# The hedgers' response to price changes in energy futures markets*

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**Abstract**

In this paper, we investigate whether hedgers' positions in commodity markets are related to contemporaneous and past returns. From CFTC releases, the positions of traders are publicly available at the weekly frequency, while futures prices can easily be accessed on a daily basis. We make use of mixed-data sampling (MIDAS) as developed in Ghysels et al. (2006, 2007) to use higher frequency variables (returns) as explanatory variables for lower frequency variables (positions of traders). We show that financial practices in energy futures markets differ from practices in other commodity markets. Specifically, hedgers' positions in energy futures markets cannot be statistically related to past or present returns while returns help to predict positions in non-energy commodity markets.

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*Keywords*: energy futures markets, crude oil, hedging, speculation.

# 1 Introduction

This paper deals with the reaction of hedgers to past and present returns in U.S. energy commodity futures markets. Using recent econometric techniques allowing to consider explanatory variables at various frequencies, we consider daily returns as exogenous variables to explain weekly positions of numerous categories of traders as classified by the Commodity Futures Trading Commission (CFTC). Our results indicate that there is no significant relationship between positions and past returns in energy commodity futures markets while the opposite is found in a panel of non-energy commodity markets.

Following the 2008 boom/bust in commodity markets and in energy markets in particular, the Dodd-Frank Act commissioned the CFTC to set position limits to avoid what is called *excessive speculation*. While difficult to precisely define, *excessive speculation* is widely blamed in policy circles and in medias for causing higher prices and possible bubbles in commodity markets. The CFTC is still working on the possibility to set such limits but fears that setting position limits would affect liquidity and also reduce counterparties for *bona fide* hedgers. (see Feb. 26, CFTC meeting). Commodity markets have undergone major changes over the past two decades. The popularity of commodity-related financial instruments, such as commodity indices, has led many observers to conclude that commodity markets are now more intimately connected to financial markets, and so may also co-move more significantly (Tang and Xiong (2012), Cheng and Xiong (2013), Basak and Pavlova (2016), Hamilton and Wu (2015)). While a greater number of participants in commodity markets may bring about improved risk sharing, the *financialization* process also has been widely criticized as a potential source of excessive price volatility.

Recent literature on the financialization of commodity markets has been interested in analyzing the impact of traders' behavior on commodity prices. The usual research question used to be: "Do large positions from index or hedge funds have an impact on the price level of commodities?" An extensive literature has developed to answer this issue either theoretically (Liu et al. (2012), Baker (2014), Basak and Pavlova (2016)), or empirically (Sanders et al. (2009), Alquist and Gervais (2013), Cheng et al. (2015), Irwin and Sanders (2012), Büyükşahin and Harris (2011), Büyükşahin and Robe (2014), Etienne et al. (2015)).[1] The underlying question simple was to investigate the potential destabilizing effect of financial commodity markets on commodity prices. It seems that the literature has reached a consensus on this question in that most researchers accept the idea that positions from various groups of traders – and in particular speculators as defined by the CFTC – do not statistically cause prices. In other words, the impact of larger positions by speculators in the recent period does not appear to have an impact on price evolution in the last decade.

[1] See the surveys by Rouwenhorst and Tang (2012) or Cheng and Xiong (2014).

Our contribution to the literature in the present paper lies in examining the reverse issue that is commonly studied in recent papers. Specifically, we focus on the potential impact of prices on positions. This question has been examined in a few instances mainly in agricultural markets (Sanders and Irwin (2011), Sanders et al. (2009, 2010)). To our best knowledge, we are only aware of the paper by Boris et al. (2004) that considers the impact of prices on positions in energy futures markets. From these papers, results point to a unambiguous positive effect from prices to positions.

In contrast to the aforementioned references, we specifically consider the difference in frequencies between position and price data. Indeed, while prices are observable in almost continuous time, and easily available at a daily frequency, information on traders' positions are only publicly released weekly through the Commitments of Traders (CoT) from the CFTC. Previous contributions have aggregated price data at the weekly or monthly frequency to make regression analysis possible. Unfortunately, this practice yields a significant loss of information as most price observations are disregarded. We suggest to use MIDAS regression techniques that are especially designed to deal with variables at various frequencies. MIDAS allows, for a given futures market, to model weekly position as the dependent variable and daily prices as exogenous variables, choosing the number of days to consider as a tuning parameter. Importantly, to assess the importance of considering MIDAS regressions, we explicitly show that these regressions help in modeling the relationship between prices and positions as statistical tests conclude in the rejection of the null hypothesis that all daily weights for the lagged explanatory variables are equal.

Using data from 2006 to 2015 is U.S. futures markets, thereby covering the period of high interest known as the raise of the financialization in commodity futures markets, we study the explanatory power of prices to model positions in four energy futures markets (crude oil, heating oil, natural gas and gasoline). As such, we first extend the work by Sanders et al. (2004) focused on the 1992-1999 period where CFTC data were aggregated at a higher level thereby giving less opportunity to discover real hedger and speculator practices. On this period, the main conclusion in Sanders et al. (2004) was that a statistical relationship between prices and positions used to exist over the 1990s or, differently said, prices were able to explain future positions in energy futurs markets. Our results show the contrary on the 2006-2015 recent period considering, in addition, variables at different frequencies thereby increasing the overall explanatory power of regressions.

Our paper contributes to both the literature on the financialization of commodity markets and the existing work on financial energy markets. First, we show that energy markets are different form other commodity markets in that hedgers do not take positions in reaction to the recent evolution of prices. This result contrasts with the earlier findings in Sanders et al. (2004). We do not, however, conclude to a change of practices in energy futures markets as the methodology retained in our study is quite different from the in Sanders et al. (2004) and, in addition, the specification of categories by the CFTC has been renewed and made more precise in 2006. As such, while we are able to reach more precise conclusions than in past studies, these are not directly comparable with those from previous analysis.

Second, we show that the approach in Kang et al. (2014) consisting in running cross-section analysis for a set of commodities considering that all commodities obey a similar pattern with respect to the link between prices and position may be misleading. Indeed, we show that energy and non-energy markets exhibits very different properties. This has important implications for our understanding of energy financial markets as well as for future studies considering several commodities. Furthermore, it calls into question the deep nature of energy markets as investment tools where competitive behaviors of numerous agents such as banks, hedge funds and other investors might have an impact on the predictability of trading variables such as positions using prices as explanatory variables.

Our work also has implications on the recent debate that has followed the 2008 boom-and-bust in commodity prices about the possible limitations of positions for given categories of traders. The study by Cheng and Xiong (2014b) demonstrates that hedgers in agricultural futures markets trade too much with respect to their hedging needs.[2] We show this is not the case in energy futures markets thereby questioning the issue of imposing limits in these markets.

The plan of the rest of the paper is as follows. In the next Section, we present the MIDAS methodology along with the price and position that are used for the estimation. Section 3 provides empirical results. The last Section concludes.

# 2 Empirical approach

## 2.1 Data

We consider four energy commodity markets (crude oil, gas, gasoline, heating oil) along with four non-energy commodity markets (copper, wheat, coffee and live cattle) for the sake of comparison. The data covers the period from 2006/06/13 to 2015/02/10. The samples include 453 weekly observations of the positions and around 2200 daily observations of the excess returns. In the case of coffee, the sample starts on 2007/09/14, containing 389 weekly positions and 1936 daily returns. Price data are from DataStream.

[2]The authors show that the positions do not move only in response to output changes but also in response to price changes. In other words, hedgers *speculate* in agricultural futures markets and might reasonably be imposed position limits if this is the case for speculators.

Position data are from the Commitment of Traders (CoT) made publicly available by the CFTC each week on its website. We use the Disaggregated Commitment of Traders (DCoT) that makes a more precise categorization of participants in commodity futures markets. The DCoT dates back to 2006. At this date, the CFTC undertook to make changes to the COT report. The reasons for this review were given as follows (CFTC 2008a): Over time, for some commodities the nature of the positions carried in the COT reports has changed significantly. Prior to 1991, both the long and the short side of the commercial open interest listed in the COT reports represented traditional hedgers (producers, processors, manufacturers or merchants handling the commodity or its products or byproducts). Since that time, trading practices have evolved to such an extent that, today, a significant proportion of the long-side open interest in a number of major physical commodity futures contracts is held by so-called nontraditional hedgers (e.g. swap dealers), while the traditional hedgers may be either net long or net short (more often, the latter). This has raised questions as to whether the COT report can reliably be used to assess overall futures activity by persons who are directly involved in the underlying physical commodity markets.[3] Importantly, positions data are for the all contracts available to participants. This means that the rollover process taking place when agents switch form one contract to the next one should not have any impact on position data and, as a consequence, no impact on our empirical estimates.

In the following, the superscript $D$ designs a variable sampled at a daily frequency and the superscript $W$ denotes a weekly variable. We focus on the relationship between the daily returns and the weekly change in positions. Daily returns are calculated as the log-difference between two consecutive prices in day $t$ and $t-1$: $R_t^D = ln(p_t^D) - ln(p_{t-1}^D)$. For the sake of comparison across commodities, the variation of positions $Q^W$ between weeks $t$ and $t-1$ is normalized by open interest: $Y_t^W = \frac{Q_t^W - Q_{t-1}^W}{OI_{t-1}^W}$. The position and price changes $Y_t^W$ and $R_t^D$ are found stationary with Dickey Fuller tests at the usual significance levels. Table 1 provides summary statistics about the two variables of interest. We observe that the mean position change is between 0.52% and 2.79% meaning that substantial variations exist in commodity futures on a weekly basis. Also, extreme variations in positions (¿10%) are observed for several commodities. As for returns, mean daily returns are almost null but, again, substantial variations are observed with standard deviations that are generally above 2%.

[3]See also the explanations provided in Dewally et al. (2013) and the notes available at http://www.cftc.gov/MarketReports/CommitmentsofTraders/DisaggregatedExplanatoryNotes/index.htm

## 2.2 MIDAS regressions

Let $Y_t^W$ denote the *weekly* variation of the position between weeks $t$ and $t-1$ normalized by open interest and $R_{t-d}^D$ the *daily* return observed $d$ days before week $t$. To study the relationship between the weekly positions and the daily returns, we use MIDAS regressions. It is convenient to deal with the difference in sampling frequencies. In these models, it is not necessary to aggregate the daily returns at the weekly frequency which may lead to a loss of information and therefore to inefficient and/or biased estimates (Andreou, Ghysels and Kourtellos, 2010).

Formally, we consider the following equation:

$$Y_t^W = c + \beta \sum_{d=0}^{N_D} b_d(\theta_1, \theta_2) R_{t-d}^D + \sum_{p=1}^{P} \phi_p Y_{t-p}^W + \varepsilon_t^W \tag{1}$$

where $\varepsilon_t^W$ is the error term. In this equation, the weights $b_d(\theta_1, \theta_2)$, $d = 0, \ldots, N_D$ are assigned to the present and lagged returns $R_{t-d}^D$ and the coefficient $\beta$ gives the final impact of the aggregated returns on the dependent variable.

To keep the specification parsimonious, functional polynomial lags are employed for the weights. The function $b_d(\theta_1, \theta_2)$ is the exponential Almon lag[4]:

$$b_d(\theta_1, \theta_2) = \frac{exp[\theta_1(d+1) + \theta_2(d+1)^2]}{\sum_{d=0}^{N_D} exp[\theta_1(d+1) + \theta_2(d+1)^2]} \tag{2}$$

with $d = 0, \ldots, N_D$. This function implies that the weights are positive and sum up to one. It allows a parsimonious specification since only two coefficients ($\theta_1$ and $\theta_2$) are needed for the $N_D$ lags and it is is quite flexible. For different values of the two parameters, the function can take various shapes. In particular, the weights can decay at different rates as the lag $d$ increases. A declining weight with $d$ is guaranteed as long as $\theta_2$ is negative. In the particular case where $\theta = \{0, 0\}$, we obtain the standard equal weighting aggregation scheme (in this case, the daily data are aggregated to the weekly frequency with a simple average). This restriction can be tested with a LM test (Andreou, Ghysels and Kourtellos, 2010).

Our suggested model is a generalization of the regressions considered in Kang, Rouwenhorst and Tang (2014) and Fishe, Janzen and Smith (2014). In these papers, the specification involves weekly returns calculated using Tuesday-to-Tuesday closing prices, namely $R_t^W = ln(p_t^D / p_{t-5}^D)$, such that standard econometric tools can be employed. This amounts to imposing equal weights on the first 5 daily returns and constraining the other weights to be zero. In our work, we do not impose uniform weights of the returns

[4] Other possible specifications of the MIDAS polynomials are based on beta or step functions. See Ghysels et al. (2007) for a presentation of the various parameterizations of the weights.

over the current week. Moreover, we incorporate the information provided by returns beyond the current week and the MIDAS framework allows weights to vary across commodities.

The parameters of the model are estimated by nonlinear least squares.[5] The numerical estimation is done with 100 random draws of the initial values of the parameters. The autoregressive order $P$ is selected by minimizing the BIC criterion in the range $\{1, \ldots, 4\}$. In the estimation procedure, we consider a maximum number of lagged returns $N_D = 15$. This means that we allow a dependence on the past returns over the last three weeks. This is sufficient since the function flattens for lags around 10-12 in our application, as detailed in the next section. The parameter $\theta_2$ of the Almon function is constrained to be negative, which guarantees a declining weight of $R_{t-d}$ as the daily lag $d$ increases. The standard errors are estimated using a Newey-West estimator.

# 3 Results

## 3.1 MIDAS regressions

Tables 2-3 provide the estimates and tests of significance of the models for producers and money managers. We also report the Lagrange Multiplier (LM) test of equal weights for aggregating daily returns and the $R^2$ coefficient of the regression relating the weekly change in position on the weekly change in price, as done in the earlier literature ($R^2C$). Relying on the BIC criterion[6], one autoregressive lag is generally found sufficient, except in three cases. Two lags are necessary for hedgers in long position trading crude oil and heating oil, while four lags are selected for gasoline. When the autoregressive term is significant, we generally find a positive dependence of the position change on the last variation (in line with Kang et al., 2014).

Regarding the trading behaviors, the estimated regressions suggest that hedgers in aggregate trade commodities in non-energy markets as contrarians: hedgers short more futures contracts in response to price increases and reduce their short position as the future price falls. This is visible from the estimated negative $\beta$ for long positions and estimated positive $\beta$ for short positions. As expected, speculators that are known as standard counterparties for hedgers are found to be trend followers, i.e. they increase their long position and cut their short position after price increases – estimated $\beta$ is found to be positive for long positions and negative for short positions.

[5] We use the Matlab code provided by Eric Ghysels for the estimation of the MIDAS regressions (see Ghysels, 2014 for a description of the software).

[6] The use of the AIC criterion provides very similar results. The results are available from the authors upon request.

Interestingly, the results are very different for energy commodities. First, we do not find any impact of past and contemporaneous price changes on the positions of hedgers. Indeed, while estimates are of the expected sign (except for crude oil in the case of long positions), these are not significant. The only exception is heating oil for which the estimates are significant at the 5% threshold only. Overall, our results for producers suggest that the financial practices in energy futures markets differ from practices in other commodity markets. Anyway, it seems that in energy futures markets, changes in positions cannot be associated with past price variations meaning that hedgers are not likely to be considered as having a speculative behavior. This result contrasts with the findings in Cheng and Xiong (2014b) where hedgers are found to trade on speculative motives.

Beside, we find a considerable heterogeneity among commodities and groups in the effect of price change on the positions of hedgers and speculators. For instance, the response of the short position of hedgers to the aggregated returns over the past 15 days is between 0.15 and 2.57. For money managers in long position, the coefficient on the returns ranges from 0.23 to 1.65. Hence, using cross-section analysis for a set of commodities as done in Kang et al. (2014) may be misleading. The magnitude of the coefficient $\beta$ (in absolute value) and the estimated autoregressive parameters in the regressions for long and short positions is also quite different. This result holds for both categories of traders. Hence, it is more relevant to consider short and long positions separately rather than the net position.

There is also a great disparity in the goodness of fit of the models. Overall, the models have a better fit for agricultural and metal commodities. In particular, a good explanatory power is obtained for coffee in all regressions (the $R^2$ coefficient stands around 40% for traders in short positions). By contrast, the quality of regression is very limited for crude oil and gas, especially for producers. In this case, the coefficient does not exceed 6%. The $R^2$ coefficients are higher too for speculators than for hedgers. The regressions look particularly fragile for hedgers in long position.

Finally, the results are supportive of the MIDAS approach adopted in this paper. The comparison of $R^2$ and $R^2C$ shows that the quality of regression is improved when the daily data are not converted to the weekly frequency. For instance, for hedgers in long position for wheat, the $R^2$ stands at 7% in the MIDAS regression against 3% in the model estimated on weekly data as done in the previous literature. For short positions, the coefficient increases from 17 to 23%. We also note a large improvement of the explanatory power of the model for speculative traders, especially for agricultural commodities. On average, there is a 30% increase of the coefficient for agricultural commodities and 10% for energy commodities.

An important feature of MIDAS regressions is that they allow for various weights depending on the return lag. We demonstrate the interest of such a characteristic by observing the LM test statistics reported in Tables 2-3. From these estimates, we note that the flat aggregation scheme is strongly rejected. This is confirmed by the plot of the estimated weights in Figures 1-2. The functions are hump-shaped and flatten generally for lags between 10 and 12 days, showing that the impact of daily prices changes is not uniform and persists beyond the current week. Importantly, again, there is considerable heterogeneity in the weights patterns meaning that the reaction of participants in commodity futures markets to price variations are substantially different from one commodity to another.

### 3.2 Robustness checks

To assess the stability of the results, we perform rolling regressions from June 2006 to February 2015. Figures 3-4 display the estimated coefficient of the returns in the MIDAS regressions and the corresponding t-statistics. For simplicity, the models are estimated with the autoregressive order selected in the whole sample. The results are reported for a window of 250 weekly observations (around half of our sample).[7]

Rolling regressions do not show a major change in the estimated coefficients and their significance. The coefficients keep the same sign, negative for hedgers in long position (except again for crude oil) and speculators in short position; positive for hedgers in short position and speculators in long position. However, the magnitude of the coefficient increases sharply for copper, gasoline and heating oil. The increase is more limited for wheat. For the other commodities, the coefficients are relatively steady. As found in the whole sample, the returns do not affect the positions of hedgers for crude oil and natural gas. For gasoline, the coefficient is significant at the end of the period.

## 4 Discussion and conclusion

In this paper, we investigate the impact of returns on the positions of hedgers and speculators on commodity futures markets. We find that hedgers' positions in energy futures markets are not correlated with prices while prices help to predict positions in non-energy commodity markets. Hedgers in non-energy markets act as contrarians, while speculators are trend followers.

Our findings are partly consistent with the earlier literature. For agriculture, Sanders, Irwin and Merrin (2009) obtain similar results on a set of 10 agricultural commodities for the period 1995-2006. Their results mostly reveal positive feedback trading on the side of commercial traders and contrarian strategies in the commercial group. Fishe, Janzen and Smith (2014) provide similar evidence for 6 agricultural

[7] The results are similar for other sizes of the window: 200 and 300 observations. Again, the results are available upon request.

commodities for the 2006-2012 period with weekly data from DCOT. Cheng and Xiong (2014) also find a positive correlation between hedgers' short positions and price changes on monthly data from 2006 to 2012. For energy, the results obtained by Sanders, Boris and Manfredo (2004) on the four energy commodities considered in this study over the 1992-1999 period also show that speculators follow momentum strategies while hedgers trade as contrarians. They find a significant correlation between hedgers' positions and past returns for energy commodities. Our results obtained on a more recent period suggest that energy financial markets have evolved.

An important implication of our findings is on regulation of futures markets. Should we regulate speculative positions only or, if hedgers also speculate, should we create a uniform regulation for all market participants? Our results for energy futures markets suggest that hedgers are not found to trade on price movements. While this does not mean that hedgers do not speculate, our results do not indicate that hedgers speculate, which is in contrast with the findings in Cheng and Xiong (2014b) for agricultural futures markets. As such the suggestion in Cheng and Xiong (2014b) that hedgers might also be imposed limits on position is still called into question in the case of energy markets.

# Tables

**Table 1**

Summary statistics - weekly change in positions

| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
|---|---|---|---|---|---|---|---|---|
| **PRODUCERS - LONG POSITIONS** | | | | | | | | |
| abs mean | 0.96% | 0.60% | 2.54% | 2.02% | 0.88% | 1.25% | 1.40% | 0.80% |
| std | 1.28% | 0.80% | 3.24% | 2.59% | 1.18% | 1.80% | 1.98% | 1.07% |
| max | 4.03% | 3.12% | 10.96% | 8.72% | 5.00% | 6.16% | 10.48% | 3.63% |
| min | -8.21% | -3.79% | -10.90% | -9.43% | -3.70% | -8.69% | -7.44% | -6.31% |
| T | 453 | 453 | 453 | 453 | 453 | 453 | 389 | 453 |
| **PRODUCERS - SHORT POSITIONS** | | | | | | | | |
| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
| abs mean | 1.00% | 0.61% | 2.79% | 2.17% | 1.54% | 1.94% | 2.29% | 1.30% |
| std | 1.38% | 0.84% | 3.58% | 2.76% | 2.03% | 2.61% | 3.08% | 1.67% |
| max | 3.71% | 3.27% | 13.33% | 9.45% | 9.95% | 10.44% | 11.01% | 4.32% |
| min | -10.48% | -3.66% | -10.26% | -7.92% | -6.63% | -9.06% | -15.31% | -6.70% |
| T | 453 | 453 | 453 | 453 | 453 | 453 | 389 | 453 |
| **MONEY MANAGERS - LONG POSITIONS** | | | | | | | | |
| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
| abs mean | 0.62% | 0.70% | 1.55% | 1.29% | 0.84% | 1.69% | 1.35% | 1.01% |
| std | 0.80% | 1.09% | 2.08% | 1.78% | 1.11% | 2.36% | 1.98% | 1.35% |
| max | 2.94% | 5.29% | 10.02% | 7.40% | 4.03% | 9.20% | 8.52% | 3.93% |
| min | -2.69% | -9.85% | -9.33% | -7.05% | -3.86% | -10.30% | -8.88% | -5.52% |
| T | 453 | 453 | 453 | 453 | 453 | 453 | 389 | 453 |
| **MONEY MANAGERS - SHORT POSITIONS** | | | | | | | | |
| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
| abs mean | 0.52% | 1.11% | 0.73% | 0.81% | 1.36% | 1.61% | 1.47% | 1.03% |
| std | 0.71% | 1.53% | 1.09% | 1.08% | 1.94% | 2.33% | 2.09% | 1.48% |
| max | 2.82% | 4.61% | 8.89% | 4.44% | 9.12% | 9.36% | 7.21% | 6.77% |
| min | -3.15% | -10.89% | -3.51% | -3.30% | -13.07% | -10.91% | -7.11% | -5.51% |
| T | 453 | 453 | 453 | 453 | 453 | 453 | 389 | 453 |
| **DAILY RETURNS** | | | | | | | | |
| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
| mean | 0.01% | 0.01% | 0.02% | 0.02% | 0.04% | 0.01% | 0.03% | 0.04% |
| std | 2.27% | 3.12% | 2.24% | 1.89% | 2.17% | 2.18% | 2.02% | 0.98% |
| max | 13.63% | 30.81% | 22.08% | 10.41% | 11.72% | 19.92% | 11.46% | 7.94% |
| min | -13.37% | -20.26% | -10.66% | -9.23% | -9.34% | -13.50% | -10.64% | -6.95% |
| T | 2217 | 2211 | 2210 | 2212 | 2219 | 2201 | 1936 | 2206 |

Notes: The table gives summary statistics for the weekly change in positions normalized by open interest and for the daily returns: the mean absolute value (the simple average for the returns), the standard deviation, the maximum and minimum values and the number of observations.

**Table 2**
Estimation results for producers

**LONG POSITIONS**

| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
|---|---|---|---|---|---|---|---|---|
| $c$ | 0.0003 | 0.0000 | 0.0020 | 0.0015 | 0.0001 | 0.0004 | 0.0005 | 0.0003 |
| | [0.234] | [-0.038] | [0.736] | [0.694] | [0.100] | [0.302] | [0.301] | [0.290] |
| $\phi_1$ | -0.0545 | 0.0041 | 0.0073 | 0.0146 | 0.0669 | 0.0295 | 0.0646 | 0.1273 |
| | [-0.657] | [0.047] | [0.063] | [0.160] | [0.417] | [0.301] | [0.848] | [1.330] |
| $\phi_2$ | -0.2101 | - | -0.2443 | -0.2374 | - | - | - | - |
| | [-2.102] | | [-2.573] | [-2.622] | | | | |
| $\phi_3$ | - | - | -0.1702 | - | - | - | - | - |
| | | | [-1.896] | | | | | |
| $\phi_4$ | - | - | 0.2011 | - | - | - | - | - |
| | | | [1.863] | | | | | |
| $\beta$ | 0.1950 | -0.0732 | -0.6072 | -0.5432 | -0.3536 | -0.6171 | -0.7284 | -0.7893 |
| | [1.130] | [-0.889] | [-1.196] | [-2.076] | [-2.345] | [-2.931] | [-2.655] | [-1.720] |
| R2 | 0.06 | 0.02 | 0.19 | 0.10 | 0.07 | 0.08 | 0.12 | 0.07 |
| R2C | 0.05 | 0.01 | 0.18 | 0.10 | 0.04 | 0.07 | 0.10 | 0.03 |
| LM | 3.58 | 5.07 | 5.66 | 13.97 | 18.09 | 26.62 | 38.35 | 7.91 |
| | [0.06] | [0.02] | [0.02] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |

**SHORT POSITIONS**

| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
|---|---|---|---|---|---|---|---|---|
| $c$ | 0.0002 | 0.0000 | 0.0025 | 0.0008 | -0.0009 | 0.0006 | -0.0012 | -0.0006 |
| | [0.193] | [-0.002] | [0.755] | [0.347] | [-0.596] | [0.288] | [-0.5] | [-0.44] |
| $\phi$ | -0.0279 | 0.0252 | 0.1804 | 0.0219 | 0.1448 | 0.1136 | 0.1973 | 0.2515 |
| | [-0.27] | [0.217] | [2.04] | [0.309] | [1.595] | [1.215] | [2.033] | [2.553] |
| $\beta$ | 0.2266 | 0.1483 | 0.5679 | 1.0098 | 1.4534 | 1.5489 | 2.5734 | 2.0291 |
| | [0.809] | [1.382] | [1.469] | [1.951] | [4.923] | [2.357] | [3.662] | [3.719] |
| R2 | 0.01 | 0.04 | 0.07 | 0.07 | 0.41 | 0.17 | 0.39 | 0.23 |
| R2C | 0.00 | 0.01 | 0.06 | 0.06 | 0.37 | 0.12 | 0.33 | 0.17 |
| LM | 1.90 | 5.29 | 11.43 | 22.29 | 113.96 | 23.41 | 58.33 | 35.40 |
| | [0.17] | [0.02] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |

Notes: The table gives the parameter estimations and the corresponding t-statistics in brackets. The t-statistics are computed using the Newey West standard errors. The table also reports the R-squared (R2), the R-squared of the regression on weekly data (R2C), the LM test of the null hypothesis of equal weights and its p-value in brackets (LM).

**Table 3**
Estimation results for money managers

**LONG POSITIONS**

| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
|---|---|---|---|---|---|---|---|---|
| $c$ | 0.0004 | 0.0003 | 0.0008 | -0.0002 | -0.0002 | 0.0003 | -0.0005 | -0.0004 |
| | [0.533] | [0.341] | [0.473] | [-0.117] | [-0.209] | [0.15] | [-0.306] | [-0.339] |
| $\phi$ | 0.0793 | 0.0596 | 0.2207 | 0.1236 | 0.0193 | 0.2387 | 0.1971 | 0.2050 |
| | [0.918] | [0.501] | [2.845] | [1.069] | [0.196] | [2.067] | [1.787] | [2.606] |
| $\beta$ | 0.3673 | 0.2300 | 0.9298 | 0.9688 | 0.6393 | 1.6539 | 1.4259 | 1.6521 |
| | [1.845] | [1.66] | [1.895] | [2.384] | [3.47] | [2.853] | [2.59] | [3.126] |
| R2 | 0.15 | 0.07 | 0.21 | 0.22 | 0.23 | 0.33 | 0.31 | 0.21 |
| R2C | 0.15 | 0.06 | 0.20 | 0.18 | 0.18 | 0.32 | 0.27 | 0.11 |
| LM | 41.21 | 22.24 | 36.82 | 68.92 | 59.13 | 71.80 | 54.96 | 34.43 |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |

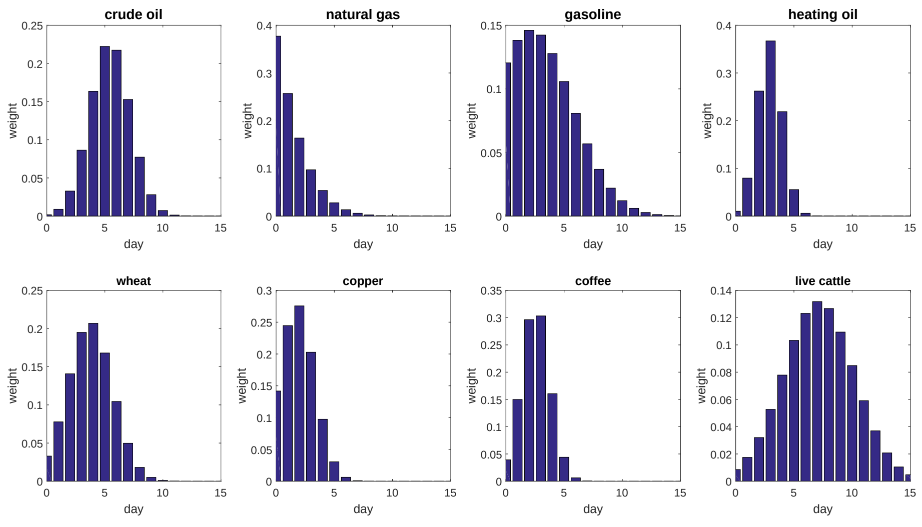
**SHORT POSITIONS**

| | crude oil | gas | gasoline | heating oil | wheat | copper | coffee | live cattle |
|---|---|---|---|---|---|---|---|---|
| $c$ | -0.0001 | 0.0005 | 0.0004 | 0.0005 | 0.0007 | 0.0011 | 0.0008 | 0.0006 |
| | [-0.088] | [0.391] | [0.445] | [0.555] | [0.427] | [0.596] | [0.592] | [0.489] |
| $\phi$ | -0.0831 | 0.1337 | 0.1021 | 0.1056 | 0.1848 | 0.1937 | 0.2046 | 0.1859 |
| | [-0.721] | [1.319] | [1.035] | [0.964] | [1.475] | [1.914] | [2.277] | [2.086] |
| $\beta$ | -0.4034 | -0.4864 | -0.2634 | -0.6413 | -1.1471 | -1.0185 | -1.6392 | -1.5474 |
| | [-2.148] | [-2.68] | [-1.445] | [-4.014] | [-3.151] | [-2.642] | [-4.023] | [-2.505] |
| R2 | 0.13 | 0.16 | 0.06 | 0.20 | 0.27 | 0.15 | 0.38 | 0.14 |
| R2C | 0.13 | 0.15 | 0.05 | 0.19 | 0.22 | 0.14 | 0.27 | 0.09 |
| LM | 24.28 | 44.84 | 16.44 | 53.44 | 54.13 | 42.85 | 55.36 | 9.53 |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |

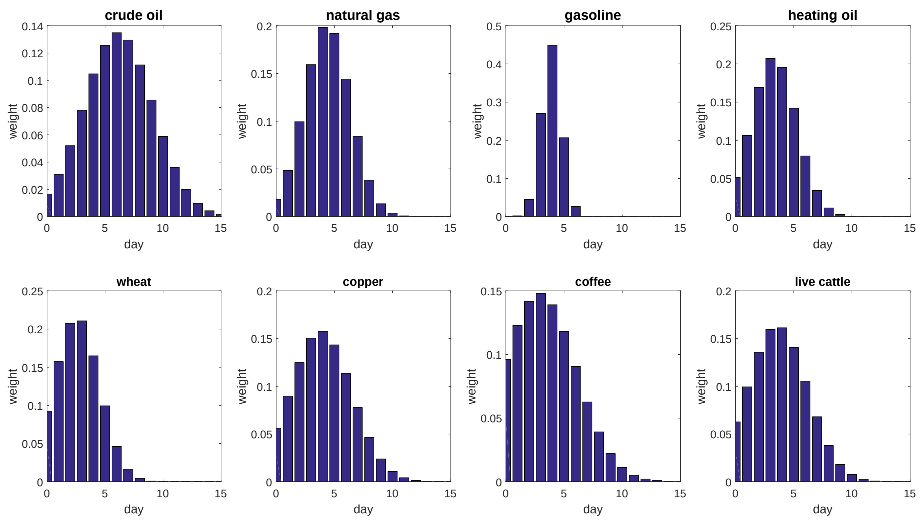
Notes: The table gives the parameter estimations and the corresponding t-statistics in brackets. The t-statistics are computed using the Newey West standard errors. The table also reports the R-squared (R2), the R-squared of the regression on weekly data (R2C), the LM test of the null hypothesis of equal weights and its p-value in brackets (LM).

# Figures

## Figure 1
Estimated weights - Producers

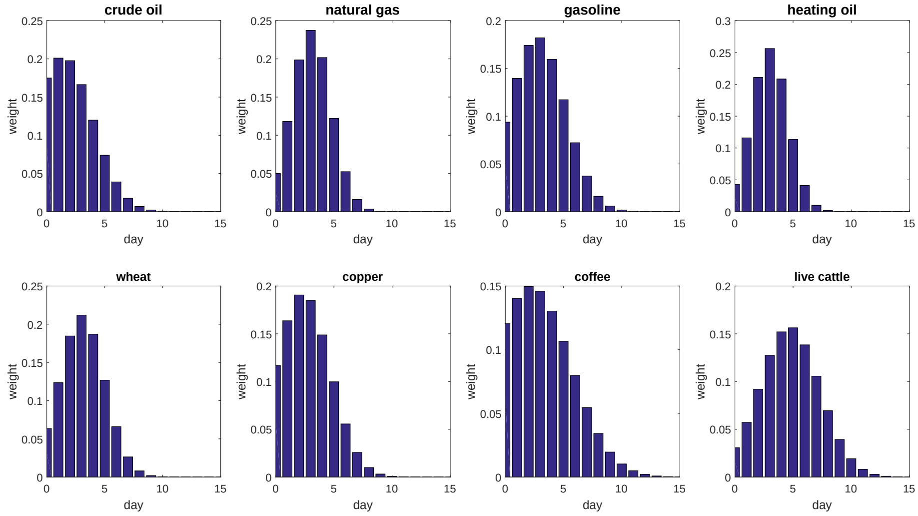



(a) Long positions

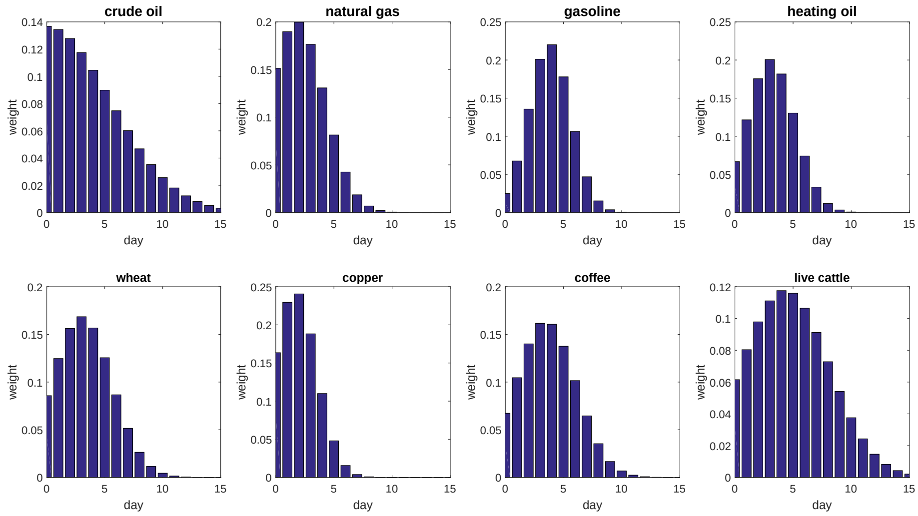



(b) Short positions

**Figure 2**
Estimated weights - Money managers

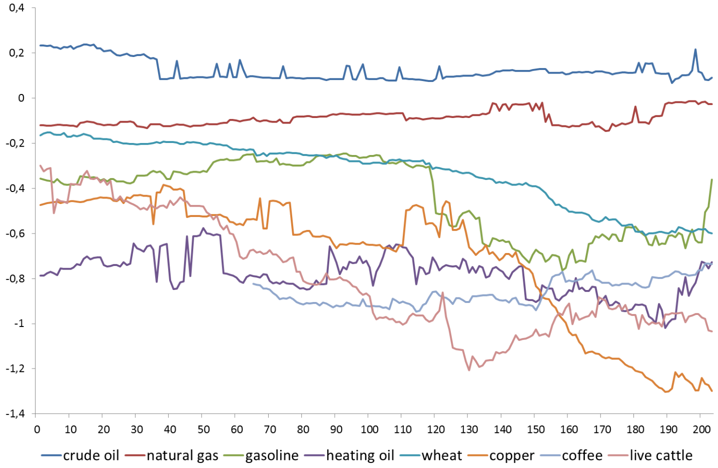



(a) Long positions

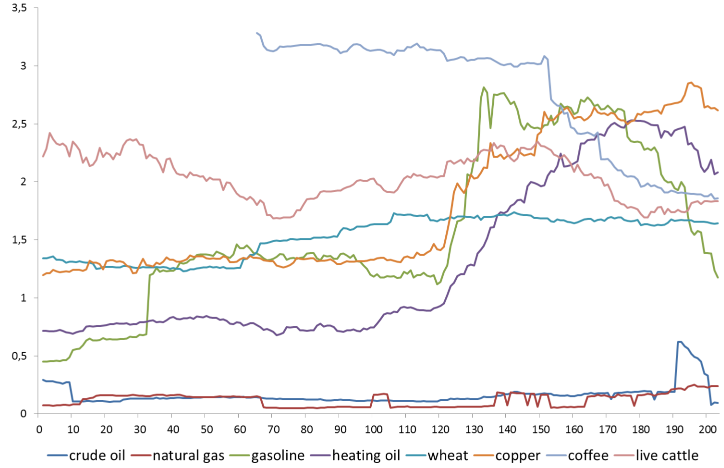



(b) Short positions

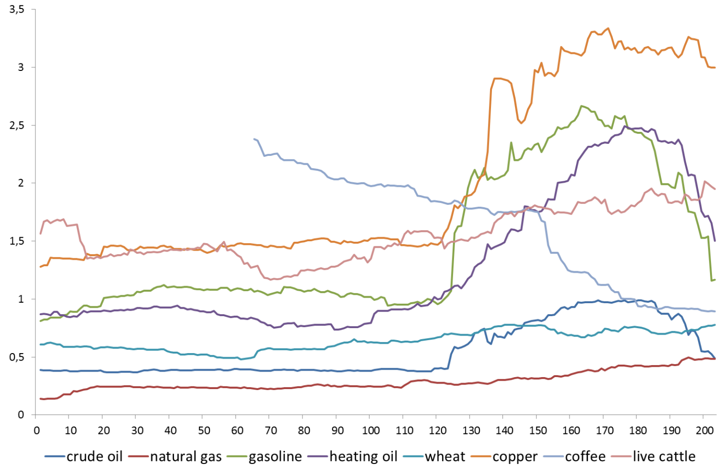
**Figure 3**
Estimated beta in rolling regressions



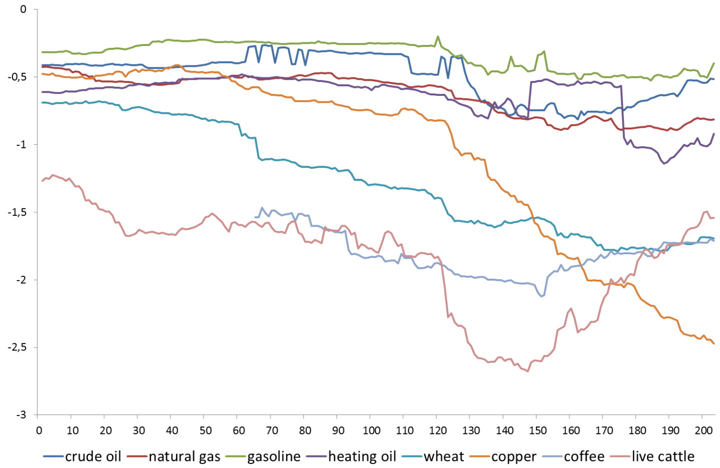

(a) Producers - Long positions




(b) Producers - Short positions

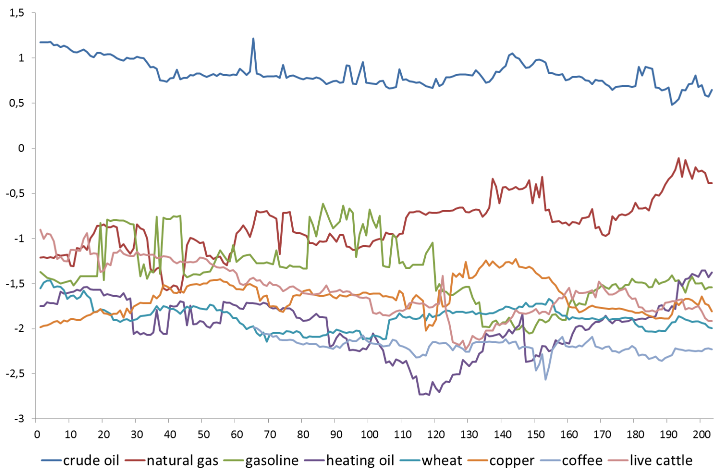



(c) Money managers - Long positions

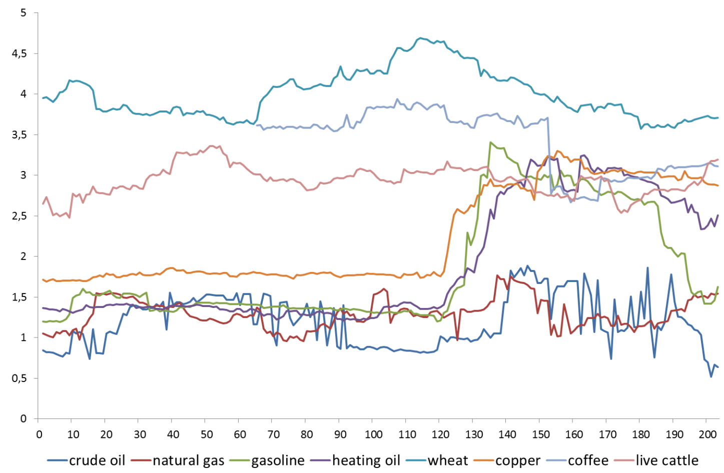



(d) Money managers - Short positions

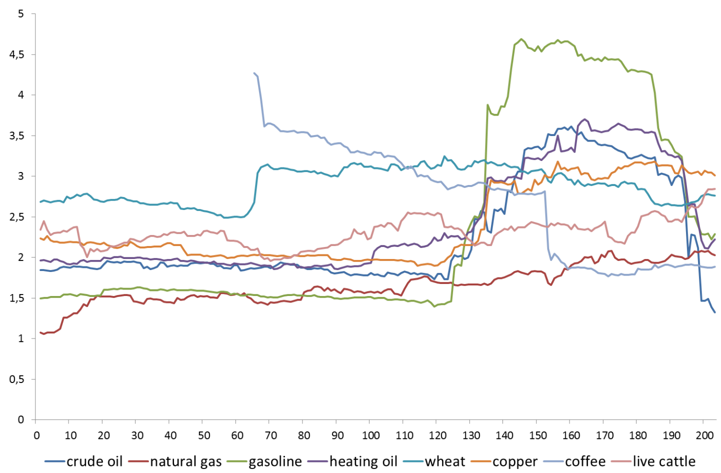
**Figure 4**
t-statistics in rolling regressions



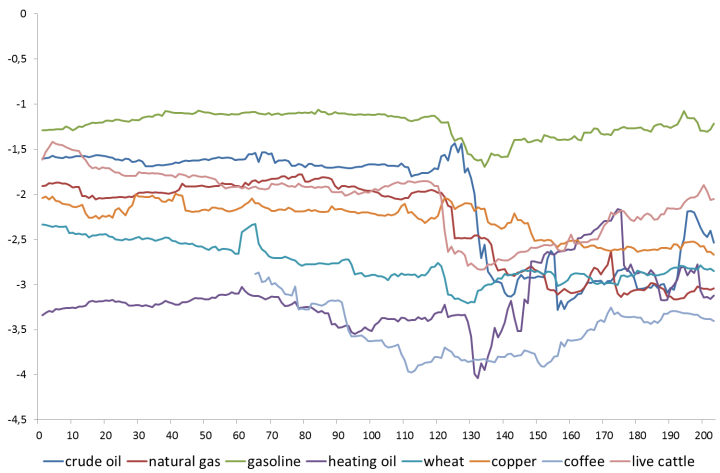
(a) Producers - Long positions



(b) Producers - Short positions



(c) Money managers - Long positions



(d) Money managers - Short positions

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