the aforementioned exception, there are no clear-cut, uni-directional change patterns between periods such as those observed for the global market variables above for upper and lower extreme quantiles. This refines further our evidence in support of the financialization hypothesis for extreme spot price growth, in the sense that changes in the coefficients of the S factors, while often significant, do not generally follow a unidirectional sign pattern or display comparably large magnitudes even when statistically significant. Overall, our evidence on the dynamics of coefficients from the 1986-1999 to the 2000-2009 period uncover robust and economically important increases in the sensitivities of extreme commodity spot prices to US equity returns and US dollar returns versus other major currencies, with gold playing an important additional role within the sub-universe of metals.

7 Conclusion

We use quantile regression models to explore the importance of various global (G) and commodity-specific (S) determinants in explaining extreme movements in commodity prices. We find that common global (G) factors have played a dominant role in driving extreme changes in daily commodity prices during our entire sample, which begins in 1986. But we also find that global variables have become even more important for explaining extreme changes in commodity prices since the turn of the millennium, including during the 2007-2009 period of market turmoil. Global variables affect commodity prices through two distinct channels. Global risk factors, on the one hand, appear to affect commodity prices, and hence extreme prices, primarily through their effect on the conditional volatility of price innovations. Global market variables, on the other hand, affect extreme commodity prices through their effect on conditional expectations, as well as through conditional higher moments, such as skewness and kurtosis. To the extent that commodity-specific (S) factors play a role, the short-maturity commodity basis stands out as the commodity-specific variable most often significant in explaining both mean and extreme price changes. Taken together, our findings shed light on the long-standing question of what drives extreme moves in the prices of major global commodities, and have important implications for further modeling of extreme changes in commodity prices. As we find that extreme moves in prices are more difficult to explain on average for agricultural commodities than for fuels and metals, an important task for future researchers is to understand what additional factors or techniques can be used to better understand what drives major price moves in these markets. We hope the groundwork we have laid in this paper will be useful in informing such attempts, as well as serving as an input to important applications, such as optimal risk management and hedging of commodity price fluctuations by consumers, producers, and financial market participants.

8 Appendices

8.1 List of variables and data sources

The list of variables (and their corresponding name in the database in parentheses) and data sources employed in empirical analysis are as follows:

- **log_vix** - log of VIX S&P 500 volatility index. From Bloomberg
- **fedfuneffec** - 10 year Treasury bonds rate. From Federal Reserve Bank.
- **yield_spread** - defined as the difference between Moody's Aaa corporate bond yield and the fedfuneffec. From Moody's

- **rt_dowjones** - return on Dow Jones Industrial Average Index. From Bloomberg
- **rt_tradedollarindex** - return trade-weighted dollar index. From Global Financial Data (GFD)
- **rt_gold** - change in gold spot price. From GFD
- **d_log_balticdry** - first difference of the log of the Baltic Dry Exchange index. From Bloomberg.
- **momentum** (**l1_rt_commodity_geoavg21**) - lagged value of the change of commodity momentum constructed as 21-trading day geometric average of commodity spot price growth. Original data from GFD
- **basis LM** (**l1_cdtybasis_commodity_lm**) - lagged of commodity basis, long maturity, for construction details see the Section 3. Futures data are from Reuters.
- **basis SM** (**l1_cdtybasis_commodity_sm**) - lagged of commodity basis, short maturity.
- **OI LM** (**l1_commodity_l_oi_geoavg21**) - commodity open interest, long maturity, for construction details see the Section 3. From Datastream-Reuters.
- **OI SM** (**l1_commodity_s_oi_geoavg21**) - commodity open interest, short maturity.

8.2 GARCH filter

We use an asymmetric version of GARCH (1,1) model, first introduced by Zakoïan (1994). In this model, the conditional variance of asset price returns h_t is allowed to have different reactions to the sign of past innovations[14]:

$$R_t = \omega + \sqrt{h_t}\varepsilon_t$$

$$h_t = \alpha_0 + \alpha^+ \varepsilon_{t-1}^2 D_{\varepsilon_{t-1} \geq 0} + \alpha^- \varepsilon_{t-1}^2 D_{\varepsilon_{t-1} < 0} + \beta h_{t-1}$$

where ε_t is iid, and D_E is the indicator function that event E occurs.

[14] Several authors, e.g., Christie (1982), Schwert (1989), have pointed out to a certain asymmetry in the correlation between the present volatility of stock series and the past values of the series.

Commodity	q	log_vix	short_rate	yield_spread	rt_DJ	rt_TradeWDI	rt_gold	d_log_BD
Crude oil	0.05	-0.009	-0.1632	-0.8404 **	0.4325 ***	-0.9872 ***	0.0027	0.2132 **
Crude oil	0.1	1e-04	-0.1843	-0.4729 **	0.4617***	-0.9856 ***	0.0886	-0.0828
Crude oil	0.5	-0.0022	0.0834	0.1729	0.1964***	-0.6115 ***	0.1253*	-0.0013
Crude oil	0.9	9e-04	0.247	0.7141 ***	0.2874**	-0.3434	0.1602	-0.0452
Crude oil	0.95	-0.006	0.1943	0.7306 ***	0.4695***	-0.2823	0.0279	-0.0701
Heating oil	0.05	0.0062	0.0057	0.2679	-0.2818	0.2214	0.4766**	-0.0306
Heating oil	0.1	-0.002	0.1894	0.2699	-0.0858	0.0554	0.1068	-0.0038
Heating oil	0.9	0.0123***	-0.2167	-0.269	0.0549	-0.0286	-0.0611	-0.0039
Heating oil	0.95	0.0154***	-0.1926	-0.2408	0.2077 **	0.2797	9e-04	-0.0043
Copper	0.05	-0.014***	0.1147	0.0161	0.2261 **	-0.2744	0.2877***	-0.2674***
Copper	0.1	-0.0099***	0.208	-0.0204	0.1347 *	-0.5649***	0.2404**	-0.1447 *
Copper	0.5	-0.003 *	0.0047	0.0643	0.2098***	-0.3284***	0.1646***	-0.0339
Copper	0.9	0.0149***	-0.2588 *	0.1529	0.248***	-0.4364***	0.2611***	-0.0224
Copper	0.95	0.0233***	-0.3035	0.0724	0.2738**	-0.4911**	0.3228 **	0.1116
Platinum	0.05	0.0028	0.0224	0.0217	0.364***	-0.1559	0.0057	0.1514
Platinum	0.1	9e-04	0.1271	0.1246	0.2985***	-0.1488	0.0043	0.0647
Platinum	0.5	0.0023 **	-0.0795	-0.0857	0.1743***	-0.0592	-0.0308	0.0113
Platinum	0.9	-0.0044	-0.1284	-0.0798	0.1367	-0.3028 **	-0.0962	0.0315
Platinum	0.95	-0.0022	-0.0788	-0.1261	0.0041	-0.4227 ***	-0.2043 **	0.0409
Silver	0.05	-0.0031	0.6959***	0.9846 ***	0.2414***	-0.5647***	0.1068	0.0859
Silver	0.1	-0.0061 **	0.5165***	0.7475***	0.1292**	-0.7667***	0.1939***	0.0233
Silver	0.5	-0.0043***	0.1665***	0.2132***	0.0734***	-0.4055***	0.1109***	0.0109
Silver	0.9	-4e-04	-0.0483	-0.1478	0.1139 **	-0.4088***	0.1373**	0.0558
Silver	0.95	-0.001	-0.1795	-0.3799 **	0.1156	-0.438**	0.0517	0.1666**
Cocoa	0.05	-0.0012	0.5753**	0.3723	-0.1101	-0.017	0.3033 **	-0.1017
Cocoa	0.1	0.0028	0.196	-0.0402	0.0289	0.0153	0.1763 *	-0.1632**
Cocoa	0.5	0.0019	0.005	0.0281	0.0091	-0.0649	-0.0164	-0.034
Cocoa	0.9	0.0107***	-0.1562	0.1159	-0.0281	-0.2864	0.1715	0.0824
Cocoa	0.95	0.0159***	-0.4603*	-0.2973	-0.1344	0.2577	0.3467**	0.1197
Coffee	0.05	-0.0117**	-0.6514***	-0.4071	-0.0252	0.226	0.0312	0.1722
Coffee	0.1	-0.0072**	-0.6314***	-0.623***	-0.081	0.0985	0.098	0.0474
Coffee	0.9	-0.0018	1.3652***	1.5126 ***	-0.0797	0.1507	0.099	0.1025
Coffee	0.95	0.0034	1.7898***	1.9424***	-0.071	0.0051	0.0424	0.1073
Corn	0.05	-0.0115**	0.4442 *	0.4338 *	0.0419	-0.1989	0.2148 **	-0.1118
Corn	0.1	-0.004	0.2491*	0.3228*	0.1458	-0.1929	0.1478	0.0098
Corn	0.5	0.0013	-0.0944	-0.0939	0.0443	-0.3043***	0.0999**	-0.0107
Corn	0.9	6e-04	-0.4374***	-0.5555***	0.039	-0.3927**	0.1606	-0.0505
Corn	0.95	-6e-04	-0.838***	-0.9146***	0.0982	-0.5304***	0.0718	-0.041
Cotton	0.05	-0.0083 **	0.2396	0.1769	0.2195**	-0.3652**	0.0517	-0.0535
Cotton	0.1	-0.0033	0.0158	-0.0063	0.2135 ***	-0.4229 **	0.108	-0.0174
Cotton	0.5	-1e-04	-0.0207	0.0036	0.1282***	-0.3543***	0.084*”	0.0402
Cotton	0.9	0.0039	-0.0734	0.0107	-0.0241	-0.3754**	0.103	-0.0268
Cotton	0.95	0.0077	-0.17	-0.0044	0.0168	-0.4361*	-0.0555	-0.0215
Soybeans	0.05	-0.0032	0.6214***	0.5049***	0.0777	-0.4876***	-0.1041	0.1832**
Soybeans	0.1	0.0021	0.3178***	0.2666*	0.1543**	-0.3394**	-0.0824	0.1088*
Soybeans	0.5	2e-04	-0.025	-0.0092	0.0993***	-0.2964***	0.0771*	0.0428
Soybeans	0.9	-0.0054**	-0.2697***	-0.0914	0.066	-0.4133***	0.0857	0.0639
Soybeans	0.95	-0.0111***	-0.3582***	-0.0404	-0.0761	-0.2423	0.1008	0.1165**
Wheat	0.05	-0.0179***	1.3662***	1.3719***	-0.0552	-0.2341	-0.0716	0.1148
Wheat	0.1	-0.017***	0.8846***	0.9433***	0.0299	-0.2286	-0.0543	0.1166*
Wheat	0.5	8e-04	-0.0021	-0.0744	0.0484	-0.4411***	0.1168*	0.0197
Wheat	0.9	0.0055	-0.346**	-0.5206***	0.0203	-0.458**	-0.035	-0.018
Wheat	0.95	0.0038	-0.8358***	-0.9882***	0.0357	-0.7818***	-0.048	0.0282

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Test of differences in the estimated quantile regression coefficients between the 2000-2009 and the 1986-1999 periods: Global (G) factors

9 Online Appendix

(not for publication)

Commodity	q	Momentum	Basis LM	Basis SM	OI LM	OI SM
Crude oil	0.05	-0.5958	-0.0421	-0.0092	0.2726	0.0514
Crude oil	0.1	-0.2967	-0.0371**	-0.0079	0.1273	-0.0232
Crude oil	0.5	-0.013	0.0123	-0.0119**	-0.1823	0.0453
Crude oil	0.9	0.3932	0.0351	-0.0138	-0.5956***	-0.0068
Crude oil	0.95	0.5537	0.03	-0.0094	-0.759**	-0.0826
Heating oil	0.05	-0.1188	-0.0699***	0.022***	0.5559**	-0.0175
Heating oil	0.1	0.1588	-0.0181	0.0128***	0.0547	-0.0069
Heating oil	0.9	-0.1199	-0.0417***	0.0243***	0.1666*	-0.0454
Heating oil	0.95	0.0669	-0.0294	0.0202***	0.3007*	-0.2587***
Copper	0.05	0.5702*	0.0152	-0.0899***	0.0517	0.0227
Copper	0.1	0.7089***	0.0585**	-0.0831***	0.0129	0.0124
Copper	0.5	0.0924	0.0035	-0.0095*	0.0019	0.0075
Copper	0.9	-0.6417***	-0.0711***	0.0133	0.0588	0.0236
Copper	0.95	-0.799**	-0.0837**	0.0038	0.1	0.0607*
Platinum	0.05	0.4782	-0.2536***	0.104***	-0.0033	-0.0213
Platinum	0.1	0.7762***	-0.1486***	0.0574***	0.0041	0.0142
Platinum	0.5	0.0638	-0.0061	0.0267***	4e-04	0.0129
Platinum	0.9	-0.1914	0.1646***	-0.047**	1e-04	-0.0297
Platinum	0.95	-0.2484	0.1724***	-0.0466**	0.0154	-0.0122
Silver	0.05	0.3656*	0.3222***	-0.0668***	-0.099***	-0.0051
Silver	0.1	0.4358**	0.2556***	-0.052***	-0.0611***	-0.0032
Silver	0.5	-0.0023	0.041	0.0032	-0.0295**	6e-04
Silver	0.9	-0.5905***	-0.2859***	0.0328***	-0.0296	0.0021
Silver	0.95	-0.9145***	-0.3348***	0.0349*	-0.0056	0.006
Cocoa	0.05	-0.2155	0.023	0.0184	0.244**	-0.0211
Cocoa	0.1	-0.3759	0.0053	0.0041	0.0283	0.054**
Cocoa	0.5	0.3613**	0.0254*	0.0034	-0.0104	0.0262**
Cocoa	0.9	-0.1709	0.051*	-0.0044	-0.0189	-0.0042
Cocoa	0.95	-0.961*	0.0945**	-0.0099	-0.0096	0.0027
Coffee	0.05	-0.8116**	-0.0729***	0.0365***	-0.0243	0.0087
Coffee	0.1	-0.4486*	-0.0587***	0.0442***	0.0345	-0.0124
Coffee	0.9	-0.7334***	-0.0111	0.0352***	0.067	-0.0106
Coffee	0.95	-0.4979	0.0055	0.0231**	-0.0469	-0.0771**
Corn	0.05	0.3975	0.0348*	-0.0015	0.1032	-0.0022
Corn	0.1	0.0758	0.0111	0.0032	0.0295	0.0133
Corn	0.5	-0.0199	0.0109	-0.0019	8e-04	0.0142
Corn	0.9	0.3921*	0.0105	-0.0121***	-0.0926*	0.0374
Corn	0.95	0.6283**	0.0203	-0.0139***	-0.1186*	0.0578
Cotton	0.05	-0.6279**	0.0076	0.0014	-0.0279	0.0483***
Cotton	0.1	-0.1859	-0.0088	0.0041	-0.0278	0.038*
Cotton	0.5	-0.0578	9e-04	-5e-04	-0.0164	0.0064
Cotton	0.9	-0.1073	0.0136	0.0013	0.0019	-0.0483***
Cotton	0.95	0.2385	0.0045	0.0031**	-0.0168	-0.0421
Soybeans	0.05	1.0052***	-0.0186	-0.0036	0.0306	-0.0249
Soybeans	0.1	0.8106***	-0.0136	0	-0.019	-0.017
Soybeans	0.5	0.4534***	0.0014	-0.0038	-0.0083	-0.015
Soybeans	0.9	-0.2844	0.0131	-0.0015	0.0717	0.0029
Soybeans	0.95	-0.4209	0.0201	0.0021	0.0201	0.0018
Wheat	0.05	-0.8344*	-0.0245*	0	0.1601**	0.0393
Wheat	0.1	-0.3102	-0.0067	0.001**	0.0741*	0.0653
Wheat	0.5	-0.117	0.0025	-8e-04	-0.008	0.0514
Wheat	0.9	0.0059	-0.0028	-2e-04	-0.086**	-0.0504
Wheat	0.95	0.0939	-0.0036	-0.0034	-0.1201**	-0.0625

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Test of differences in the estimated quantile regression coefficients between the 2000-2009 and the 1986-1999 periods: Commodity-specific (S) factors

					Correlation with			
Panel A:	*Unfiltered*							
	Variable	Mean (%)	St. Deviation (%)	Autocorr.	Crude oil	Copper	Wheat	Cocoa
Energies	Crude oil	0.017	2.60	-0.016	1			
	Heating oil	0.005	2.23	-0.009	0.024	0.012	-0.017	-0.003
Metals	Copper	0.026	1.79	-0.054	0.126	1.000	0.081	0.063
	Platinum	0.031	1.55	0.004	0.116	0.145	0.087	0.080
	Silver	0.031	1.69	-0.001	0.152	0.220	0.102	0.117
Softs	Cocoa	0.014	1.85	-0.108	0.035	0.063	0.042	1
	Coffee	0.004	2.08	-0.011	0.014	0.018	0.011	0.055
	Cotton	0.022	1.86	-0.013	0.049	0.085	0.113	0.055
Grains	Wheat	0.004	2.11	-0.055	0.105	0.081	1.000	0.042
	Soybeans	0.021	1.52	-0.029	0.117	0.117	0.325	0.080
	Corn	0.021	1.74	0.013	0.112	0.101	0.415	0.052
Panel B:	*Filtered*							
Energies	Crude oil	-0.531	99.84	-0.012	1			
	Heating oil	-0.145	100.27	-0.007	0.0475	0.0057	-0.0273	-0.0038
Metals	Copper	0.728	99.95	-0.013	0.0926	1.0000	0.0469	0.0494
	Platinum	-36.573	3205.25	0.000	0.0006	-0.0054	-0.0037	0.0304
	Silver	0.961	100.00	-0.003	0.1278	0.1791	0.0671	0.1071
Softs	Cocoa	-0.022	99.97	-0.088	0.0315	0.0494	0.0365	1
	Coffee	1.571	130.36	0.015	0.0169	0.0195	0.0222	0.0317
	Cotton	-7.385	572.86	0.000	-0.0151	0.0123	0.0118	0.0173
Grains	Wheat	0.118	99.89	0.009	0.0768	0.0469	1	0.0365
	Soybeans	-0.246	99.99	-0.030	0.0824	0.0922	0.296	0.0783
	Corn	-0.605	99.90	0.006	0.0847	0.0593	0.388	0.0406

Table 4: Descriptive Statistics for Daily Unfiltered and Filtered Commodity Spot Change Growth
This table reports the mean, standard deviation, autocorrelation, and the correlation of daily unfiltered and filtered commodity spot price change with four key commodities of each category.

		Correlation with						
		LVIX	DLBalticDry	Yield spread	Short rate	Basis lm	Basis sm	OI lm
	LVIX	1						
	DLBalticDry	-0.008	1					
	Yield spread	0.1723	0.0048	1				
	Short rate	-0.069	-0.0095	-0.7315	1			
Crude	Basis long	0.0386	-0.0033	0.1253	-0.2861	1		
	Basis short	0.0499	0.0021	0.0838	-0.2497	0.8115	1	
	OI long	-0.1199	0.0898	-0.051	0.104	-0.2654	-0.1953	1
	OI short	-0.0437	0.0761	-0.0046	-0.002	-0.0663	-0.0088	0.1471
Heat.Oil	Basis long	-0.1263	-0.0134	0.0642	-0.2177	1		
	Basis short	-0.0883	0.0477	0.0162	-0.1138	0.6437	1	
	OI long	-0.08	0.0457	-0.0351	0.024	-0.001	-0.0408	1
	OI short	-0.0204	0.0287	-0.0005	0.0019	-0.0433	0.0753	0.0437
Copper	Basis long	0.4761	0.005	0.3274	-0.3577	1		
	Basis short	0.234	0.0308	-0.0648	0.0127	0.4571	1	
	OI long	-0.041	0.0534	-0.0918	0.1038	-0.0576	-0.0251	1
	OI short	-0.0023	-0.0069	-0.0019	0.0166	-0.0242	-0.0044	-0.7966
Platinum	Basis long	-0.1861	0.0197	-0.149	-0.0695	1		
	Basis short	-0.1738	0.0344	-0.1131	-0.2015	0.9537	1	
	OI long	-0.0012	-0.0541	-0.0017	-0.0341	0.0149	-0.0018	1
	OI short	0.0290	-0.0239	-0.0575	0.1762	0.0136	-0.0159	0.0571
Silver	Basis long	-0.1672	-0.0141	-0.3207	0.7554	1		
	Basis short	-0.116	-0.0078	-0.1091	0.2387	0.5321	1	
	OI long	-0.0476	0.0209	0.0042	-0.0243	-0.0142	-0.0118	1
	OI short	0.0648	-0.0179	-0.0201	0.0243	0.0146	-0.006	-0.5689
Cocoa	Basis long	-0.1323	-0.0205	-0.142	0.0536	1		
	Basis short	0.1241	0.024	0.0125	-0.0298	0.2722	1	
	OI long	-0.0430	0.0043	0.0035	-0.0049	-0.0173	-0.5163	1
	OI short	-0.1447	-0.0182	-0.0704	0.1299	0.0413	-0.0913	0.2021
Coffee	Basis long	-0.2373	-0.0024	0.1045	-0.0431	1		
	Basis short	-0.2342	0.0153	0.0127	0.201	0.6664	1	
	OI long	0.0002	0.0212	0.0061	-0.0072	-0.0238	-0.3155	1
	OI short	0.0954	-0.0282	-0.0005	0.1269	-0.0714	-0.045	0.2581
Cotton	Basis long	0.1949	0.0283	0.2647	-0.4565	1		
	Basis short	0.0741	0.0459	0.1257	-0.0946	0.4498	1	
	OI long	-0.0455	-0.048	-0.0093	0.0102	-0.0377	0.0627	1
	OI short	0.0402	0.0569	0.0178	-0.0805	0.2378	0.0362	-0.31
Wheat	Basis long	0.2381	-0.0617	0.1171	-0.2475	1		
	Basis short	0.1393	0.022	0.1406	-0.1997	0.5761	1	
	OI long	-0.0527	-0.0377	-0.0193	0.0007	-0.0117	0.0488	1
	OI short	0.0215	-0.0112	-0.0258	0.042	-0.0195	-0.0582	0.1464
Soybeans	Basis long	-0.0411	0.0128	-0.3418	0.3847	1		
	Basis short	-0.0044	0.0104	-0.2758	0.113	0.6512	1	
	OI long	0.0024	0.0028	-0.008	-0.0085	0.0389	0.2173	1
	OI short	0.0395	0.0228	0.0373	-0.005	0.0572	0.0286	-0.3628
Corn	Basis long	0.19	0.0461	0.0068	-0.1248	1		
	Basis short	0.1066	0.001	-0.1091	-0.0641	0.7654	1	
	OI long	-0.029	-0.0581	-0.0145	0.0027	-0.0234	0.1218	1
	OI short	0.0889	0.0053	0.0904	-0.041	0.0527	0.0329	-0.1091

Table 5: Descriptive Statistics for Global and Commodity-specific factors

This table reports the correlation of some global factors and commodity-specific factors. Global factors include: log VIX (LVIX), first difference of log Baltic Dry (DLBalticDry), yield spread and short rate proxied by Federal Effective Rate. The correlations of basis and open interest (OI) are for two levels of maturity, short (sm) and long (lm), and the correlations of each pair of basis and OI are for each commodity.

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.0214***	-0.0156***	-0.00129	0.0119***	0.021***	-0.002*
	(0.00305)	(0.00203)	(0.000893)	(0.00194)	(0.003)	(0.001)
short_rate	0.0914*	0.0989**	-0.0117	-0.00687	-0.042	0.015
	(0.0533)	(0.0439)	(0.0210)	(0.0437)	(0.067)	(0.025)
yield_spread	0.166*	0.142**	-0.0300	-0.0397	-0.156*	-0.001
	(0.0916)	(0.0612)	(0.0301)	(0.0665)	(0.093)	(0.031)
rt_dowjones	0.0726	0.0114	0.0417	0.00252	-0.049	0.017
	(0.110)	(0.0868)	(0.0292)	(0.0667)	(0.114)	(0.050)
rt_tradewdollarindex	-0.135	-0.211	-0.126**	-0.287**	-0.375**	-0.156
	(0.186)	(0.137)	(0.0582)	(0.122)	(0.181)	(0.111)
rt_gold	0.118*	0.134	0.197***	0.250***	0.340***	0.301***
	(0.0688)	(0.0853)	(0.0405)	(0.0832)	(0.113)	(0.068)
d_log_balticdry	0.152	0.0828	0.0471	-0.0527	-0.029	0.041
	(0.0968)	(0.0602)	(0.0297)	(0.0551)	(0.046)	(0.035)
momentum	0.718***	0.679***	-0.0130	-0.605***	-1.030***	0.054
	(0.226)	(0.231)	(0.112)	(0.198)	(0.262)	(0.123)
basis LM	0.00509	-0.00214	-0.00264	-0.00882	0.007	0.002
	(0.0155)	(0.0111)	(0.00784)	(0.0119)	(0.017)	(0.010)
basis SM	0.000421	-0.000461	-0.000555	0.0124***	0.009	0.003
	(0.00449)	(0.00470)	(0.00351)	(0.00443)	(0.009)	(0.005)
OI LM	-0.0680	-0.136	-0.0380	0.0901	0.181	-0.70
	(0.141)	(0.119)	(0.0414)	(0.116)	(0.187)	(0.058)
OI SM	0.00213	-0.0248	0.0457*	0.0419	0.097**	0.033
	(0.0617)	(0.0408)	(0.0233)	(0.0358)	(0.046)	(0.026)
Constant	0.0170**	0.0108*	0.00590**	-0.00707	-0.020**	0.005
	(0.00849)	(0.00648)	(0.00271)	(0.00625)	(0.009)	(0.003)
Observations	5,483	5,483	5,483	5,483	5,483	5,483
Pseudo R2/R2	0.0540	0.0385	0.00710	0.0403	0.0709	0.019

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 6: Regression results: unfiltered crude oil spot price growth

Quantiles	.05	.10	.90	.95	OLS
log_vix	-0.0157***	-0.00552***	0.00224	-0.001	-0.001
	(0.00334)	(0.00202)	(0.00153)	(0.003)	(0.001)
short_rate	0.178**	0.0240	0.0301	-0.007	0.032*
	(0.0822)	(0.0415)	(0.0287)	(0.068)	(0.019)
yield_spread	0.279***	0.0759	0.0780	0.119	0.040*
	(0.0948)	(0.0499)	(0.0490)	(0.122)	(0.024)
rt_dowjones	0.0114	-0.0760*	-0.0142	-0.083	-0.060*
	(0.115)	(0.0402)	(0.0241)	(0.056)	(0.035)
rt_tradewdollarindex	-0.473***	-0.189***	0.0379	0.087	0.029
	(0.183)	(0.0710)	(0.0675)	(0.115)	(0.063)
rt_gold	-0.0740	-0.0710*	0.00334	-0.014	0.008
	(0.0883)	(0.0383)	(0.0361)	(0.049)	(0.031)
d_log_balticdry	0.0525	-0.0103	0.0224	0.023	0.038
	(0.0720)	(0.0245)	(0.0267)	(0.046)	(0.037)
momentum	0.672***	0.363***	0.0958	0.152	0.028
	(0.255)	(0.114)	(0.0659)	(0.161)	(0.085)
basis LM	0.0348**	0.000638	-0.0513***	-0.062***	-0.021***
	(0.0156)	(0.00473)	(0.00590)	(0.008)	(0.004)
basis SM	0.0176***	0.00830***	0.0317***	0.046***	0.022***
	(0.00323)	(0.00253)	(0.00300)	(0.002)	(0.002)
OI LM	-0.0499	-0.0657	0.00493	0.035	0.029
	(0.128)	(0.0563)	(0.0344)	(0.073)	(0.027)
OI SM	-0.0288	-0.0384*	-0.0142	-0.052	-0.043***
	(0.0636)	(0.0232)	(0.0216)	(0.054)	(0.014)
Constant	0.00157	0.00445	0.000616	0.020*	-0.003
	(0.0119)	(0.00360)	(0.00496)	(0.011)	0.003)
Observations	5,504	5,504	5,504	5,504	5,504
Pseudo R2/R2	0.122	0.0217	0.130	0.239	0.135

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 7: Regression results: unfiltered heating oil spot price growth

	.05	.10	.50	.90	.95	OLS
log_vix	-0.0125***	-0.00964***	-0.00232***	0.00285**	0.007***	-0.004***
	(0.00234)	(0.00137)	(0.000581)	(0.00123)	(0.003)	(0.001)
short_rate	0.438***	0.272***	-0.0190	-0.307***	-0.348***	-0.015
	(0.0635)	(0.0419)	(0.0147)	(0.0332)	(0.065)	(0.022)
yield_spread	0.510***	0.340***	-0.0314*	-0.322***	-0.397***	0.015
	(0.0838)	(0.0556)	(0.0182)	(0.0447)	(0.091)	(0.030)
rt_dowjones	0.281***	0.319***	0.133***	0.305***	0.324***	0.261***
	(0.0679)	(0.0383)	(0.0237)	(0.0329)	(0.070)	(0.029)
rt_tradewdollarindex	-0.301**	-0.311***	-0.127***	-0.306***	-0.328***	-0.297***
	(0.141)	(0.0871)	(0.0308)	(0.0829)	(0.126)	(0.054)
rt_gold	0.301***	0.264***	0.153***	0.237***	0.273***	0.242***
	(0.0784)	(0.0491)	(0.0256)	(0.0494)	(0.076)	(0.036)
d_log_balticdry	0.130**	0.0641	0.0169	-0.00390	0.027	0.040*
	(0.0505)	(0.0424)	(0.0216)	(0.0369)	(0.081)	(0.024)
momentum	0.353**	0.291*	-0.119*	-0.363**	-0.408	-0.103
	(0.177)	(0.163)	(0.0647)	(0.145)	(0.249)	(0.120)
basis LM	0.108***	0.0683***	-0.000111	-0.0634***	-0.076***	0.001
	(0.0208)	(0.00941)	(0.00428)	(0.00845)	(0.017)	(0.006)
basis SM	0.0372**	0.00895	0.00657***	0.0487***	0.055***	0.027***
	(0.0168)	(0.00975)	(0.00243)	(0.00470)	(0.007)	(0.005)
OI LM	-0.0601*	-0.0356	-0.00877	0.0409	0.083	0.004
	(0.0363)	(0.0293)	(0.0118)	(0.0293)	(0.052)	(0.016)
OI SM	-0.0245	-0.0110	0.00122	0.0205*	0.033	0.006
	(0.0180)	(0.0113)	(0.00480)	(0.0107)	(0.025)	(0.007)
Constant	-0.00556	-0.00321	0.0101***	0.0372***	0.037***	0.019***
	(0.00862)	(0.00518)	(0.00231)	(0.00441)	(0.010)	(0.003)
Observations	4,598	4,598	4,598	4,598	4,598	4,598
Pseudo R2/R2	0.123	0.0845	0.0135	0.0754	0.0874	0.076

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 8: Regression results: unfiltered copper spot price growth

	.05	.10	.50	.90	.95	OLS
log_vix	-0.00962***	-0.00692***	0.000320	0.00857***	0.010***	0.000
	(0.00240)	(0.00123)	(0.000536)	(0.00113)	(0.002)	(0.001)
short_rate	-0.0638	-0.0663*	0.0173	0.0780***	0.081*	0.022
	(0.0540)	(0.0352)	(0.0173)	(0.0302)	(0.042)	(0.021)
yield_spread	-0.0433	-0.0699*	0.0203	0.0649*	0.080	0.022
	(0.0736)	(0.0407)	(0.0214)	(0.0384)	(0.052)	(0.024)
rt_dowjones	0.119	0.0463	0.0390**	0.0379	0.052	0.062**
	(0.0807)	(0.0469)	(0.0197)	(0.0458)	(0.055)	(0.027)
rt_tradewdollarindex	-0.238**	-0.335***	-0.230***	-0.389***	-0.356***	-0.317***
	(0.117)	(0.0815)	(0.0374)	(0.0797)	(0.102)	(0.050)
rt_gold	0.566***	0.493***	0.498***	0.528***	0.515***	0.511***
	(0.0813)	(0.0451)	(0.0252)	(0.0453)	(0.057)	(0.035)
d_log_balticdry	0.0724	0.0510	0.0310**	0.0119	0.038	0.037*
	(0.0526)	(0.0444)	(0.0150)	(0.0327)	(0.035)	(0.022)
momentum	-0.0897	-0.261	-0.171	0.202	0.145	-0.055
	(0.235)	(0.188)	(0.108)	(0.175)	(0.191)	(0.112)
basis LM	-0.00502	-0.00259	-0.0284**	-0.0655***	-0.060**	-0.033**
	(0.0454)	(0.0244)	(0.0116)	(0.0229)	(0.024)	(0.015)
basis SM	0.0484	0.0498***	0.0305***	0.0336***	0.037***	0.037***
	(0.0305)	(0.0170)	(0.00814)	(0.00966)	(0.012)	(0.010)
OI LM	-0.00501	-0.000551	-0.00413**	-0.0130***	-0.023***	-0.007***
	(0.00706)	(0.00527)	(0.00190)	(0.00368)	(0.005)	(0.002)
OI SM	-0.0241***	-0.0176***	-0.00272	0.00447	0.002	-0.005*
	(0.00786)	(0.00661)	(0.00220)	(0.00502)	(0.007)	(0.003)
Constant	0.0114	0.0108**	-0.00225	-0.0162***	-0.017***	-0.003
	(0.00711)	(0.00429)	(0.00191)	(0.00342)	(0.005)	(0.002)
Observations	3,718	3,718	3,718	3,718	3,718	3,718
Pseudo R2	0.130	0.113	0.0945	0.121	0.139	0.168

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 9: Regression results: unfiltered platinum spot price growth

	.05	.10	.50	.90	.95	OLS
log_vix	-0.00544***	-0.00451***	0.000666	0.00245*	0.005***	0.000
	(0.00168)	(0.00107)	(0.000435)	(0.00127)	(0.002)	(0.001)
short_rate	-0.0247	0.0437	-0.0980***	-0.163***	-0.119*	-0.048*
	(0.0979)	(0.0595)	(0.0200)	(0.0469)	(0.069)	(0.026)
yield_spread	-0.00805	0.0417	-0.0836***	-0.141***	-0.109	-0.033
	(0.0824)	(0.0543)	(0.0193)	(0.0482)	(0.070)	(0.023)
rt_dowjones	0.0203	0.0222	-0.00924	0.0251	0.014	0.018
	(0.0508)	(0.0409)	(0.0162)	(0.0372)	(0.048)	(0.022)
rt_tradewdollarindex	-0.521***	-0.481***	-0.260***	-0.304***	-0.481***	-0.388***
	(0.0956)	(0.0600)	(0.0264)	(0.0601)	(0.084)	(0.0411)
rt_gold	0.864***	0.793***	0.699***	0.711***	0.780***	0.789***
	(0.0610)	(0.0493)	(0.0276)	(0.0571)	(0.043)	(0.035)
d_log_balticdry	0.0955*	0.0657*	0.0282**	0.0166	-0.042	0.036**
	(0.0508)	(0.0364)	(0.0126)	(0.0255)	(0.038)	(0.018)
momentum	-0.0384	-0.128	-0.237***	-0.172	0.017	-0.154
	(0.200)	(0.145)	(0.0603)	(0.115)	(0.128)	(0.097)
basis LM	0.0664	-0.0213	-0.0329***	-0.0609**	-0.102**	-0.044**
	(0.0706)	(0.0337)	(0.0117)	(0.0282)	(0.048)	(0.018)
basis SM	0.0760***	0.0912***	0.0893***	0.0989***	0.098***	0.091***
	(0.0133)	(0.00713)	(0.00389)	(0.00744)	(0.010)	(0.006)
OI LM	-0.00722	-0.000567	-0.0125**	-0.00935	-0.029	-0.005
	(0.0220)	(0.0144)	(0.00603)	(0.0156)	(0.025)	(0.007)
OI SM	-0.00275	-0.000759	-0.000676	0.00143	0.000	0.001
	(0.00239)	(0.00275)	(0.00106)	(0.00238)	(0.003)	(0.001)
Constant	-0.00554	-0.00326	0.00576***	0.0189***	0.017***	0.004**
	(0.00564)	(0.00326)	(0.00142)	(0.00321)	(0.004)	(0.002)
Observations	5,373	5,373	5,373	5,373	5,373	5,373
Pseudo R2/R2	0.289	0.267	0.227	0.265	0.288	0.433

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 10: Regression results: unfiltered silver spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.00465*	-0.00338**	-0.000118	0.00148	0.003	-0.01
	(0.00239)	(0.00132)	(0.000809)	(0.00211)	(0.003)	(0.001)
short_rate	0.0447	0.00270	-0.0143	0.00512	0.053	-0.010
	(0.0812)	(0.0428)	(0.0140)	(0.0445)	(0.065)	(0.020)
yield_spread	0.0800	-0.0204	-0.0177	0.0628	0.104	0.012
	(0.122)	(0.0635)	(0.0201)	(0.0716)	(0.109)	(0.031)
rt_dowjones	0.0192	0.0390	0.0243	0.0443	0.072	0.047*
	(0.0854)	(0.0429)	(0.0193)	(0.0562)	(0.095)	(0.025)
rt_tradewdollarindex	-0.429***	-0.449***	-0.397***	-0.425***	-0.263*	-0.452***
	(0.160)	(0.0881)	(0.0595)	(0.118)	(0.152)	(0.052)
rt_gold	0.260**	0.185***	0.0982***	0.180***	0.196	0.155***
	(0.117)	(0.0555)	(0.0341)	(0.0672)	(0.122)	(0.029)
d_log_balticdry	0.0446	0.0278	-0.000441	-0.0673	-0.076	-0.005
	(0.0726)	(0.0383)	(0.0155)	(0.0421)	(0.077)	(0.021)
momentum	-0.961***	-0.571***	-0.214***	0.245	0.279	-0.302***
	(0.238)	(0.170)	(0.0802)	(0.187)	(0.333)	(0.088)
basis LM	0.0592***	0.0416***	-5.43e-05	-0.0176	-0.019	0.008*
	(0.0134)	(0.0119)	(0.00517)	(0.0108)	(0.016)	(0.005)
basis SM	0.00251	0.00321	0.00324	-0.00321	-0.004	0.002
	(0.00899)	(0.00472)	(0.00250)	(0.00638)	(0.011)	(0.003)
OI LM	0.0391	0.00751	0.00789	0.00423	0.048	0.013
	(0.0740)	(0.0451)	(0.0227)	(0.0450)	(0.082)	(0.023)
OI SM	-0.0156	-0.00112	-0.00253	-0.00781	-0.000	-0.001
	(0.0284)	(0.0140)	(0.00685)	(0.0141)	(0.017)	(0.007)
Constant	-0.0116	-0.00351	0.00307	0.00993	0.011	0.004
	(0.0106)	(0.00524)	(0.00303)	(0.00788)	(0.012)	(0.003)
Observations	4,219	4,219	4,219	4,219	4,219	4,219
Pseudo R2/R2	0.0543	0.0412	0.0127	0.0179	0.0159	0.034

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 11: Regression results: unfiltered cocoa spot price growth

Quantiles	.05	.10	.90	.95	OLS
log_vix	0.00666***	0.00611***	-0.00226	-0.004	0.001
	(0.00218)	(0.00193)	(0.00175)	(0.003)	(0.001)
short_rate	-0.0764	-0.0394	-0.161***	-0.090	-0.078***
	(0.0841)	(0.0484)	(0.0550)	(0.076)	(0.023)
yield_spread	-0.229*	-0.181**	0.0553	0.150	-0.028
	(0.122)	(0.0706)	(0.0804)	(0.098)	(0.034)
rt_dowjones	0.121*	0.0618	0.0637	0.107	0.030
	(0.0635)	(0.0497)	(0.0499)	(0.083)	(0.028)
rt_tradewdollarindex	-0.220	-0.0810	-0.0334	0.029	-0.047
	(0.180)	(0.105)	(0.114)	(0.211)	(0.058)
rt_gold	0.252***	0.158***	-0.0197	0.062	0.085***
	(0.0965)	(0.0545)	(0.0739)	(0.085)	(0.033)
d_log_balticdry	0.0528	0.00609	-0.116**	-0.183**	-0.021
	(0.0872)	(0.0553)	(0.0477)	(0.089)	(0.023)
momentum	-0.580***	-0.391***	0.0933	0.293	-0.181**
	(0.216)	(0.124)	(0.143)	(0.227)	(0.071)
basis LM	0.0161	0.00820	-0.0532***	-0.061***	-0.018***
	(0.0137)	(0.00824)	(0.00922)	(0.010)	(0.004)
basis SM	0.0239***	0.0220***	0.0364***	0.036***	0.020***
	(0.00687)	(0.00457)	(0.00500)	(0.006)	(0.002)
OI LM	0.0643	0.0504*	0.0527	0.041	0.045***
	(0.0438)	(0.0271)	(0.0334)	(0.054)	(0.013)
OI SM	0.0192	0.0156	-0.0179	-0.040	-0.005
	(0.0347)	(0.0214)	(0.0170)	(0.037)	(0.010)
Constant	-0.0297***	-0.0225***	0.0473***	0.054***	0.009***
	(0.00952)	(0.00629)	(0.00653)	(0.009)	(0.003)
Observations	4,406	4,406	4,406	4,406	4,406
Pseudo R2/R2	0.0427	0.0327	0.0476	0.0534	0.021

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 12: Regression results: unfiltered coffee spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.00996***	-0.00750***	0.000189	0.00409***	0.008**	-0.001
	(0.00251)	(0.00155)	(0.000727)	(0.00139)	(0.003)	(0.001)
short_rate	0.215***	0.225***	0.0305*	-0.171***	-0.206***	0.012
	(0.0625)	(0.0406)	(0.0165)	(0.0391)	(0.050)	(0.022)
yield_spread	0.259***	0.307***	0.0417*	-0.260***	-0.280***	0.016
	(0.0877)	(0.0596)	(0.0244)	(0.0562)	(0.073)	(0.032)
rt_dowjones	0.164**	0.178**	0.0474**	0.0998**	0.173**	0.115***
	(0.0721)	(0.0690)	(0.0207)	(0.0470)	(0.073)	(0.029)
rt_tradewdollarindex	-0.265	-0.213**	-0.0921**	-0.263***	-0.347**	-0.264***
	(0.171)	(0.0904)	(0.0435)	(0.0686)	(0.140)	(0.054)
rt_gold	0.0576	0.0826	0.0846***	0.0991*	0.171**	0.097***
	(0.0842)	(0.0720)	(0.0241)	(0.0542)	(0.082)	(0.035)
d_log_balticdry	0.0797	0.0155	0.00151	-0.0917**	-0.142**	-0.001
	(0.0553)	(0.0506)	(0.0236)	(0.0425)	(0.062)	(0.030)
momentum	0.309	0.438***	0.130*	0.0507	0.169	0.151
	(0.226)	(0.124)	(0.0788)	(0.115)	(0.214)	(0.105)
basis LM	0.0268***	0.0101	-0.00123	-0.0118	-0.024**	-0.000
	(0.00951)	(0.00702)	(0.00301)	(0.00755)	(0.010)	(0.004)
basis SM	-0.00441	-0.00148	0.00134*	0.00700***	0.013***	0.002**
	(0.00287)	(0.00196)	(0.000767)	(0.00215)	(0.003)	(0.001)
OI LM	0.00706	0.000319	-0.00535	-0.0183	-0.041	0.000
	(0.0406)	(0.0307)	(0.0138)	(0.0225)	(0.039)	(0.015)
OI SM	0.0195	0.0120	-0.00250	-0.0160	-0.040***	-0.002
	(0.0139)	(0.00931)	(0.00479)	(0.0112)	(0.015)	(0.005)
Constant	-0.0156**	-0.0158***	-0.00353	0.0198***	0.017*	0.000
	(0.00732)	(0.00586)	(0.00277)	(0.00503)	(0.009)	(0.003)
Observations	4,588	4,588	4,588	4,588	4,588	4,588
Pseudo R2	0.0361	0.0271	0.00237	0.0376	0.0530	0.021

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 13: Regression results: unfiltered corn spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.00570***	-0.00367**	-9.53e-05	3.48e-05	0.003	-0.001
	(0.00180)	(0.00143)	(0.000515)	(0.00154)	(0.003)	(0.001)
short_rate	0.240***	0.162***	-0.00318	-0.0573	-0.092	0.039
	(0.0439)	(0.0410)	(0.00881)	(0.0482)	(0.066)	(0.026)
yield_spread	0.0164	-0.00388	-0.00445	0.102	0.112	0.020
	(0.0591)	(0.0511)	(0.0146)	(0.0679)	(0.080)	(0.029)
rt_dowjones	0.123*	0.146***	0.00292	0.0794*	0.077	0.103***
	(0.0634)	(0.0433)	(0.0128)	(0.0481)	(0.059)	(0.028)
rt_tradewdollarindex	-0.427***	-0.322***	-0.00415	0.0126	0.021	-0.195***
	(0.0931)	(0.0897)	(0.0198)	(0.0951)	(0.086)	(0.049)
rt_gold	-0.0498	-0.0191	0.000911	0.0924*	0.002	0.020
	(0.0577)	(0.0467)	(0.00804)	(0.0506)	(0.088)	(0.030)
d_log_balticdry	0.0873	0.0577*	0.00582	-0.0214	0.053	0.031
	(0.0594)	(0.0307)	(0.0122)	(0.0548)	(0.065)	(0.023)
momentum	0.155	-0.00353	0.00131	0.204	0.339	0.134*
	(0.151)	(0.142)	(0.0165)	(0.155)	(0.221)	(0.071)
basis LM	0.000486	-0.000735	-0.000313	0.00585	0.011	0.005
	(0.00535)	(0.00597)	(0.00142)	(0.00642)	(0.007)	(0.006)
basis SM	0.00147**	0.00118	0.000144	0.00248*	0.003	0.002***
	(0.000710)	(0.000805)	(0.000764)	(0.00132)	(0.002)	(0.000)
OI LM	-0.0544*	-0.0292	-0.000833	-0.0137	-0.019	-0.026*
	(0.0313)	(0.0259)	(0.00607)	(0.0310)	(0.037)	(0.014)
OI SM	-0.0380**	-0.0414***	-0.000202	0.0160	0.020	-0.012
	(0.0158)	(0.0125)	(0.00139)	(0.0137)	(0.021)	(0.008)
Constant	-0.0223***	-0.0169***	0.000515	0.0182***	0.018***	-0.000
	(0.00521)	(0.00440)	(0.00178)	(0.00574)	(0.006)	(0.003)
Observations	4,482	4,482	4,482	4,482	4,482	4,482
Pseudo R2/R2	0.0668	0.0399	3.40e-05	0.0339	0.0608	0.025

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 14: Regression results: unfiltered cotton spot price growth

	.05	.10	.50	.90	.95	OLS
log_vix	-0.00471**	-0.00397***	0.000214	0.00202	0.003	-0.000
	(0.00207)	(0.00106)	(0.000468)	(0.00125)	(0.002)	(0.001)
short_rate	0.154***	0.125***	0.0151	-0.0582**	-0.099**	0.015
	(0.0433)	(0.0305)	(0.0176)	(0.0238)	(0.050)	(0.018)
yield_spread	0.232***	0.195***	0.0315	-0.0486	-0.032	0.048**
	(0.0700)	(0.0453)	(0.0225)	(0.0338)	(0.070)	(0.025)
rt_dowjones	0.107*	0.128***	0.0537***	0.0898**	0.086	0.099***
	(0.0548)	(0.0372)	(0.0174)	(0.0386)	(0.061)	(0.021)
rt_tradewdollarindex	-0.504***	-0.370***	-0.173***	-0.286***	-0.216**	-0.317***
	(0.115)	(0.0717)	(0.0405)	(0.0760)	(0.102)	(0.043)
rt_gold	0.127*	0.0875*	0.0544**	0.0405	0.095*	0.075***
	(0.0661)	(0.0472)	(0.0242)	(0.0374)	(0.052)	(0.026)
d_log_balticdry	0.0883**	0.0716***	-0.000405	-0.0271	-0.093**	0.027
	(0.0445)	(0.0269)	(0.0208)	(0.0377)	(0.047)	(0.025)
momentum	0.266	0.326**	0.0326	0.00233	-0.036	0.140
	(0.226)	(0.130)	(0.0850)	(0.144)	(0.173)	(0.094)
basis LM	0.0575***	0.0303***	-0.00365	-0.0392***	-0.050***	0.000
	(0.0149)	(0.00920)	(0.00461)	(0.00649)	(0.009)	(0.005)
basis SM	-0.00601	0.00290	0.00583***	0.0140***	0.019***	0.006***
	(0.00616)	(0.00245)	(0.00189)	(0.00264)	(0.003)	(0.002)
OI LM	-0.000645	-0.0339	-0.0195*	-0.0405	-0.055	-0.024*
	(0.0419)	(0.0237)	(0.0110)	(0.0261)	(0.036)	(0.013)
OI SM	-0.0196	-0.0215	-0.0138**	-0.0323**	-0.045**	-0.019*
	(0.0293)	(0.0184)	(0.00702)	(0.0145)	(0.021)	(0.010)
Constant	-0.0245***	-0.0174***	-0.00278	0.0137***	0.019***	-0.002
	(0.00571)	(0.00431)	(0.00204)	(0.00378)	(0.006)	(0.002)
Observations	5,444	5,444	5,444	5,444	5,444	5,444
Pseudo R2	0.0575	0.0416	0.00855	0.0335	0.0532	0.029

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 15: Regression results: unfiltered soybeans spot price growth

	(1)	(2)	(3)	(4)	(5)	OLS
log_vix	-0.0126***	-0.00731***	0.000923	0.00360**	0.006***	-0.000
	(0.00250)	(0.00178)	(0.000776)	(0.00163)	(0.002)	(0.001)
short_rate	0.380***	0.212***	0.00728	-0.271***	-0.352***	0.013
	(0.0597)	(0.0541)	(0.0182)	(0.0456)	(0.052)	(0.025)
yield_spread	0.414***	0.239***	0.00780	-0.263***	-0.369***	0.007
	(0.0844)	(0.0726)	(0.0278)	(0.0661)	(0.062)	(0.035)
rt_dowjones	0.141	0.0849	0.0745**	0.0578	0.078	0.134***
	(0.0858)	(0.0695)	(0.0352)	(0.0561)	(0.068)	(0.042)
rt_tradewdollarindex	-0.502***	-0.398***	-0.202***	-0.242**	-0.240**	-0.368***
	(0.189)	(0.120)	(0.0542)	(0.0952)	(0.099)	(0.071)
rt_gold	-0.00792	0.0182	0.0695**	0.102**	0.087	0.077*
	(0.116)	(0.0827)	(0.0299)	(0.0517)	(0.065)	(0.046)
d_log_balticdry	0.126	0.0249	-0.00977	-0.0748*	-0.122***	-0.014
	(0.0891)	(0.0439)	(0.0304)	(0.0432)	(0.044)	(0.032)
momentum	-0.198	-0.0923	0.0465	0.229	0.264*	0.026
	(0.194)	(0.135)	(0.0848)	(0.150)	(0.136)	(0.103)
basis LM	-0.00341	-0.00211	0.00264	-0.000203	0.003	-0.001
	(0.00582)	(0.00437)	(0.00235)	(0.00324)	(0.004)	(0.003)
basis SM	-0.000971	-0.000426	-4.86e-05	0.00154***	0.002***	0.000
	(0.000899)	(0.000492)	(0.000267)	(0.000515)	(0.000)	(0.000))
OI LM	0.0503	0.00438	-0.0150	-0.0222	-0.048	-0.005
	(0.0439)	(0.0224)	(0.0101)	(0.0224)	(0.031)	(0.013)
OI SM	-0.0187	-0.00483	-0.0233**	-0.0375***	-0.059***	-0.018**
	(0.0274)	(0.0255)	(0.00970)	(0.00894)	(0.013)	(0.008)
Constant	-0.0214***	-0.0160***	-0.00380	0.0298***	0.035***	-0.000
	(0.00779)	(0.00551)	(0.00238)	(0.00580)	(0.006)	(0.003)
Observations	4,312	4,312	4,312	4,312	4,312	4,312
Pseudo R2	0.0740	0.0426	0.00328	0.0626	0.0936	0.018

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 16: Regression results: unfiltered wheat spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.280***	-0.0800	-0.0548	-0.00126	0.062	-0.055
	(0.0951)	(0.0751)	(0.0351)	(0.0640)	(0.100)	(0.037)
short_rate	1.784	2.122	-0.568	-2.311	0.239	-0.335
	(2.638)	(1.803)	(1.062)	(1.734)	(2.714)	(0.972)
yield_spread	2.875	1.163	-1.181	-2.675	-1.871	-0.969
	(3.755)	(2.290)	(1.689)	(2.324)	(4.450)	(1.389)
rt_dowjones	-2.597	0.623	1.566	-3.115	-4.336	-0.916
	(3.514)	(2.575)	(1.137)	(2.597)	(3.000)	(1.403)
rt_tradewdollarindex	-3.948	0.209	-5.804**	-9.235**	-8.580	-5.205*
	(6.613)	(4.160)	(2.934)	(4.595)	(5.808)	(3.066)
rt_gold	3.418	6.686**	8.462***	11.70***	12.477***	9.287***
	(4.108)	(2.749)	(1.812)	(2.647)	(3.744)	(1.734)
d_log_balticdry	1.940	4.512**	1.690	0.705	-2.849	1.517
	(2.666)	(1.940)	(1.157)	(2.016)	(2.206)	(1.012)
momentum	11.42	5.053	0.516	-11.03	-17.952*	0.149
	(12.03)	(7.670)	(4.180)	(8.073)	(9.900)	(3.419)
basis LM	0.490	0.191	-0.0334	-0.349	-0.061	0.024
	(0.683)	(0.447)	(0.243)	(0.441)	(0.706)	(0.244)
basis SM	0.0294	0.0136	-0.0276	0.327	0.315	0.091
	(0.225)	(0.138)	(0.111)	(0.221)	(0.399)	(0.113)
OI LM	-7.759	-2.813	-1.750	1.846	0.722	-2.779
	(7.112)	(4.297)	(1.967)	(5.544)	(4.829)	(1.941)
OI SM	1.783	0.320	1.849**	2.937**	5.282***	2.050**
	(2.588)	(1.756)	(0.942)	(1.448)	(1.733)	(0.940)
Constant	-0.964***	-1.062***	0.238*	1.308***	1.378***	0.198
	(0.330)	(0.244)	(0.124)	(0.224)	(0.348)	(0.126)
Observations	5,483	5,483	5,483	5,483	5,483	5,483
Pseudo R2	0.00788	0.00551	0.00715	0.0144	0.0187	0.015

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 17: Regression results: filtered crude oil spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.631***	-0.208**	0.00530***	0.0329	-0.055	-0.017
	(0.184)	(0.104)	(0.000363)	(0.0684)	(0.099)	(0.036)
short_rate	7.456*	0.607	-0.110***	1.590	0.918	1.012
	(4.478)	(2.021)	(0.00646)	(1.482)	(3.608)	(0.937)
yield_spread	9.496*	2.839	-0.133***	4.738	8.027	1.088
	(5.702)	(2.478)	(0.00832)	(2.943)	(5.773)	(1.372)
rt_dowjones	-3.511	-3.730*	-0.00532	-0.674	-3.639	-3.590***
	(6.615)	(2.207)	(0.0116)	(1.068)	(2.526)	(1.133)
rt_tradewdollarindex	-26.57***	-8.720**	-0.0314	0.161	3.871	-0.499
	(9.102)	(4.256)	(0.0234)	(2.690)	(6.265)	(2.377)
rt_gold	-3.124	-2.695	0.00476	0.407	0.535	0.791
	(5.815)	(2.117)	(0.0123)	(1.651)	(3.134)	(1.328)
d_log_balticdry	2.816	-0.340	0.0156	0.803	0.478	1.911**
	(4.304)	(1.156)	(0.00990)	(1.109)	(2.190)	(0.957)
momentum	29.23*	15.56**	0.182***	3.661	6.261	3.290
	(16.79)	(6.138)	(0.0344)	(2.935)	(7.240)	(3.090)
basis LM	1.201*	-0.0700	-0.00936***	-2.257***	-3.273***	-1.019***
	(0.698)	(0.304)	(0.00131)	(0.236)	(0.443)	(0.132)
basis SM	0.781***	0.373***	0.00237***	1.443***	2.334***	0.981***
	(0.151)	(0.131)	(0.000515)	(0.118)	(0.117)	(0.038)
OI LM	-3.682	-2.421	0.0240**	1.213	2.241	1.083
	(6.743)	(2.530)	(0.0100)	(1.662)	(3.682)	(1.391)
OI SM	0.571	-1.765*	-0.0202***	-0.479	-2.305	-1.904**
	(3.468)	(1.064)	(0.00627)	(0.884)	(2.499)	(0.774)
Constant	-0.103	0.101	-0.0408***	0.189	0.926*	-0.134
	(0.623)	(0.189)	(0.00117)	(0.208)	(0.477)	(0.123)
Observations	5,504	5,504	5,504	5,504	5,504	5,504
Pseudo R2	0.111	0.0218	0.00130	0.126	0.228	0.130

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 18: Regression results: filtered heating oil spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.292***	-0.369***	-0.118***	-0.0913	-0.189	-0.213***
	(0.0999)	(0.0852)	(0.0316)	(0.0742)	(0.119)	(0.042)
short_rate	3.279	1.101	-0.783	-6.770***	-2.853	-1.542
	(2.934)	(2.814)	(0.888)	(2.149)	(3.221)	(1.205)
yield_spread	10.29**	4.523	-0.955	-4.864	-3.507	-0.091
	(4.099)	(3.568)	(1.135)	(3.029)	(4.719)	(1.606)
rt_dowjones	12.84***	14.40***	8.357***	13.31***	13.772***	12.657***
	(2.945)	(1.909)	(1.539)	(1.875)	(2.969)	(1.240)
rt_tradewdollarindex	-13.58*	-11.11*	-8.234***	-15.38***	-13.687*	-14.113***
	(7.344)	(6.278)	(2.183)	(3.705)	(7.867)	(2.698)
rt_gold	14.39***	13.51***	8.458***	7.730***	9.699**	10.329***
	(3.548)	(2.405)	(1.493)	(2.885)	(3.809)	(1.612)
d_log_balticdry	5.244**	4.633***	0.907	0.964	-0.170	2.143**
	(2.359)	(1.583)	(1.087)	(1.838)	(2.203)	(0.969)
momentum	4.102	-0.466	-7.820**	-6.788	6.343	-5.006
	(10.53)	(9.747)	(3.863)	(9.661)	(10.396)	(4.099)
basis LM	1.275	0.530	-0.131	-1.088	-0.453	-0.023
	(1.012)	(0.613)	(0.232)	(0.673)	(1.035)	(0.305)
basis SM	2.755***	1.702***	0.380***	1.690***	2.123***	1.305***
	(0.735)	(0.516)	(0.140)	(0.318)	(0.520)	(0.230)
OI LM	-0.828	-2.288	-0.139	1.797	4.046*	0.234
	(1.987)	(1.771)	(0.694)	(1.574)	(2.337)	0.818
OI SM	-0.235	-0.574	0.155	0.952	1.635	0.269
	(0.990)	(0.822)	(0.287)	(0.656)	(1.012)	(0.381)
Constant	-0.369	0.265	0.476***	2.037***	2.681***	0.976***
	(0.406)	(0.292)	(0.129)	(0.294)	(0.510)	(0.164)
Observations	4,598	4,598	4,598	4,598	4,598	4,598
Pseudo R2	0.0663	0.0480	0.0138	0.0360	0.0359	0.057

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 19: Regression results: filtered copper spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	0.159	0.0867	-0.0132	0.0234	0.093	0.020
	(0.127)	(0.100)	(0.0443)	(0.0983)	(0.128)	(0.048)
short_rate	-4.685	-2.790	0.736	0.993	4.765	0.656
	(3.745)	(2.665)	(1.460)	(2.378)	(2.906)	(1.330)
yield_spread	-3.490	-2.330	0.889	0.717	4.530	0.351
	(5.779)	(3.723)	(1.946)	(3.616)	(3.231)	(1.847)
rt_dowjones	5.688	2.403	2.275	-0.0121	-0.410	1.996
	(4.471)	(2.918)	(1.692)	(2.450)	(3.234)	(1.537)
rt_tradewdollarindex	-14.57	-19.07***	-17.66***	-24.43***	-33.144***	-20.123***
	(9.636)	(6.021)	(3.268)	(5.833)	(7.112)	(3.554)
rt_gold	37.76***	35.60***	36.92***	36.60***	37.496***	36.592***
	(4.211)	(3.683)	(2.177)	(3.533)	(4.025)	(2.250)
d_log_balticdry	1.062	0.746	1.410	0.916	2.947	1.118
	(3.911)	(2.308)	(0.995)	(3.108)	(3.606)	(1.144)
momentum	16.47	0.354	-8.598	3.601	6.838	-3.030
	(14.27)	(9.932)	(5.445)	(10.71)	(13.756)	(5.262)
basis LM	0.274	-1.597	-2.532***	-3.202**	-5.095**	-2.532***
	(2.613)	(1.568)	(0.771)	(1.402)	(2.093)	(0.919)
basis SM	3.048**	3.798***	2.316***	2.246***	3.553***	2.647***
	(1.519)	(1.369)	(0.508)	(0.773)	(0.968)	(0.615)
OI LM	-0.607	-0.171	-0.292*	-1.130***	-1.546***	-0.547***
	(0.546)	(0.389)	(0.177)	(0.358)	(0.416)	(0.176)
OI SM	-0.748	-0.523	-0.115	0.0101	-0.230	-0.201
	(0.470)	(0.342)	(0.197)	(0.302)	(0.456)	(0.163)
Constant	-1.788***	-1.201***	-0.00472	0.998***	0.908**	-0.098
	(0.489)	(0.388)	(0.153)	(0.308)	(0.387)	(0.155)
Observations	3,718	3,718	3,718	3,718	3,718	3,718
Pseudo R2	0.0889	0.0884	0.0853	0.0880	0.0969	0.157

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 20: Regression results: filtered platinum spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.229**	-0.139**	0.00101	0.0381	0.122	-0.020
	(0.0948)	(0.0602)	(0.0321)	(0.0598)	(0.092)	(0.034)
short_rate	-1.567	-2.790	-3.750***	-1.409	-0.194	-2.008
	(3.928)	(3.547)	(1.257)	(2.908)	(3.304)	(1.476)
yield_spread	0.828	-0.529	-3.475***	-2.673	0.187	-0.966
	(4.370)	(3.543)	(1.185)	(3.109)	(3.256)	(1.482)
rt_dowjones	-1.461	-0.608	-1.843*	-2.867*	-2.240	-0.797
	(2.937)	(2.127)	(0.998)	(1.683)	(3.445)	(1.051)
rt_tradewdollarindex	-21.54***	-21.87***	-18.57***	-12.69***	-19.119***	-19.245***
	(6.690)	(3.457)	(1.977)	(3.442)	(5.531)	(2.193)
rt_gold	45.31***	45.41***	39.92***	40.46***	42.243***	42.098***
	(3.290)	(2.899)	(1.476)	(2.826)	(3.137)	(1.577)
d_log_balticdry	0.541	2.540	1.363**	-1.239	1.459	1.179
	(3.475)	(1.699)	(0.629)	(1.757)	(2.948)	(0.812)
momentum	19.26*	1.331	-15.45***	-19.51***	-16.213*	-8.854**
	(11.00)	(7.417)	(3.413)	(6.770)	(9.465)	(3.817)
basis LM	0.736	0.481	-3.402***	-6.393***	-5.613**	-3.542***
	(2.331)	(2.247)	(0.878)	(1.846)	(2.410)	(0.979)
basis SM	5.603***	5.334***	5.785***	6.407***	5.846***	5.946***
	(0.580)	(0.530)	(0.251)	(0.445)	(0.617)	(0.301)
OI LM	-2.241*	-0.361	-0.753*	0.122	-0.384	-0.611
	(1.249)	(0.993)	(0.457)	(0.902)	(1.348)	(0.446)
OI SM	-0.325**	-0.125	0.00764	0.244*	0.199	0.014
	(0.162)	(0.161)	(0.0752)	(0.137)	(0.167)	(0.071)
Constant	-0.607*	-0.391*	0.358***	1.098***	1.009***	0.259**
	(0.350)	(0.221)	(0.103)	(0.168)	(0.269)	(0.101)
Observations	5,373	5,373	5,373	5,373	5,373	5,373
Pseudo R2	0.247	0.234	0.220	0.228	0.230	0.402

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 21: Regression results: filtered silver spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.265**	-0.180*	-0.00802	0.142	0.095	-0.051
	(0.116)	(0.0952)	(0.0475)	(0.0864)	(0.155)	(0.044)
short_rate	2.102	-1.486	-0.789	-1.882	2.001	-1.062
	(4.446)	(1.975)	(0.777)	(1.901)	(3.659)	(1.029)
yield_spread	1.662	-1.311	-0.895	-0.135	6.276	0.225
	(7.008)	(2.952)	(1.231)	(3.204)	(5.711)	(1.525)
rt_dowjones	0.963	2.937	1.527	4.211	3.654	2.680**
	(4.277)	(2.911)	(1.179)	(2.973)	(4.173)	(1.284)
rt_tradewdollarindex	-30.44***	-24.28***	-21.75***	-26.49***	-20.483**	-24.929***
	(7.990)	(5.118)	(3.264)	(5.212)	(8.081)	(2.874)
rt_gold	12.71**	10.85***	5.834***	10.03***	9.082*	8.738***
	(5.855)	(2.915)	(2.021)	(2.971)	(5.222)	(1.677)
d_log_balticdry	-1.671	0.797	0.000561	-4.030*	-0.895	-0.413
	(3.209)	(2.154)	(0.829)	(2.203)	(3.896)	(1.064)
momentum	-14.04	-14.94	-10.46***	-5.512	-7.272	-14.509***
	(13.41)	(10.22)	(3.811)	(9.135)	(13.855)	(4.726)
basis LM	1.819**	1.081*	-0.0126	0.161	0.568	0.336
	(0.880)	(0.618)	(0.254)	(0.522)	(0.674)	(0.240)
basis SM	-0.0697	-0.0579	0.157	-0.440	0.182	0.084
	(0.543)	(0.253)	(0.134)	(0.311)	(0.539)	(0.147)
OI LM	-0.245	0.193	0.238	-1.705	3.527	0.338
	(3.270)	(2.697)	(1.262)	(2.173)	(4.014)	(1.228)
OI SM	-1.695	-0.338	-0.120	0.0423	0.173	-0.099
	(1.441)	(0.856)	(0.388)	(0.688)	(0.956)	(0.380)
Constant	-0.823	-0.432	0.144	0.507	1.239*	0.262
	(0.569)	(0.342)	(0.173)	(0.366)	(0.665)	(0.167)
Observations	4,219	4,219	4,219	4,219	4,219	4,219
Pseudo R2	0.0298	0.0263	0.0130	0.0168	0.0121	0.035

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 22: Regression results: filtered cocoa spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	0.158	0.173	0.00912**	0.115	0.125	0.131***
	(0.128)	(0.111)	(0.00437)	(0.0967)	(0.155)	(0.053)
short_rate	-8.742**	-2.434	0.200	-9.317***	-6.808*	-5.511***
	(4.182)	(2.847)	(0.138)	(2.836)	(3.599)	(1.326)
yield_spread	-8.497	0.108	0.250	-4.702	-6.740	-3.642*
	(6.334)	(3.573)	(0.195)	(4.014)	(5.506)	(1.953)
rt_dowjones	5.979	3.651	0.0980	4.274	7.856*	2.062
	(3.754)	(2.771)	(0.103)	(3.141)	(4.763)	(1.599)
rt_tradewdollarindex	-12.31	-3.836	-0.196	3.536	6.505	-0.519
	(9.544)	(6.837)	(0.152)	(7.001)	(9.990)	(3.312)
rt_gold	9.756**	7.262**	0.409**	1.367	1.026	5.561***
	(4.781)	(3.467)	(0.193)	(3.981)	(4.936)	(1.871)
d_log_balticdry	0.830	1.728	0.0984	-2.963	-4.482	-0.618
	(3.419)	(2.047)	(0.138)	(2.081)	(2.980)	(1.322)
momentum	-2.626	1.171	-0.421	-2.812	0.331	-7.113*
	(10.93)	(5.636)	(0.345)	(6.988)	(11.211)	(3.995)
basis LM	-1.673***	-0.651*	-0.0354*	-1.611***	-1.516***	-0.916***
	(0.544)	(0.389)	(0.0184)	(0.339)	(0.484)	(0.203)
basis SM	1.865***	1.060***	0.0346***	1.736***	1.691***	1.157***
	(0.374)	(0.304)	(0.0123)	(0.227)	(0.374)	(0.130)
OI LM	4.088**	3.924**	0.108**	2.002	0.689	2.916***
	(2.034)	(1.587)	(0.0513)	(1.373)	(2.137)	(0.765)
OI SM	-0.188	-0.187	-0.0195	0.729	1.262	-0.388
	(1.678)	(0.986)	(0.0394)	(0.897)	(1.566)	(0.553)
Constant	-0.698	-1.067**	-0.0107	2.095***	2.444***	0.450**
	(0.505)	(0.434)	(0.0158)	(0.384)	(0.478)	(0.185)
Observations	4,406	4,406	4,406	4,406	4,406	4,406
Pseudo R2	0.0240	0.0151	0.000799	0.0320	0.0329	0.024

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 23: Regression results: filtered coffee spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.244**	-0.0706	0.0190	-0.0699	-0.051	-0.052
	(0.116)	(0.0736)	(0.0358)	(0.0841)	(0.120)	(0.043)
short_rate	-0.185	3.543	1.644	-2.719	-0.778	0.313
	(2.849)	(2.162)	(1.105)	(1.774)	(2.526)	(1.096)
yield_spread	3.305	4.477	2.192	-3.529	-2.009	0.807
	(4.231)	(3.431)	(1.802)	(2.549)	(4.394)	(1.676)
rt_dowjones	9.041***	7.706***	2.805**	5.586**	6.402*	5.257***
	(3.413)	(2.597)	(1.236)	(2.366)	(3.560)	(1.333)
rt_tradewdollarindex	-16.45***	-12.51**	-5.715*	-19.04***	-17.536***	-12.005***
	(6.276)	(5.775)	(3.055)	(5.450)	(6.215)	(2.823)
rt_gold	-0.204	2.634	4.739***	3.556	5.774*	4.487***
	(3.673)	(2.991)	(1.598)	(2.640)	(3.423)	(1.598)
d_log_balticdry	-1.885	0.229	0.0338	-5.768***	-4.954	-0.853
	(2.745)	(2.207)	(1.135)	(1.895)	(3.418)	(1.147)
momentum	-13.96	-2.932	6.326	22.40***	16.514*	7.103*
	(10.64)	(8.770)	(3.971)	(6.818)	(9.118)	(4.188)
basis LM	0.358	0.183	-0.0547	0.0597	-0.125	0.074
	(0.466)	(0.393)	(0.192)	(0.375)	(0.512)	(0.192)
basis SM	0.140	0.120*	0.0768	0.124	0.216	0.099**
	(0.125)	(0.0666)	(0.0475)	(0.0972)	(0.146)	(0.041)
OI LM	1.422	1.188	-0.251	-0.410	-2.582	-0.107
	(2.396)	(1.632)	(0.758)	(1.406)	(2.061)	(0.872)
OI SM	0.331	0.505	-0.181	-0.384	-0.985	-0.175
	(0.872)	(0.396)	(0.353)	(0.550)	(0.702)	(0.336)
Constant	-1.069***	-1.348***	-0.249	1.576***	1.721***	0.051
	(0.387)	(0.259)	(0.156)	(0.265)	(0.404)	(0.149)
Observations	4,588	4,588	4,588	4,588	4,588	4,588
Pseudo R2	0.0160	0.00867	0.00264	0.0162	0.0190	0.015

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 24: Regression results: filtered corn spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	0.0217	-0.0295	-0.0223	-0.0876	-0.006	-0.303
	(0.115)	(0.0980)	(0.0235)	(0.0736)	(0.115)	(0.264)
short_rate	2.714	5.040*	-0.239	1.566	2.497	13.512
	(3.703)	(2.922)	(0.534)	(2.831)	(4.058)	(11.478)
yield_spread	0.832	3.874	-0.189	3.498	5.783	7.646
	(4.060)	(4.148)	(0.864)	(3.773)	(5.239)	(5.940)
rt_dowjones	3.448	6.542***	0.636	3.648	5.801*	2.524
	(4.432)	(2.078)	(0.730)	(3.185)	(3.239)	(2.886)
rt_tradewdollarindex	-14.75*	-14.39***	-1.090	1.483	4.624	-8.926**
	(8.163)	(5.570)	(0.972)	(5.494)	(8.785)	(3.769)
rt_gold	-3.614	1.249	0.137	4.313	0.383	3.694
	(3.751)	(3.144)	(0.404)	(3.052)	(5.542)	(3.259)
d_log_balticdry	2.559	2.397	0.514	1.069	5.649	2.933*
	(2.798)	(1.707)	(0.527)	(2.324)	(3.805)	(1.736)
momentum	-4.305	9.126	0.381	7.474	0.124	32.155
	(12.46)	(6.966)	(0.871)	(8.048)	(12.980)	(29.372)
basis LM	-0.0601	0.366	0.0768**	-0.0470	-0.084	4.531
	(0.390)	(0.349)	(0.0353)	(0.363)	(0.645)	(4.418)
basis SM	0.0746***	0.0596***	0.0162	0.0376	0.189*	-0.049
	(0.0262)	(0.0150)	(0.0138)	(0.0863)	(0.113)	(0.094)
OI LM	-3.874	-3.424*	-0.162	0.0773	2.328	-2.041
	(2.425)	(1.873)	(0.290)	(1.523)	(2.395)	(1.656)
OI SM	-3.765***	-3.588***	0.0599	1.269	1.473	-4.091
	(0.970)	(0.792)	(0.0843)	(0.919)	(1.499)	(3.871)
Constant	-1.953***	-1.565***	0.0449	1.289***	1.355***	-0.421
	(0.369)	(0.274)	(0.0886)	(0.274)	(0.371)	(0.390)
Observations	4,482	4,482	4,482	4,482	4,482	4,482
Pseudo R2	0.00981	0.0108	0.00188	0.00439	0.00978	0.006

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 25: Regression results: filtered cotton spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.0760	-0.141**	0.000214	-0.0353	-0.133	-0.054
	(0.117)	(0.0657)	(0.000448)	(0.0618)	(0.103)	(0.037)
short_rate	1.371	1.675	0.0151	0.856	2.520	1.060
	(2.948)	(1.795)	(0.0129)	(1.722)	(2.453)	(1.021)
yield_spread	6.563	5.596*	0.0315	2.531	6.860**	3.672**
	(4.146)	(2.885)	(0.0197)	(2.569)	(3.201)	(1.525)
rt_dowjones	8.925**	5.852***	0.0537***	3.407*	5.535	5.186***
	(3.844)	(2.136)	(0.0174)	(1.842)	(3.670)	(1.171)
rt_tradewdollarindex	-33.56***	-23.45***	-0.173***	-18.50***	-14.906**	-19.388***
	(7.331)	(5.331)	(0.0325)	(4.635)	(6.399)	(2.502)
rt_gold	4.878	6.725**	0.0544**	2.413	3.602	4.214***
	(3.607)	(2.851)	(0.0248)	(2.216)	(3.034)	(1.431)
d_log_balticdry	3.181	0.990	-0.000405	1.689	0.318	1.021
	(3.209)	(2.825)	(0.0195)	(2.018)	(2.549)	(1.130)
momentum	9.629	18.07*	0.0326	0.441	1.418	8.254*
	(11.71)	(9.492)	(0.0927)	(8.047)	(9.059)	(4.532)
basis LM	0.406	0.169	-0.00365	-0.540	-0.991	-0.092
	(0.899)	(0.398)	(0.00419)	(0.503)	(0.690)	(0.242)
basis SM	0.552*	0.488***	0.00583***	0.424**	0.750***	0.415***
	(0.296)	(0.144)	(0.00192)	(0.177)	(0.272)	(0.101)
OI LM	-2.208	-2.068	-0.0195	-1.261	-2.625	-1.792**
	(2.238)	(1.901)	(0.0119)	(1.339)	(2.415)	(0.819)
OI SM	-1.237	-1.890*	-0.0138*	-1.320	-2.709*	-1.199**
	(1.278)	(1.121)	(0.00750)	(0.947)	(1.460)	(0.566)
Constant	-1.742***	-1.084***	-0.00278	1.111***	1.526***	-0.063
	(0.327)	(0.210)	(0.00170)	(0.213)	(0.316)	(0.136)
Observations	5,444	5,444	5,444	5,444	5,444	5,444
Pseudo R2	0.0229	0.0231	0.00855	0.00964	0.0142	0.025

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 26: Regression results: filtered soybeans spot price growth

Quantiles	.05	.10	.50	.90	.95	OLS
log_vix	-0.186	-0.0742	0.0437	-0.117*	-0.046	-0.022
	(0.128)	(0.0823)	(0.0406)	(0.0687)	(0.105)	(0.047)
short_rate	5.946*	0.726	0.504	-4.164*	-5.151**	0.486
	(3.188)	(2.305)	(1.013)	(2.189)	(2.602)	(1.159)
yield_spread	9.852**	2.443	0.168	-5.052	-6.959**	0.918
	(4.233)	(3.130)	(1.624)	(3.282)	(3.007)	(1.702)
rt_dowjones	2.389	5.943*	3.797**	5.410**	6.996**	5.438***
	(4.069)	(3.069)	(1.668)	(2.175)	(3.437)	(1.501)
rt_tradewdollarindex	-23.13**	-16.70***	-11.47***	-10.69**	-2.561	-13.232***
	(9.787)	(5.133)	(3.073)	(4.895)	(5.954)	(2.937)
rt_gold	-2.340	1.667	2.951*	6.481**	1.236	2.806*
	(4.848)	(3.247)	(1.518)	(3.250)	(4.101)	(1.695)
d_log_balticdry	0.137	-1.201	-0.236	-1.487	-1.969	-0.673
	(3.247)	(1.833)	(1.084)	(1.682)	(2.911)	(1.131)
momentum	-5.117	-1.798	3.235	13.87**	25.070***	1.590
	(12.88)	(6.976)	(3.536)	(6.327)	(9.262)	(3.880)
basis LM	-0.262	-0.0118	0.0850	-0.119	-0.090	-0.020
	(0.280)	(0.156)	(0.0991)	(0.141)	(0.222)	(0.100)
basis SM	0.00479	-0.00910	-0.00114	0.0312***	0.025*	0.004
	(0.0112)	(0.0122)	(0.00685)	(0.0121)	(0.014)	(0.006)
OI LM	1.680	-0.366	-0.848	-0.277	-2.157	-0.722
	(2.007)	(1.194)	(0.566)	(1.227)	(1.929)	(0.642)
OI SM	-3.753**	-2.048	-1.389**	-0.952*	-1.921**	-1.366***
	(1.867)	(1.460)	(0.635)	(0.511)	(0.971)	(0.509)
Constant	-1.568***	-1.069***	-0.183	1.835***	2.092***	-0.003
	(0.455)	(0.239)	(0.123)	(0.258)	(0.298)	(0.143)
Observations	4,312	4,312	4,312	4,312	4,312	4,312
Pseudo R2	0.0172	0.00872	0.00357	0.0131	0.0149	0.012

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This table reports estimates for our set of determinants with robust t-statistics obtained by bootstrap method in case of quantile regressions, and with heteroscedasticity-consistent t-statistics, obtained by using Newey-West correction in case of OLS regression. For definition of variables, see Appendix 8.1

Table 27: Regression results: filtered wheat spot price growth

Commodity	Quantile	GS vs. Baseline	G vs. Baseline	GS vs. G	S vs. Baseline	GS vs. S
Crude oil	0.05	0.054 ***	0.0452 ***	0.0092 ***	0.0159 ***	0.0387 ***
	0.1	0.0385 ***	0.0332 ***	0.0054 ***	0.0094 ***	0.0294 ***
	0.5	0.0071 ***	0.0063 ***	8e-04	0.0011 *	0.006 ***
	0.9	0.0403 ***	0.0259 ***	0.0148 ***	0.0165 ***	0.0242 ***
	0.95	0.0709 ***	0.0434 ***	0.0287 ***	0.0301 ***	0.042 ***
Heating oil	0.05	0.1223 ***	0.0286 ***	0.0964 ***	0.0984 ***	0.0265 ***
	0.1	0.0217 **	0.0011	0.0206 ***	0.0153 ***	0.0065
	0.9	0.1301 ***	0.0069	0.124 ***	0.1274 ***	0.0031
	0.95	0.2385 ***	0.0188 ***	0.2239 ***	0.2348 ***	0.0048
Copper	0.05	0.123 ***	0.0725 ***	0.0543 ***	0.0207 ***	0.1044 ***
	0.1	0.0845 ***	0.0604 ***	0.0257 ***	0.01 ***	0.0753 ***
	0.5	0.0135 ***	0.011 ***	0.0025 ***	0	0.0135 ***
	0.9	0.0754 ***	0.0469 ***	0.0299 ***	0.0253 ***	0.0514 ***
	0.95	0.0874 ***	0.0539 ***	0.0354 ***	0.0367 ***	0.0526 ***
Platinum	0.05	0.1299 ***	0.1058 ***	0.027 ***	0.0292 ***	0.1037 ***
	0.1	0.1133 ***	0.0926 ***	0.0229 ***	0.0201 ***	0.0952 ***
	0.5	0.0945 ***	0.0875 ***	0.0077 ***	0.0064 ***	0.0886 ***
	0.9	0.1213 ***	0.1105 ***	0.012 ***	0.0105 ***	0.112 ***
	0.95	0.1389 ***	0.1227 ***	0.0185 ***	0.0158 ***	0.1252 ***
Silver	0.05	0.2887 ***	0.2302 ***	0.076 ***	0.1251 ***	0.187 ***
	0.1	0.2666 ***	0.2085 ***	0.0733 ***	0.1177 ***	0.1688 ***
	0.5	0.2268 ***	0.1577 ***	0.0821 ***	0.1037 ***	0.1374 ***
	0.9	0.2649 ***	0.1827 ***	0.1006 ***	0.1406 ***	0.1447 ***
	0.95	0.2879 ***	0.2039 ***	0.1056 ***	0.1492 ***	0.1631 ***
Cocoa	0.05	0.0543 ***	0.0234 ***	0.0316 ***	0.0349 ***	0.0201 ***
	0.1	0.0412 ***	0.0211 ***	0.0205 ***	0.0205 ***	0.0211 ***
	0.5	0.0127 ***	0.0115 ***	0.0012	3e-04	0.0125 ***
	0.9	0.0179 ***	0.0146 ***	0.0034	0.0044 *	0.0136 ***
	0.95	0.0159 **	0.0124 **	0.0036	0.0059	0.0101 *
Coffee	0.05	0.0427 ***	0.0107 **	0.0323 ***	0.028 ***	0.0151 ***
	0.1	0.0327 ***	0.0072 **	0.0257 ***	0.0227 ***	0.0102 ***
	0.9	0.0476 ***	0.0151 ***	0.033 ***	0.0276 ***	0.0206 ***
	0.95	0.0534 ***	0.0116 **	0.0424 ***	0.0382 ***	0.0158 ***
Corn	0.05	0.0361 ***	0.03 ***	0.0063 *	0.0038	0.0325 ***
	0.1	0.0271 ***	0.0203 ***	0.007 ***	0.0041 **	0.0231 ***
	0.5	0.0024	7e-04	0.0017 **	0	0.0024 **
	0.9	0.0376 ***	0.028 ***	0.0099 ***	0.0156 ***	0.0224 ***
	0.95	0.053 ***	0.033 ***	0.0207 ***	0.0238 ***	0.0299 ***
Cotton	0.05	0.0668 ***	0.0616 ***	0.0055 *	0.0204 ***	0.0473 ***
	0.1	0.0399 ***	0.0352 ***	0.0049 **	0.0109 ***	0.0293 ***
	0.5	0	0	0	0	0
	0.9	0.0339 ***	0.0193 ***	0.0148 ***	0.022 ***	0.0121 ***
	0.95	0.0608 ***	0.0355 ***	0.0263 ***	0.0468 ***	0.0147 ***
Soybeans	0.05	0.0575 ***	0.0349 ***	0.0235 ***	0.0332 ***	0.0252 ***
	0.1	0.0416 ***	0.0288 ***	0.0132 ***	0.0169 ***	0.0251 ***
	0.5	0.0086 ***	0.0059 ***	0.0026 ***	0.0018 ***	0.0067 ***
	0.9	0.0335 ***	0.0196 ***	0.0143 ***	0.0232 ***	0.0106 ***
	0.95	0.0532 ***	0.0322 ***	0.0217 ***	0.0354 ***	0.0184 ***
Wheat	0.05	0.074 ***	0.0663 ***	0.0083 **	0.0376 ***	0.0378 ***
	0.1	0.0426 ***	0.0373 ***	0.0055 **	0.0213 ***	0.0218 ***
	0.5	0.0033 *	0.0019 *	0.0014	0	0.0033 ***
	0.9	0.0626 ***	0.0412 ***	0.0223 ***	0.0403 ***	0.0233 ***
	0.95	0.0936 ***	0.062 ***	0.0338 ***	0.0635 ***	0.0322 ***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 28: Statistical significance in $L_T(q)$ test: the case of unfiltered commodity price growth

Commodity	Quantile	GS vs. Baseline	G vs. Baseline	GS vs. G	S vs. Baseline	GS vs. S
Crude oil	0.05	0.0079	0.0046	0.0033	0.0019	0.006
	0.1	0.0055 *	0.0049 ***	7e-04	7e-04	0.0048 **
	0.5	0.0072 ***	0.0064 ***	8e-04	0.0012 *	0.006 ***
	0.9	0.0144 ***	0.0107 ***	0.0037 **	0.0046 **	0.0098 ***
	0.95	0.0187 ***	0.011 ***	0.0078 ***	0.0089 ***	0.0098 ***
Heating oil	0.05	0.1112 ***	0.0267 ***	0.0867 ***	0.0954 ***	0.0175 **
	0.1	0.0218 **	0.0011	0.0207 ***	0.0164 ***	0.0055
	0.5	0.0013 ***	9e-04 ***	4e-04 ***	4e-04 ***	9e-04 ***
	0.9	0.1264 ***	0.0069	0.1204 ***	0.1243 ***	0.0024
	0.95	0.2283 ***	0.0139 **	0.2174 ***	0.2241 ***	0.0054
Copper	0.05	0.0663 ***	0.0366 ***	0.0308 ***	0.0221 ***	0.0452 ***
	0.1	0.048 ***	0.0375 ***	0.0109 ***	0.0067 ***	0.0416 ***
	0.5	0.0138 ***	0.0118 ***	0.002 ***	3e-04	0.0135 ***
	0.9	0.036 ***	0.0252 ***	0.0111 ***	0.0114 ***	0.0249 ***
	0.95	0.0359 ***	0.0201 ***	0.0161 ***	0.0179 ***	0.0183 ***
Platinum	0.05	0.0889 ***	0.0708 ***	0.0195 ***	0.0113 ***	0.0785 ***
	0.1	0.0884 ***	0.0758 ***	0.0136 ***	0.0106 ***	0.0787 ***
	0.5	0.0853 ***	0.0788 ***	0.0071 ***	0.0057 ***	0.0801 ***
	0.9	0.088 ***	0.0761 ***	0.0129 ***	0.015 ***	0.0741 ***
	0.95	0.0969 ***	0.0745 ***	0.0241 ***	0.015 ***	0.0831 ***
Silver	0.05	0.2467 ***	0.1761 ***	0.0857 ***	0.1231 ***	0.141 ***
	0.1	0.234 ***	0.1716 ***	0.0753 ***	0.1123 ***	0.1371 ***
	0.5	0.2197 ***	0.1507 ***	0.0812 ***	0.0987 ***	0.1342 ***
	0.9	0.2279 ***	0.1442 ***	0.0979 ***	0.1234 ***	0.1192 ***
	0.95	0.23 ***	0.142 ***	0.1026 ***	0.1262 ***	0.1188 ***
Cocoa	0.05	0.0298 ***	0.0227 ***	0.0073 *	0.0083 **	0.0216 ***
	0.1	0.0263 ***	0.0219 ***	0.0044 **	0.0057 ***	0.0207 ***
	0.5	0.013 ***	0.0117 ***	0.0013	3e-04	0.0126 ***
	0.9	0.0168 ***	0.0156 ***	0.0012	6e-04	0.0162 ***
	0.95	0.0121	0.0109 **	0.0012	8e-04	0.0113 **
Coffee	0.05	0.024 ***	0.0069	0.0173 ***	0.0149 ***	0.0092 **
	0.1	0.0151 ***	0.0057 **	0.0094 ***	0.0112 ***	0.0039
	0.5	8e-04 ***	5e-04 ***	3e-04 *	4e-04 ***	4e-04 **
	0.9	0.032 ***	0.0046	0.0275 ***	0.021 ***	0.0112 ***
	0.95	0.0329 ***	0.0069	0.0262 ***	0.0266 ***	0.0064
Corn	0.05	0.016 ***	0.0092 **	0.0069 **	0.0044	0.0117 ***
	0.1	0.0087 **	0.0053 **	0.0034	0.0021	0.0066 **
	0.5	0.0026 *	0.0011	0.0015 *	4e-04	0.0022 **
	0.9	0.0162 ***	0.0084 ***	0.0079 ***	0.0089 ***	0.0073 ***
	0.95	0.019 ***	0.0123 ***	0.0068 **	0.0083 ***	0.0108 ***
Cotton	0.05	0.0098 ***	0.0058 **	0.004 **	0.0051 ***	0.0048 **
	0.1	0.0108 ***	0.0054 ***	0.0055 ***	0.0053 ***	0.0056 ***
	0.5	0.0019 **	7e-04	0.0012 **	0.0015 ***	4e-04
	0.9	0.0044	0.0019	0.0025	0.0024	0.002
	0.95	0.0098	0.0057	0.0041	0.0053	0.0045
Soybeans	0.05	0.0229 ***	0.0159 ***	0.0071 **	0.0054 *	0.0176 ***
	0.1	0.0231 ***	0.0152 ***	0.008 ***	0.0064 ***	0.0168 ***
	0.5	0.0089 ***	0.0063 ***	0.0026 ***	0.0019 ***	0.007 ***
	0.9	0.0096 ***	0.0075 ***	0.0022	0.0023	0.0073 ***
	0.95	0.0142 ***	0.0082 ***	0.0061 **	0.0067 ***	0.0075 **
Wheat	0.05	0.0172 ***	0.0137 ***	0.0036	0.0076 **	0.0097 **
	0.1	0.0087 ***	0.0071 ***	0.0016	0.002	0.0067 ***
	0.5	0.0036 **	0.0021 *	0.0015	0	0.0035 ***
	0.9	0.0131 ***	0.0081 ***	0.005 **	0.0048 **	0.0083 ***
	0.95	0.0149 **	0.0057	0.0093 ***	0.0092 ***	0.0058

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 29: Statistical significance in $L_T(q)$ test: the case of filtered commodity price growth

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