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A dynamic model of hedging and speculation in the commodity futures markets

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ABSTRACT

Over the 1990–2010 time period, a dynamic interaction between spot and futures returns in five commodity markets (copper, cotton, oil, silver, and soybeans) is empirically validated. An error correction relationship for the cash returns and a non-linear parameterization of the corresponding futures returns are combined with a bivariate CCC-GARCH representation of the conditional variances. Hedgers and speculators are contemporaneously at work in the futures markets, the role of the latter being far from negligible. In order to capture the consequences of the growing turbulence of these markets, a two-state regime-switching model for futures returns is developed. In this way financial traders' time-varying risk appetites are allowed to interact with hedgers' demand in determining both future and spot prices.

1. Introduction

This paper focuses on the two main activities associated with futures trading: hedging and speculation. They do not have to be considered as referring to two separate agents. It may well be that typical hedgers, such as commercial firms, take a view on the market (speculate on price direction). Alternatively, speculators can find it profitable to engage in hedging activities (Stulz, 1996; Irwin, Sanders, and Merrin, 2009).

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Consequently, it could be misleading to consider hedgers as pure risk-averse agents and speculators as risk-seekers. The futures' demand functions used in this paper will avoid this simplistic divide.

Futures trading involves an exchange between people with opposite views of the market as to the future behavior of prices and/or a different degree of risk aversion. It allows a shifting of the risk from a party that desires less risk to a party that is willing to accept it in exchange for an expected profit.[1]

Speculation is essential for the smooth functioning of commodity markets as it assures liquidity and assumes the risks laid off by hedgers. Speculators, mainly non-commercial firms or private investors, are ready to take up risks in order to earn profits stemming from expected price changes. No physical delivery is involved in this futures trade and speculation does not intervene directly in the cash market.

The literature on commodity market speculation has followed three main strands. A direct approach, based either on an attempt to micro model simultaneously speculative and hedging behavior, or on an investigation of the interaction between chartists/noise/feedback traders and fundamentalist speculators, and an indirect approach. In the latter, the excess co-movement of commodity prices is analyzed and this evidence is attributed to “herding” behavior. In addition, some recent studies have tried to exploit the information on the commitments of traders.

Johnson (1960) suggests that hedging and speculation in futures markets are interrelated. Speculation is mainly attributed to traders' expectations on future price changes that bring about an increase/decrease of the optimal hedging ratio in a short hedging context. Ward and Fletcher (1971) generalize Johnson's approach to both long and short hedging and find that speculation is associated with optimal futures positions (short or long) that are in excess of the 100% hedging level. Westerhoff and Reitz (2005) and Reitz and Westerhoff (2007), building on Frankel and Froot (1986), Cutler, Poterba, and Summers (1990), and De Long et al. (1990), among others, attribute commodity price fluctuations to the non-linear interaction between noise traders and fundamentalist speculators. (Their approach is further adapted to the basic tenets of behavioral price setting dynamics by ter Ellen and Zwinkels (2010).)

A different strand of analysis on speculation in the commodity markets focuses on the presence of excess (with respect to a component explained by fundamentals) co-movement of returns of unrelated commodities (Pyndick and Rotemberg, 1990). Subsequent research (e.g., Cashin, McDermott, and Scott, 1999; Ai, Chatrath, and Song, 2006; Lescaroux, 2009) challenged the excess co-movement hypothesis on both empirical and methodological grounds. The overall results are mixed and could indeed depend on the selection of the estimation techniques and/or of the information set (Le Pen and Sévi, 2010).

In recent years, the availability of data on the Commitments of Traders Reports, provided by the Commodity Futures Trading Commission, has generated a large body of papers as researchers use it to assess the impact of speculation on commodity prices, measuring speculative positions in terms of open interest. The weekly open interest of each commodity is broken down, according to the purposes of traders, into long and short reporting of commercial hedging, long and short speculation by reporting non-commercial firms, and positions of non-reporting traders. The empirical results, however, are mixed (e.g., Fagan and Gencay, 2008; Sanders and Irwin, 2011).

In the 1960s, optimal hedging behavior was identified by Stein (1961) and McKinnon (1967). They associated it with the minimization of the variance of the return of the portfolio of a hedger, constructed with cash and futures contracts. This approach allows to compute an optimal cover ratio β (the minimum variance hedge ratio or MVH ratio), defined as the percentage of cash contracts matched by futures positions that minimizes the variance of the hedged portfolio. It owes its popularity to its simplicity, since β, given by the ratio between the covariance of cash and futures returns and the variance of futures returns, can be easily estimated.

The MVH strategy focuses on the variance of the hedged portfolio and pays no attention to its expected return. Subsequent improvements include strategies based on hedged portfolio return mean

[1] Fagan and Gencay (2008) find that hedgers and speculators are often counterparties, since they tend to take opposing positions. Their respective long positions exhibit a strong negative correlation.

and variance expected utility maximization[2] (Cecchetti, Cumby, and Figlewski, 1988; Lence, 1995), minimization of the extended mean-Gini coefficient (Kolb and Okunev, 1992), or based on the generalized semivariance (GSV) (Lien and Tse, 2000). It has been shown, however, that if futures prices are martingale processes and if the spot and futures returns are jointly normal, then the optimal hedge ratio will converge to the ratio obtained with the MVH strategy. Subsequent improvements see the implementation of new estimation techniques, which account for the non-stationarity and the heteroscedasticity of the time series.

Given the stochastic nature of futures and spot prices, the hedge ratio is unlikely to be constant. Ederington (1979) and Figlewski (1984) allow the correlation between the futures and spot prices to be less than perfect using the static ordinary least squares hedge ratio estimation, but impose the restriction of a constant correlation between spot and futures price rates of change. As such their approach could lead to sub-optimal hedging decisions in periods of high basis volatility and/or to inefficient revisions of the hedge ratio.

Many researchers have examined the dynamics of the joint distribution of the returns and with the time-varying nature of the optimal hedge ratio, using the growing family of generalized autoregressive conditional heteroscedasticity (GARCH) models. These researchers suggest that optimal hedge ratios are time dependent and that dynamic hedging reduces in-sample portfolio variance substantially more than static hedging.[3] They are based on the estimation of bivariate conditional variance models of varying complexity [see, among others, the seminal works of Baillie and Myers (1991), and of Kroner and Sultan (1993) and Chan and Young (2006), who incorporate a jump component in a bivariate GARCH, and Lee and Yoder (2007), who implement a Markov-switching GARCH]. The parameterization of the conditional means reflects the standard characteristics of financial time series. Indeed, since the logarithms of the futures and cash prices are non-stationary and usually cointegrated, the conditional mean return relationships have to be modelled as bivariate vector error correction models (VECMs). Their rich dynamic properties – typically disregarded in the literature – are carefully investigated in this paper and given an economic interpretation with the help of a plausible model of short-run hedger and speculator reaction to expected returns and volatility shifts. The empirical findings seem to corroborate our a priori hypotheses and provide innovative insights on the impact on futures pricing of the interaction between hedging and speculation across volatility regimes. We bridge in this way the usual dichotomy between the growing sophistication of the estimation procedures and the rather simplistic interpretation of the results in terms of efficiency of the MVH paradigm, criticized by Alexander and Barbosa (2007).

In more detail, this paper contributes to the current debate as follows:

a. Using a complex non-linear CCC-GARCH approach, we model explicitly the reaction of hedgers and speculators to volatility shifts in the commodity markets. In this way the literature is extended by adding a dynamic component to the standard two-step optimal hedge ratio computation.
b. A two-state Markov-switching procedure is used to model the impact of changes in the behavior of commodity markets, changes due to bullish/bearish reactions to futures price changes, and/or to shifts in risk aversion brought about by return volatility changes. We identify in this way a financial pattern that seems to play a growing role in recent commodity market pricing.
c. We model and assess empirically the relative impact of speculative versus hedging drivers on futures pricing, and investigate whether periods of high futures return volatility are to be associated with a more intense speculative activity.

[2] The MVH is not only compatible with a quadratic utility function but, as shown by Benninga, Eldor, and Zilcha (1983), under certain conditions, it is consistent with expected utility maximization, a result that does not depend on the nature of the utility function.

[3] Others, however, considering the trade-off between the benefits of a dynamic hedge and both the complexity of the implementation of the GARCH method and the costs of portfolio rebalancing, conclude that static hedging is to be preferred (Lence, 1995; Miffre, 2004).

Following a discussion of the properties of a dynamic model of hedging and speculation (Section 2), we outline the main features of the non-linear multivariate CCC-GARCH model used in the empirical investigation (Section 3), set forth the estimates for five main commodity markets (Section 4), and present a Markov-switching framework in which the drivers of futures returns are assumed to switch between two different processes, dictated by the state of the market (Section 5). In the conclusion (Section 6), we discuss some extensions of the regime-switching investigation.

2. A dynamic model of hedging and speculation

Commodity futures trading is analyzed in this section, focusing on hedging and speculative behavior. A hedging transaction is intended to reduce the risk of unwanted future cash price changes to an acceptable level. Spot market trades are associated with trades of the opposite sign in the corresponding futures market. If the current cash and futures prices are positively correlated, the financial loss in one market will be compensated by the earnings obtained from holding the opposite position in the other market.

In more detail, let $r^i_{c,t} = \Delta \log C^i_t = \Delta c^i_t$ and $r^i_{f,t} = \Delta \log F^i_t = \Delta f^i_t$, where C^i_t is the cash (spot) price of commodity i and F^i_t is the price of the corresponding futures contract. An investor who takes a long (short) position of one unit in the cash market i will hedge by taking a short (long) position of β units in the corresponding futures market, which he will buy (sell) back when he sells (buys) the cash. The hedge ratio β can be seen as the proportion of the long (short) cash position that is covered by futures sales (purchases).[4]

The revenue of this hedging position (or portfolio), i.e. the hedger's return $r^i_{H,t}$, is given by

$$r^i_{H,t} = r^i_{c,t} - \beta r^i_{f,t}. \tag{1}$$

The variance of this portfolio is given by

$$\sigma^2_{r^i_H,t} = \sigma^2_{r^i_c,t} + \beta^2 \sigma^2_{r^i_f,t} - 2\beta \sigma_{r^i_c,t}\sigma_{r^i_f,t}\rho_{r^i_c r^i_f,t}, \tag{2}$$

where $\sigma^2_{r^i_c,t}$ is the variance of $r^i_{c,t}$, $\sigma^2_{r^i_f,t}$ is the variance of $r^i_{f,t}$, and $\rho_{r^i_c r^i_f,t}$ is the correlation between $r^i_{c,t}$ and $r^i_{f,t}$.

The optimum hedge ratio β^* is derived from the first order condition of the hedging portfolio variance minimization and reads as (from now on we drop the superscript i):

$$\beta^* = \frac{\sigma_{r_c,t}\sigma_{r_f,t}\rho_{r_c r_f,t}}{\sigma^2_{r_f,t}}. \tag{3}$$

The optimum hedge ratio depends on both the covariance between the changes in futures and cash prices, $\sigma_{r_c r_f,t} = \sigma_{r_c,t}\sigma_{r_f,t}\rho_{r_c r_f,t}$, and the variance of the futures price changes.

In order to analyze the reaction of hedgers to shifts in commodity returns, we extend the standard hedging model by introducing a dynamic component.

We assume that the expected utility of hedgers is an inverse function of the expected variability of their optimally hedged position. The variance of this position (or portfolio) can be defined, replacing in Eq. (2) the optimal hedge ratio β^* by its determinants set out in Eq. (3), as

$$\sigma^2_{r_H,t} = \sigma^2_{r_c,t} - \frac{(\sigma_{r_c r_{f,t}})^2}{\sigma^2_{r_{f,t}}} = \sigma^2_{r_c,t}(1-\rho^2_{r_c r_f,t}), \tag{4}$$

where $\rho_{r_c r_f,t} = \sigma_{r_c r_f,t}/\sigma_{r_f,t}\ \sigma_{r_c,t}$.

The demand of futures contracts of a hedger wishing to minimize the variance of his optimal portfolio is defined as

$$D^H_t = a_0 + b^H \sigma^2_{r_c,t}(1-\rho^2_{r_c r_f,t}). \tag{5}$$

[4] The hedge ratio is also defined as the ratio between the number of futures and cash contracts.

An increase in the minimum portfolio variance may be due to a rise in the variability of cash price changes and/or to a decrease in the correlation between cash and futures price changes. We can thus reasonably assume that b^H is positive if consumers' hedging is prevailing since consumers, concerned about cash price increases, will demand more futures contracts whenever the portfolio variance increases. Conversely, b^H will be negative if producers' hedging is prevailing, since producers, worried about possible cash price decreases, will supply more (i.e., demand less) contracts if the variability of their hedged position rises.

The demand for futures contracts of a speculator is defined as

$$D_t^S = c_0 + d^S E_{t-1} r_{f,t} - e^S \sigma^2_{r_f,t}. \tag{6}$$

d^S is always positive because of the positive impact on speculation of an increase in expected futures returns, whereas e^S can be either positive or negative, according to the reaction of speculators to risk. We assume that $e^S < 0$ for risk lover and $e^S > 0$ for risk-averse agents.[5] Furthermore, as pointed out by Acharya, Lochstoer, and Ramadorai (2013), e^S could capture the impact of the cost of capital, which is found to be increasing in times of distress that are associated with high volatility periods. It is generally accepted that futures trading is a zero sum game. As pointed out by Hieronymus (1977, p. 302), among others, "for everyone who thinks the price is going up there is someone who thinks it is going down, and for everyone who trades with the flow of the market, there is someone trading against it." Thus we can assume that the net demands of both agents are balanced on a daily basis or, equivalently, that the demands of hedgers and speculators add up to 0:

$$D_t^H + D_t^S = 0. \tag{7}$$

Substituting Eqs. (5) and (6) into Eq. (7) and readjusting terms, we obtain the following expression for the expected futures return:

$$E_{t-1} r_{f,t} = \frac{1}{d^S}\left(-(a_0 + c_0) - b^H \sigma^2_{r_c,t}(1 - \rho^2_{r_c r_f,t}) + e^S \sigma^2_{r_f,t}\right).$$

Since $r_{f,t} = E_{t-1} r_{f,t} + u_{r_f,t}$, we obtain the following testable short run relationship:

$$r_{f,t} = e_0 - (b^H/d^S)\sigma^2_{r_c,t}(1 - \rho^2_{r_c r_f,t}) + (e^S/d^S)\sigma^2_{r_f,t} + u_{r_f,t}, \tag{8}$$

where $e_0 = -(a_0 + c_0)/d^S$. Eq. (8) relates futures returns to their own volatility and to the variability of the optimally hedged portfolio. The short run dynamics of this relationship are in line with the stylized facts detected in Fagan and Gencay (2008), where the negative correlation between futures returns and hedger net long positions supports the idea that large speculators are net buyers in rising markets, while large hedgers are net sellers. This behavior is encompassed by our (more general) model, when we contemplate the case of hedgers being net sellers – when b^H is negative – and futures returns going up.

3. A bivariate non-linear CCC-GARCH representation

We focus on futures prices since commodity prices are typically found in futures markets and price changes are passed from futures to cash markets (Garbade and Silber, 1983). Indeed, trading is quicker and cheaper in futures markets than in the cash markets. It is put forth in economic theory that the prices of cash assets and of the corresponding futures contracts are jointly determined (Stein, 1961). Our empirical estimation thus includes a relationship that describes the behavior of cash returns, along with a futures returns relationship, and analyzes the covariance between these two variables. Over the longer term, equilibrium prices are ultimately determined in the cash market as all commodity futures prices at delivery date converge to the cash price (plus or minus a constant). This behavior justifies the existence of a cointegration relationship between futures and cash prices and

[5] Furthermore e^S may capture the impact of the cost of capital, which is found to be increasing in time of distress, as in Acharya, Lochstoer, and Ramadorai (2013).

the use of an error correction parameterization of the conditional mean equation for $r_{c,t}$, where cash prices adjust to futures prices (the forcing variable), in line with the adopted framework of price discovery.[6] In the long run, the relation between cash and futures prices holds and accounts for the presence of an identified basis or convenience yield.

A non-linear bivariate GARCH model for futures and spot returns is thus estimated. The conditional mean of the futures returns is modeled by Eq. (8′), while the conditional mean of the cash returns, Eq. (9), is parameterized by an autoregressive error correction structure and the conditional second moments are quantified by a bivariate CCC-GARCH(1,1).[7]

$$r_{c,t} = a_0 + \sum_{j=1}^{n} a_j r_{c,t-j} + \sum_{k=1}^{m} b_k r_{f,t-k} + \varepsilon_1 (f_{t-1} - d_0 - d_1 c_{t-1}) + u_{r_c,t} \tag{9}$$

$$r_{f,t} = e_0 - (b^H/d^S)(h^2_{r_c,t} - h^2_{r_c r_f,t}/h^2_{r_f,t}) + (e^S/d^S) h^2_{r_f,t} + c_1 r_{f,t-1} + u_{r_f,t} \tag{8′}$$

$$H_t = \Delta_t R \Delta_t$$

$$R = \begin{bmatrix} 1 & \rho_{r_c r_f} \\ \rho_{r_c r_f} & 1 \end{bmatrix} \quad \Delta_t = \begin{bmatrix} h_{r_c,t} & 0 \\ 0 & h_{r_f,t} \end{bmatrix}$$

$$h^2_{r_c,t} = \varpi_c + \alpha_c h^2_{r_c,t-1} + \beta_c u^2_{r_c,t-1}; \quad h^2_{r_f,t} = \varpi_f + \alpha_f h^2_{r_f,t-1} + \beta_f u^2_{r_f,t-1}$$

$$u_t = \begin{bmatrix} u_{r_c,t} \\ u_{r_f,t} \end{bmatrix} u_t \Big| \Omega_{t-1} N(0, H_t)$$

4. The empirical behavior of five commodity markets

Our daily data span the January 3, 1990 to January 26, 2010 time period. All the contracts are traded on the NYMEX (New York Mercantile Exchange) and are taken from Datastream. Both spot (C_t) and futures prices (F_t) are expressed in U.S. dollars. Futures prices correspond to the highly liquid one month (nearest to delivery) futures contract.[8] Returns are computed as first differences of the logarithms of the price levels. The model is tested for five commodities belonging to different commodity sectors: cotton (industrial materials), copper (industrial metals), crude oil (energy), silver (precious metals), and soybeans (grains).

Summary statistics of cash and futures returns are presented in Table 1.

Average daily returns are small but not negligible; they are higher for oil and lower for soybeans, a pattern that also holds for the daily standard deviations.[9] The distributions of both cash and futures returns are always mildly skewed and significantly leptokurtic, the departure from normality being confirmed by the size of the corresponding Jarque Bera (JB) test statistics. Volatility clustering is detected in all cases, a finding that supports the choice of a GARCH parameterization of the conditional second moments.

Tables 2 and 3 present parsimonious estimates of the conditional mean equations of the bivariate non-linear CCC-GARCH(1,1) system set forth in Section 3 for the five commodities. The overall quality

[6] On this point see Figuerola-Ferretti and Gonzalo (2010). They successfully apply a VECM approach to cash and futures commodity returns where cash prices adjust to futures prices, in line with the Garbade and Silber (1983) framework of price discovery.

[7] A one period lagged rate of futures return is added as regressor in Eq. (8′) to account for a potential first order serial correlation of the dependent variable. No error correction terms are included since they turned out to have mostly insignificant coefficients in a preliminary bivariate VECM investigation.

[8] The futures contract expires on the third business day prior to the 25th calendar day of the month preceding the delivery month. If the 25th calendar day of the month is a non-business day, trading ceases on the third business day prior to the business day preceding the 25th calendar day.

[9] The logarithms of the prices of the cash and futures contracts are always $I(1)$ and their first differences $I(0)$. The test statistics are not reported for brevity.

Table 1
Descriptive statistics.
Daily sample from January 3, 1990 to January 26, 2010 (5,325 observations). Sk.: skewness; Kurt.: kurtosis; JB: Jarque Bera test statistic; ARCH(l): Lagrange Multiplier test for lth order Arch, probability levels are in brackets.

Return	Mean	Std. Dev.	Sk.	Kurt.	JB	ARCH(1)[pr.]	ARCH(6)[pr.]
Copper futures	0.0002	0.0269	−0.22	4.53	4,520.46	217.10[0.00]	1,222.1[0.00]
Copper cash	0.0002	0.0169	−0.21	4.51	4,483.09	346.76[0.00]	966.11[0.00]
Cotton futures	0.0001	0.0175	−0.79	22.07	106,878.63	14.44[0.00]	117.15[0.00]
Cotton cash	0.0001	0.0174	0.02	2.43	1,290.37	92.92[0.00]	485.26[0.00]
Oil futures	0.0003	0.0250	−0.95	17.52	67,710.60	73.16[0.00]	369.33[0.00]
Oil cash	0.0002	0.0240	−1.23	24.63	1,333,762.20	20.58[0.00]	96.35[0.00]
Silver futures	0.0002	0.0165	−0.39	6.89	10,498.50	120.53[0.00]	557.69[0.00]
Silver cash	0.0002	0.0177	−0.23	4.40	3,521.00	121.88[0.00]	415.42[0.00]
Soybeans futures	0.0001	0.0148	−0.59	5.94	8,020.70	29.21[0.00]	287.46[0.00]
Soybeans cash	0.0001	0.0152	−0.75	7.24	11,964.70	60.45[0.00]	404.08[0.00]

of fit is satisfactory.[10] The estimated parameters are significantly different from zero and the conditional heteroscedasticity of the residuals has been captured by our GARCH parameterization.[11] The usual misspecification test results indicate that the standardized residuals ν_t are always well behaved; for each system $E[\nu_t]=0$, $E[\nu_t^2]=1$, and ν_t^2 is serially uncorrelated.

Keeping in mind that d^S is positive by construction and that the sign of the coefficient ratios b^H/d^S and e^S/d^S depend on the sign of b^H and e^S, the futures return mean Eq. (8′) provides the following useful information on the market drivers. First, the coefficient b^H estimates are negative in the case of cotton, copper and soybeans, reflecting the predominance of producers on the markets, and positive for the remaining commodities of the sample (oil and silver), because of the preponderance of consumers. This result is also in line with the effects of hedging pressure, where futures prices increase when hedgers trade short and decrease when hedgers trade long.[12]

Second, the absolute value of the ratio between speculative and hedging factors $e^S\sigma^2_{r_f,t}/b^H\sigma^2_{r_c,t}(1-\rho^2_{r_cr_f,t})$ set forth in Table 4 measures the relative impact of different sources of risk on futures returns using a "level of importance" criterion.[13] It is higher than 1 for the oil and soybeans markets, where speculators seem to be more reactive than hedgers.

Third, speculators are risk-averse (since the corresponding e^S coefficient estimates are positive) in the oil and silver markets only, a finding that may be due to the size of the volatility shocks. This issue is further investigated in the next section.

The dynamic specification of our model might introduce distortive effects in the estimation of the optimal hedge ratio β that reduce its effectiveness. We have thus performed the standard comparison of its hedging performance with the performance of a naïve portfolio hedge ratio ($\beta=1$) and of an OLS hedge ratio, obtained as the futures return coefficient estimate in a regression of cash returns on a constant and on futures returns. An artificial daily portfolio is introduced where an investor is assumed to buy (sell) one unit of the cash asset and to sell (buy) β units of the corresponding futures contract. The unconditional portfolio return standard deviations are computed over the whole sample and are set forth in Table 5 for the three hedge ratio estimators. The naïve hedge portfolios are clearly outperformed by the optimal hedge portfolios, a finding that differs from the results obtained by Alexander and Barbosa (2007). Commodity markets, despite their growing financialization, cannot compare in terms of efficiency with the major stock markets and optimal hedging remains an effective

[10] The corresponding conditional variance equations are properly specified. Their parameter coefficients, always significant, are of the appropriate sign and size. They are not reported here for brevity and are available from the authors upon request.

[11] The t-ratios reported in the tables are based on the robust quasi-maximum likelihood estimation procedure of Bollerslev and Wooldridge (1992).

[12] See Chang (1985) and Bessembinder (1992). We re-estimated the model using eight additional commodities that span the five categories we analyzed. A strong similarity between the signs of commodities that belong to the same category was detected. This finding may reflect a common pattern of prominence in consumer/producer hedging, along with a similarity in the reaction of speculators to risk. The estimates are available from the authors upon request.

[13] For a definition of this measure, see Achen (1982, pp. 72–73).

Table 2
Conditional mean equations.

In this table are set out the full sample estimates of the commodity spot and futures return conditional mean parameterization – Eqs. (9) and (8′) – for copper, cotton and oil. Sk.: skewness; Kurt.: kurtosis; JB: Jarque Bera test statistic; ν_t: standardized conditional mean residual; ARCH(l): Lagrange Multiplier test for lth order Arch, probability levels are in brackets; t-statistics in parenthesis. The estimates are obtained using the QMLE robust procedure of Bollerslev and Wooldridge (1992).

Copper $n=2$, $m=2$			Cotton $n=1$, $m=2$ k: dummy in futures eq.			Oil[a] $n=1$, $m=1$		
	$r_{c,t}$	$r_{f,t}$		$r_{c,t}$	$r_{f,t}$		$r_{c,t}$	$r_{f,t}$
a_0	0.003		a_0	−2.0E−04		a_0	−0.012	
	(49.93)			(−1.84)			(−86.89)	
a_1	−0.298		a_1	−0.081		a_1	−0.219	
	(−51.67)			(−10.44)			(−25.74)	
a_2	0.258							
	(47.26)							
b_1	−0.164		b_1	0.084		b_1	0.235	
	(−24.78)			(14.72)			(32.58)	
b_2	0.171		b_2	−0.026				
	(30.19)			(−3.74)				
ε_1	0.036		ε_1	0.030		ε_1	0.065	
	(76.29)			(15.08)			(89.89)	
d_0	0.061		d_0	0.292		d_0	–	
	(31.89)			(70.37)				
d_1	1.004		d_1	0.939		d_1	0.957	
	(2,527.3)			(930.29)			(1,547.6)	
e_0		−1.0E−04	e_0		−5.6E−04	e_0		2.1E−04
		(−1.59)			(−5.22)			(1.51)
(b^H/d^S)		−25.495	(b^H/d^S)		−9.416	(b^H/d^S)		4.217
		(−15.80)			(−9.67)			(5.51)
(e^S/d^S)		−5.732	(e^S/d^S)		−1.743	(e^S/d^S)		2.401
		(−14.38)			(−4.23)			(7.61)
c_1		−0.060						
		(−9.38)						
			k		−0.280			
					(−44.63)			
$E[\nu_t]$	0.02	0.02	$E[\nu_t]$	0.007	0.005	$E[\nu_t]$	−0.016	−0.012
	(1.65)	(1.56)		(0.51)	(0.37)		(−1.16)	(−0.90)
$E[\nu_t^2]$	0.999	0.999	$E[\nu_t^2]$	1.000	1.000	$E[\nu_t^2]$	0.999	1.000
Sk.	−0.34	−0.19	Sk.	−0.008	0.03	Sk.	−0.29	−0.33
Kurt.	3.75	2.86	Kurt.	1.66	4.09	Kurt.	4.55	3.08
ARCH(1)	0.25	2.83	ARCH(1)	0.77	0.003	ARCH(1)	0.59	4.78
	[0.62]	[0.09]		[0.38]	[0.95]		[0.44]	[0.03]
ARCH(6)	3.09	5.16	ARCH(6)	8.28	5.52	ARCH(6)	12.07	1.63
	[0.80]	[0.52]		[0.22]	[0.48]		[0.06]	[0.95]
JB	3,165.96	1,815.70.	JB	602.09	3,648.35	JB	4,592.51	2,167.71

[a] The conditional variance of the futures returns is parameterized as a TGARCH(1,1).

risk reduction technique. The difference between our CCC-GARCH model and the OLS estimates is rather small, even if the former provides the minimum risk hedge in three out of five markets. Only in the case of cotton and soybeans, among the less volatile markets of the sample, does the OLS optimal hedge provide the best results.[14]

[14] If we repeat the exercise using weekly returns estimates of our CCC-GARCH(1,1) model and introduce a weekly portfolio rebalancing, the CCC-GARCH beta portfolios consistently outperform both the OLS beta and naïve beta portfolios in all commodity markets.

Table 3
Conditional mean equations.

In this table are set out the full sample estimates of the commodity spot and futures return conditional mean parameterization – Eqs. (9) and (8′) – for silver and soybeans. Sk.: skewness; Kurt.: kurtosis; JB: Jarque Bera test statistic; ν_t: standardized conditional mean residual; ARCH(l): Lagrange Multiplier test for lth order Arch, probability levels are in brackets; *t*-statistics in parenthesis. The estimates are obtained using the QMLE robust procedure of Bollerslev and Wooldridge (1992).

Silver $n=1$, $m=1$			Soybeans $n=1$, $m=1$		
	$r_{c,t}$	$r_{f,t}$		$r_{c,t}$	$r_{f,t}$
a_0	0.003		a_0	−0.001	
	(41.45)			(−14.87)	
a_1	−0.143		a_1	−0.231	
	(−22.76)			(−39.23)	
b_1	0.164		b_1	0.215	
	(43.38)			(41.30)	
ε_1	0.592		ε_1	0.047	
	(140.97)			(25.47)	
d_0	−0.002		d_0	0.012	
	(−13.54)			(8.79)	
d_1	1.001		d_1	0.998	
	(49,350.4)			(4,670.5)	
e_0		0.0002	e_0		0.0003
		(2.62)			(4.91)
(b^H/d^S)		16.050	(b^H/d^S)		−19.695
		(9.32)			(−12.62)
(e^S/d^S)		2.582	(e^S/d^S)		−5.916
		(6.11)			(−17.69)
$E[\nu_t]$	0.027	0.022	$E[\nu_t]$	0.010	0.012
	(1.94)	(1.61)		(0.74)	(0.88)
$E[\nu_t^2]$	0.999	0.999	$E[\nu_t^2]$	1.00	1.00
Sk.	−0.38	−0.31	Sk.	−0.21	−0.02
Kurt.	4.63	3.83	Kurt.	2.71	2.88
ARCH(1)	4.24	1.50	ARCH(1)	1.95	0.58
	[0.04]	[0.22]		[0.16]	[0.45]
ARCH(6)	13.09	9.76	ARCH(6)	5.11	3.74
	[0.04]	[0.13]		[0.53]	[0.71]
JB	4,796.9	3,284.8	JB	1,646.6	1,814.0

Table 4
Relative importance of speculative drivers.

This table shows the relative impact of different sources of risk on futures returns using the "level of importance criterion" – the absolute value of $e^S\sigma^2_{r_f,t}/b^H\sigma^2_{r_c,t}(1-\rho^2_{r_cr_f,t})$ – set out by Achen (1982).

Commodity	Relative importance
Copper	0.97
Cotton	0.44
Oil	1.30
Silver	0.39
Soybeans	1.21

5. Hedging, speculation, and futures pricing regime shifts

Sarno and Valente (2000) and Alizadeh and Nomikos (2004) analyzed the changes in the relationship between futures and spot stock index returns using a Markov-switching model set out

Table 5
Optimal hedge ratios and portfolio second moments.
This table presents the unconditional portfolio return standard deviations computed over the whole sample for the naïve hedge ratio, and for the hedge ratios obtained with the CCC-GARCH and OLS estimates.

	CCC-GARCH estimates		OLS estimates		Naïve
Commodity	Optimal hedge ratio β	Std. dev. of the optimal hedge portfolio	Optimal hedge ratio β	Std. dev. of the optimal hedge portfolio	Std. dev. of the naïve portfolio
Copper	0.87	0.008219	0.91	0.008374	0.008519
Cotton	0.80	0.011268	0.76	0.011179	0.011894
Oil	0.74	0.016322	0.70	0.016416	0.018017
Silver	0.71	0.010867	0.72	0.010868	0.011857
Soybeans	0.90	0.007627	0.89	0.007605	0.007770

originally by Hamilton (1994). This technique is used here in order to analyze the shifts over two regimes in hedging and speculative behavior.

Using the full sample estimates of the conditional second moments obtained in the previous section, Eq. (8′) is adapted in a second step to a two-state Markov-switching framework in which the drivers of futures returns are assumed to switch between two different processes, dictated by the state of the market.[15]

Eq. (8′) is thus rewritten as

$$r_{f,t} = e_{0s_t} - (b^H_{s_t}/d^S_{s_t})(h^2_{r_c,t} - h^2_{r_c r_f,t}/h^2_{r_f,t}) + (e^S_{s_t}/d^S_{s_t})h^2_{r_f,t} + c_{1s_t} r_{f,t-1} + u_{r_f,s_t t}, \tag{10}$$

where $u_{r_f,s_t t} \sim N(0, \sigma^2_{s_t})$ and the unobserved random variable s_t indicates the state in the market.

The value of the current regime s_t is assumed to depend on the state of the previous period only, s_{t-1}, and the transition probability $P\{s_t = j | s_{t-1} = i\} = p_{ij}$ gives the probability that state i will be followed by state j. In the two-state case, $p_{11} + p_{12} = 1$ and $p_{22} + p_{21} = 1$, and the corresponding transition matrix is

$$P = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix}. \tag{11}$$

The joint probability of $r_{f,t}$ and s_t is then given by the product:

$$p(r_{f,t}, s_t = j | Y_{t-1}, \psi) = f(r_{f,t} | s_t = j; Y_{t-1}, \psi) P(s_t = j | Y_{t-1}, \psi), \quad j = 1, 2, \tag{12}$$

where Y_{t-1} is the information set that includes all past information on the population parameters and $\psi = (e_{0s_t}, (b^H_{s_t}/d^S_{s_t}), (e^S_{s_t}/d^S_{s_t}), c_{1s_t}, \sigma^2_{s_t})$ is the vector of parameters to be estimated. $f(.)$ is the density of $r_{f,t}$, conditional on the random variable s_t, and $P(.)$ is the conditional probability that s_t will take the value j.

For the two-state case, the density distribution of $r_{f,t}$ is, following Hamilton (1994, Chapter 22),

$$g(r_{f,t}|Y_{t-1}, \psi) = \frac{1}{\sqrt{2\pi\sigma^2_1}} \exp\left\{ \frac{-u^2_{r_f,1t}}{2\sigma^2_1} \right\} + \frac{1}{\sqrt{2\pi\sigma^2_2}} \exp\left\{ \frac{-u^2_{r_f,2t}}{2\sigma^2_2} \right\}, \tag{13}$$

where $u_{r_f,s_t t}$ is the residual of Eq. (10).

If the unobserved state variable s_t is i.i.d., maximum likelihood estimates of the parameters in ψ are obtained, thereby maximizing the following log likelihood function with respect to the unknown

[15] The use of conditional volatility measures, derived from preliminary GARCH estimates, as regressors is not uncommon in the literature [see e.g. Ramachandran and Srinivasan (2007) and the papers quoted therein]. Any potential errors-in-variables distortion is more than compensated by the greater accuracy of the conditional second moments estimates provided by the GARCH procedure.

Table 6
Markov-switching regime estimates.

In this table are set out the Markov-switching estimates of the commodity futures returns of Eq. (10) over the low and high volatility regimes. SPEC: speculative to hedging factors ratio defined as the absolute value of $e^S\sigma^2_{r_f,t}/b^H\sigma^2_{r_c,t}(1-\rho^2_{r_cr_f,t})$. t-Statistics are in parenthesis.

	Copper		Cotton		Oil		Silver		Soybeans	
	$s_t=1$	$s_t=2$	$s_t=1$	$s_t=2$	$s_t=1$	$s_t=2$	$s_t=1$	$s_t=2$	$s_t=1$	$s_t=2$
$P_{st,\ not\ st}$	0.021	0.056	0.054	0.216	0.009	0.065	0.071	0.177	0.034	0.084
	(8.14)	(8.73)	(11.50)	(13.26)	(6.00)	(7.21)	(13.86)	(14.91)	(10.05)	(10.31)
e_{0st}	−0.001	0.002	−0.000	−0.002	−0.000	−0.002	−0.001	−0.001	−0.000	0.002
	(−3.75)	(3.14)	(−2.14)	(−1.65)	(−0.68)	(−1.26)	(−8.334)	(−1.12)	(−0.69)	(4.21)
(b^H_{st}/d^S_{st})	−10.364	−23.462	−6.233	−3.480	7.111	11.287	−49.878	10.719	11.367	−8.711
	(−2.82)	(−6.17)	(−3.55)	(−0.67)	(5.96)	(4.04)	(−21.33)	(2.66)	(3.20)	(−2.00)
(e^S_{st}/d^S_{st})	2.979	−11.315	0.543	−0.498	5.037	3.581	−1.178	1.317	4.368	−8.901
	(3.23)	(−11.8)	(0.77)	(−0.25)	(9.54)	(4.28)	(−1.97)	(1.31)	(5.37)	(−7.51)
c_{1st}	−0.006	0.095								
	(−0.37)	(3.95)								
σ^2_{st}	0.012	0.026	0.012	0.030	0.018	0.048	0.010	0.028	0.010	0.023
	(77.61)	(63.80)	(72.00)	(109.3)	(94.79)	(37.31)	(65.72)	(68.72)	(69.96)	(71.27)
No. of days in s_t [a]	48	18	18	5	111	21	14	6	29	12
SPEC	0.76	2.80	0.16	0.57	1.27	1.06	0.05	0.39	1.25	4.23
Optimal h. ratio β	0.86	0.93	0.92	0.68	0.74	0.64	0.73	0.87	0.94	0.87
Function value	14,434.433		14,250.008		12,672.172		14,567.170		15,168.224	

[a] Average expected duration of being in state s_t.

parameters:

$$L(\psi)=\sum_{t=1}^{T}\log g(r_{f,t}\big|Y_{t-1},\psi), \tag{14}$$

where T is the total number of sample observations.

In this paper, the identification process of the nature of the regimes, essential for the interpretation of a Markov-switching model, relies on the estimates of Eq. (10) and on the analysis of the behavior over time of the state probabilities.

Table 6 sets out the estimates of Eq. (10) for the five commodity markets. The quality of fit is highly satisfactory since, with the exception of cotton, the relevant coefficients change across regimes and are significantly different from zero. The regime (state) 2 variances are from two to three times larger than those of regime (state) 1. The probability of switching from a low variance to a high variance state p_{12} is lower than the probability of switching from a high variance to a low variance state p_{21}. For instance, in the case of oil, the transition probabilities are $p_{12}=0.9\%$ and $p_{21}=6.5\%$; these findings indicate that the average expected duration of being in state 1 is close to 111 working days (about 5 months) and the average expected duration of being in state 2 is of 21 working days.[16] The number of days of high volatility is, on the whole, rather small.

A relevant difference in hedging and speculation can be easily detected across regimes. In the case of copper and soybeans, a risk-averse speculative behavior in state 1 is reversed with the change of regime; speculators increase their demand for futures contracts whenever the volatility rises. In the remaining markets, speculators behave in the opposite way. Their reaction to a high futures return volatility decreases in the case of oil and becomes nil in the case of silver. (It is always nil in the case of cotton.) This finding is of interest for the interpretation of the main drivers of the volatility

[16] The average expected duration of being in state 1 is computed according to Hamilton (1989) as $\sum_{i=1}^{\infty} ip_{11}^{i-1}(1-p_{11})=(1-p_{11})^{-1}=(p_{12})^{-1}$.

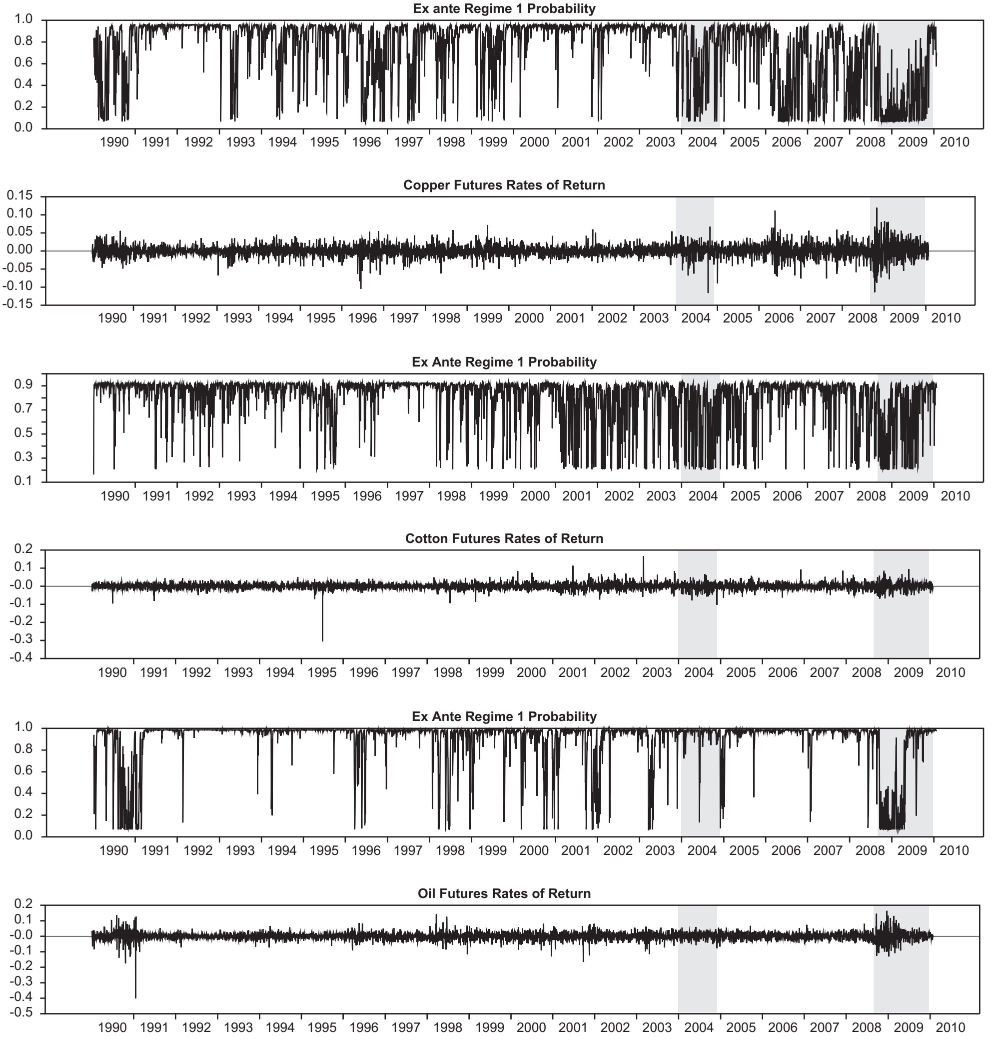

Fig. 1. Ex ante regime 1 probabilities and corresponding futures rates of return for copper, cotton and oil.

movements for these commodities: it suggests that volatility changes, in regime 2, may be due more to spillovers from monetary, financial, and exchange rate markets than to endogenous market speculation. Overall these results show that speculator risk aversion is time varying and that risk flows from hedgers to speculators according to volatility regimes, corroborating in this way, despite some qualitative differences, the findings of Cheng, Kirilenko, and Xiong (2014).

The weighted coefficient ratio (SPEC) set forth in Table 6 suggests – being greater than 1 – that in state 2 the impact of speculation on futures price dynamics is strong for all the commodities, with the exception of cotton and silver, where the probability of being in state 2 is very low. It is worth noting that for oil returns, even if the SPEC measure is always larger than 1 since speculators are more reactive than hedgers to volatility in both states, the index declines in the second regime, as consumers increase their hedging in periods of high return variability and speculators tend to leave the market.

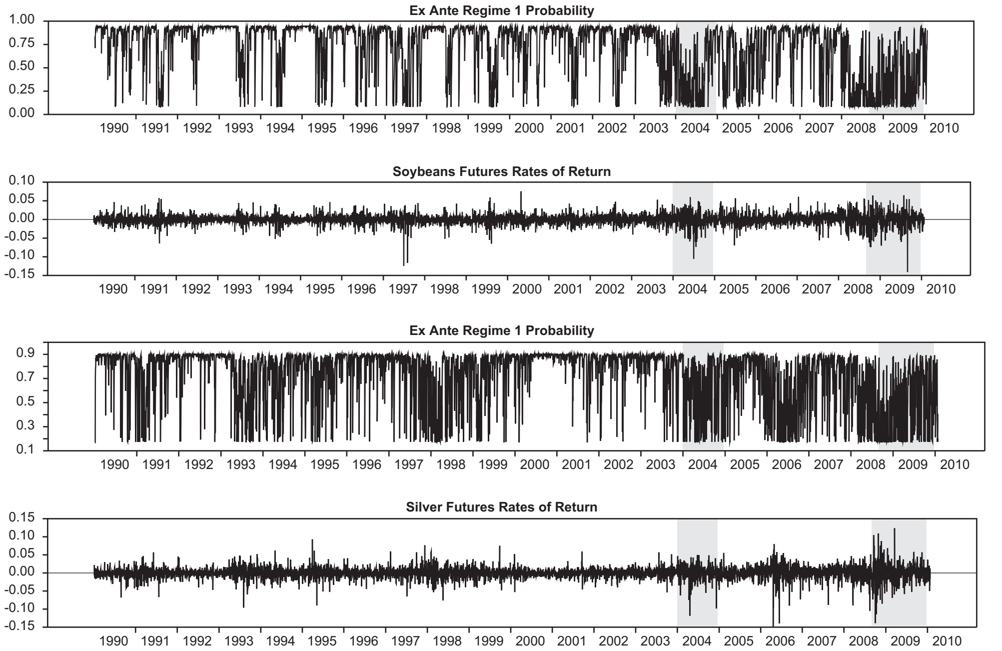

Fig. 2. Ex ante regime 1 probabilities and corresponding futures rates of return for soybeans and silver.

Finally, the optimal hedge ratio β tends to increase during the high volatility period in the case of silver and copper (a result due to the significant increase in correlation between spot and futures returns), while for oil, cotton, and soybeans the reverse holds true.[17]

Figs. 1 and 2 provide useful insights on the dating of the regime shifts. The upper graph of each figure shows the behavior over the sample of the time t ex ante probability that the market is in regime 1. The lower graph shows the rate of return of the corresponding futures contract. The figures show that regime 1 may be associated with periods in which return variability is low (and thus regime 2 with periods in which it is high). Each market is affected by bouts of high variability. They do not coincide in the first half of the sample and tend to be more synchronized in the second half, a symptom of the growing integration of the commodity markets. Shaded areas identify the 2004 and 2008/2009 periods of high volatility that are common to most commodities. The former mainly reflects the demand pressure from the BRICs, while the latter is due to the consequences of the Lehman Brothers crisis. In the context of our model, we are unable to provide additional insights. Additional idiosyncratic volatility shifts occur in each market. As for oil, the 1991 Iraq invasion of Kuwait, the 1998 Russian and Indonesian (oil) crises, and the 2003 second Iraq war can be easily detected.

Table 7 reports the correlation coefficients between the probability 1 regime and the daily rate of return and standard deviation of the corresponding futures contract. As expected, we find a large negative and significant correlation coefficient between the regime 1 probabilities and the daily standard deviations. We detect, however, also a significant positive correlation of these regime probabilities with futures returns. This result indicates, especially for silver, a more complex identification of the nature of the state variable s_t. Regime 1 is to be associated with both low futures return variability and, to a lesser extent, with positive futures price rates of change (i.e., possibly with

[17] The correlation between the spot and futures returns is generally stronger in the high volatility regime. In the case of cotton and soybeans, however, the increase is small (3.75% and 1.16%, respectively). This lack of reaction to volatility shifts may explain the portfolio risk minimization results of Table 5, where, for these commodities, the time-varying conditional hedge ratios are outperformed by the constant OLS optimal hedges.

Table 7
Identification of the nature of regime 1.
This table presents the correlation coefficients between regime 1 probability and daily futures returns and the corresponding standard deviations. *t*-Statistics are reported in parenthesis.

	Copper	Cotton	Oil	Silver	Soybeans
$r_{f,t}$	0.032	0.051	0.077	0.114	0.029
	(2.23)	(3.62)	(5.42)	(8.11)	(2.08)
$\sigma_{r_{f,t}}$	−0.582	−0.715	−0.554	−0.718	−0.627
	(−50.39)	(−72.02)	(−46.96)	(−72.70)	(−56.77)

a bullish market), and regime 2 with high return variability and negative futures price rates of change (i.e., with a bearish market).[18]

6. Conclusions

In this paper, we examine the dynamic behavior of futures returns on five commodity markets. The interaction between hedgers and speculators is modelled using a highly non-linear parameterization where hedgers react to deviations from the minimum variance of the hedged portfolio and speculators respond to standard expected risk returns considerations. The relationship between expected spot and futures returns and time-varying volatilities is estimated using a non-linear in mean CCC-GARCH approach. The results point to the suitability of this choice because of the quality of fit and of the sensible meaning of the model's parameter estimates. Our findings corroborate the idea that future prices depend on the interaction of time-varying risk-averse financial traders and hedgers (Acharya, Lochstoer, and Ramadorai, 2013; Cheng, Kirilenko, and Xiong, 2014).

We allow the demand of futures to be dependent upon the “state of the market” via a Markov regime-switching approach. Both visual inspection and correlation analysis indicate that regime 1 is associated with periods in which return variability is low and regime 2 with periods in which it is high. The analysis of the timing of the regime shifts allows us to reach an interesting result: in the second half of the sample, regimes of high volatility tend to coincide. This growing integration is due to the financialization and globalization of the commodity markets. Differences across regimes in hedging and speculative behavior are distinctive and not homogeneous across commodities. The impact on futures returns of the ratio of speculative to hedging drivers seems to be strong, when market volatility is high, in three out of the five markets of the sample.

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[18] According to the standard ADF unit root tests, the time *t* regime 1 probability time series are always I(0).

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