A TALE FOR TWO TAILS: EXPLAINING EXTREME EVENTS IN FINANCIALIZED AGRICULTURAL MARKETS

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Abstract

The substantial booms and busts in agricultural prices marked by extreme events across commodities lead to heated debates about the effects of speculative trading on commodity price fluctuations. This study proposes a new approach to understanding extreme events and boom–bust processes in agricultural markets. Using weekly futures data for seven indexed agricultural commodities during 2006 to 2014, we find that extreme price changes, located in the 10% tails of the distribution, cluster across agricultural markets. We then implement a multinomial logit model to investigate which factors are associated with the propagation of extreme events. Specifically, we disentangle three transmission conduits. (1) The macroeconomic conduit captures the possibility that the synchronized extreme price events are triggered by business-cycle driven demand shifts mainly in emerging economies. (2) The financial conduit refers to potential links between extreme returns and the increasing flow of money from financial participants into agricultural futures markets. (3) Finally, the energy conduit accounts for possible spillover effects due to oil price shocks and the demand for biofuels. Our results indicate an important role of managed money positions and ethanol prices while the real demand channel remains mostly insignificant.

Keywords: agricultural prices, futures market, tail events, GARCH analysis, multinomial logit
JEL Code: C25; C58; E44; Q14

1. Introduction

Following the collapse of stock markets in early 2000s and fueled by tentative evidence that commodity futures offer diversification against stock market downturns (Erb and Harvey, 2006), commodity futures have become a popular asset class for several financial institutions and the general investment community (Rouwenhorst and Tang, 2012). The creation of new investment vehicles, such as exchange-traded index funds, has facilitated the rapidly rising participation of financial investors in commodity markets which is reflected by an impressive growth in the levels of activity as measured by open interest in commodity futures from $103 billion at the end of 2003 to $509 billion in July 2008 (Hong and Yogo, 2010). Concurrently, a broad set of commodities across the energy and agricultural sector has experienced synchronized sequences of large price swings, drawing renewed attention from policymakers and academics to commodity markets. A central and vigorously debated question is whether traditional supply and demand fundamentals or new financial amplification mechanisms dominate price formation in financialized commodity derivatives markets (Cheng and Xiong, 2014; Irwin and Sanders, 2012).

The present study aims to broaden the discussion by assessing the occurrences of tail events in agricultural commodity markets during the boom–bust period from June 2006 to July 2014. Although fat tails in the distribution of commodity returns are a well-known phenomenon (Mandelbrot, 1963), empirical research has markedly overlooked the driving factors behind such disruptive price moves. We characterize the propagation of tails events across agricultural markets, its economic significance, and its determinants using a multinomial logit approach following Koch (2014) and Bae et al. (2003). In particular, our approach allows us to pinpoint the relevance of three conduits through which tail events may operate: (1) The "macroeconomic conduit" captures the possibility that synchronized extreme price events are triggered by business-cycle driven demand shock mainly from emerging economies (Krugman, 2008; Kilian and Hicks, 2013). (2) The "energy conduit" accounts for possible spillover effects due to oil price shocks and the demand for biofuels (e.g. Myers et al., 2014; Algieri, 2014b). (3) The "financial conduit" refers to the financialization and speculation in commodity markets and captures potential links between extreme returns and the increasing flow of speculative money into agricultural futures markets (Etienne et al., 2014; Tadesse et al., 2014).

We use weekly futures data for the seven commodities with active liquid futures contracts included in the S&P GSCI Agriculture Index, namely cocoa, coffee, corn, cotton, soybeans, sugar, and wheat. Given that commodity index investments have experienced a significant growth over time, these commodities are particularly well suited to the analysis at hand because financial factors should have a larger influence on indexed commodities (Tang and Xiong, 2012). We first filter each original return series with AR-GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models including a set of exogenous variables. This pre-filtering removes the serial clustering of extreme events that is due to serial correlation and/or periods of heightened volatility. In addition, the inclusion of common predictors of commodity returns in the procedure (e.g. exchange rate, yield spread) reduces the possibility that we attribute the clustering of extreme price changes to commonly known risk factors. We then employ the residuals from these regressions to identify extreme returns for each agricultural market. We define extreme returns as located in the 10% tails of the distribution, whereby we treat negative extreme returns ("bottom-tail events") separately from positive extreme returns ("top-tail events"). Finally, we create a categorical dependent variable that indicates the number of agricultural markets that simultaneously experience top-tail and bottom-tail events and estimate a multinomial logit model to evaluate the likelihood of observing each tail event category and their drivers. The potential drivers are grouped into three conduits and include, among others, the Baltic dry freight index (macroeconomic conduit), ethanol futures price (energy conduit), and net position changes of two types of financial traders, managed money traders and commodity index traders, provided by the US Commodity Futures Trading Commission (financial conduit).

Our main findings are as follows: First, with reference to the macroeconomic channel, demand factors remain mostly insignificant which indicates that traditional market fundamentals have little role in explaining extreme price changes despite their undisputed general impact on prices. Second, we find strong evidence that managed money positions help explaining the transmission of joint extreme price changes. In fact, this financial conduit variable has the strongest impact on tail events in either direction and, in particular, for synchronous tail events. For example, the strongest increase of the net long position results in a probability of extreme price rises in two or three (four or more) markets equal to about 26% (35%). In contrast, index traders have only little impact on tail events. In addition, there is some evidence of shock spillover effects from the stock market to agricultural markets. Finally, regarding the energy conduit, oil price returns do not trigger any tail events in agricultural market, while ethanol returns are highly significant for synchronous tail events of multiple agricultural commodities. The dominant role of ethanol prices compared to oil prices suggests that the agricultural markets are increasingly linked to energy markets through the demand side (biofuel use) rather than the production cost side.

The remainder of the study is organized as follows. Section 2 reviews the literature on the topic. Section 3 describes the data used. Section 4 first presents the GARCH and multinomial logit regression methodology, and then discusses the results. Section 5 concludes.

2. Literature review

Since the 2007-2008 price spikes, much research has focused on traditional and new drivers of agricultural commodity prices. While classical supply and demand fundamentals, like harvest failure, stock-to-use ratios and demand growth, remain important determinants of prices, energy and financial market linkages have become more important (Tadesse et al., 2014; Abbott 2009; Trostle, 2010). There are two different concerns that need to be distinguished: One is the "excessive speculation" hypothesis which claims that excessive speculation in commodity markets could push up futures and spot prices above levels justified by market fundamentals (i.e. they fuelled a "bubble"); the second is the "financialization hypothesis" stating that, driven by financial inflow and new investment vehicles, commodity markets are experiencing increasing price co-movements with financial markets, so that shocks from financial markets could transmit to commodity markets and destabilize them.

On the speculation hypothesis, theoretical models are able to assess whether specific trading strategies can destabilize prices or fuel a bubble. These models are often agent-based models where some traders have bounded rationality or behave according to stylized trading rules (e.g. Westerhoff, 2005). Nevertheless, it is also possible to show that speculation can destabilize prices in a setting of fully rationally traders without the existence of any market frictions (Hart and Kreps, 1986). As the models are very stylized or rely on assumptions that are difficult to observe on available data, their empirical validation is difficult to accomplish. Rather, empirical analysis on speculation attempts to find (statistically significant) correlations between the activities of specific trader groups and prices. This reduced-form approach is often confronted with a severe identification problem which makes it difficult to conclude about causal effects. Granger causality tests are widely used, but they show only weak or mixed evidence on the impact of trading activities on returns (Robles et al., 2009; Brunetti et al., 2011, Aulerlich et al., 2013). Granger causality tests are, however, problematic as the considered time-lag (typically one week) is too long to infer about causal effects in liquid markets where transactions have an immediate impact on prices (Gilbert and Pfuderer, 2014). Additionally, Granger causality tests are likely to suffer from omitted variable bias on market fundamentals and non-rejection of non-causality can occur despite the presence of causal effects (Grosche, 2014). Other works have integrated market fundamentals with speculation and trading activities. Tadesse et al. (2014), Algieri (2014a) and Gilbert (2010) find a significant and positive impact of speculation (non-commercial traders' market activities) or index funds investment on prices and returns, but not on volatility (Tadesse et al., 2014). Henderson et al. (2014) also find a positive and significant impact of commodity market inflows in a dataset of transactions where trading based on the arrival of new information can be ruled out. In contrast to these previous studies, we investigate the link between speculative trading and commodity price behavior exclusively during periods of extreme fluctuations. This focus on extreme events is motivated by the observation that fat tails in the distribution of commodity returns are a well-known phenomenon that is hitherto not fully understood.

With respect to the financialization hypothesis, there have been several attempts to theoretically model spillovers between financial markets and commodity markets due to investments across asset classes. Basak and Pavlova (2013) use a dynamic endowment-economy model with two heterogeneous agents in which institutional investors (in contrast to traditional investors) are benchmarked to a commodity index. They show that benchmarking creates a spillover mechanism with increases in correlations amongst commodity futures as well as in stock-commodity correlations. In a similar vein, Liu et al. (2011) predict that correlations between commodity prices increase if the different commodities are subject to correlated financial demand through cross-holdings in investor portfolios. This is in line with the intuition according to which the inflow of speculative investors has linked commodity futures markets that have been segmented before. Several findings from empirical studies are consistent with these theoretical motivations. Tang and Xiong (2012) show that price correlation between indexed commodities have increased in recent years to significantly positive levels (from levels close to zero). In addition, Silvennoinen and Thorp (2013) point out that correlations between commodities and stocks have turned significantly positive – from negative levels of the past. Büyüksahin and Robe (2014) further document that the increase in commodity-stock correlations can be explained by trading positions of hedge funds. Grosche and Heckelei (2014) find stronger volatility spillovers across asset classes during and after the subprime crisis; this increasingly reduces the benefit of agricultural commodities for diversifying investment portfolios. Other studies, motivated by the financial distress of financial institutions during the 2008-09 crisis, emphasize a risk reallocation in commodity markets between financial traders and hedgers. Cheng et al. (2014) find that financial institutions became consumers rather than providers of liquidity during the crisis. Marshall et al. (2013) show strong liquidity commonality in commodity markets with speculators withdrawing liquidity in different commodities at the same time following market declines. This liquidity crunch can amplify shocks and cause commonality in the price fluctuations across different markets. A limitation of existing studies in this strand of literature is their focus on correlations, which give equal weight to small and large price changes. Instead, we focus on the evaluation of cross-market linkages in an extreme price environment drawing on multinomial logistic regression.

3. Data description

With the objective to assess the occurrences of extreme price events and understand the impact of trading activities and other factors on extreme episodes, we have collected weekly data for the seven commodities entering the S&P GSCI Agriculture Index. Our analysis is carried out on weekly basis, given that traders' positions are not available at a higher frequency. In detail, we have considered futures closing prices released each Tuesday for each agricultural commodity. The futures contracts for corn, soybeans and wheat are traded at the Chicago Mercantile Exchange Group (CME), the futures contracts for cocoa, coffee, cotton, and sugar are traded at the Intercontinental Exchange (ICE). We have used the first generic futures contracts series (which considers at each date the price of the contract with closes maturity) for the selected commodities ranging from 20 June 2006 to 22 July 2014. Future prices have been collected from Bloomberg and their behavior is sketched in **Figure 1**.

Data on trading positions is provided by the US Commodity Futures Trading Commission (CFTC) in its Historical Commitments of Traders reports on futures contracts traded. Every Friday, the CFTC publishes the Disaggregated Commitments of Traders report that provides aggregate positions on the prior Tuesday of traders identified through the CFTC's and the exchanges' reporting systems. The report provides a breakdown of positions held by different types of traders. "Commercial traders" (known as "hedgers") are distinguished into (i) processors and merchants, and (ii) swap dealers. "Non-commercial traders" (commonly referred to as speculators) are categorized as (iii) managed money (MM) traders and (iv) other non-commercial traders. Since 2007, the CFTC also publishes the Supplemental Commodity Index Traders report that contains the positions of commodity index traders (CIT) for seven considered grain and soft commodities.

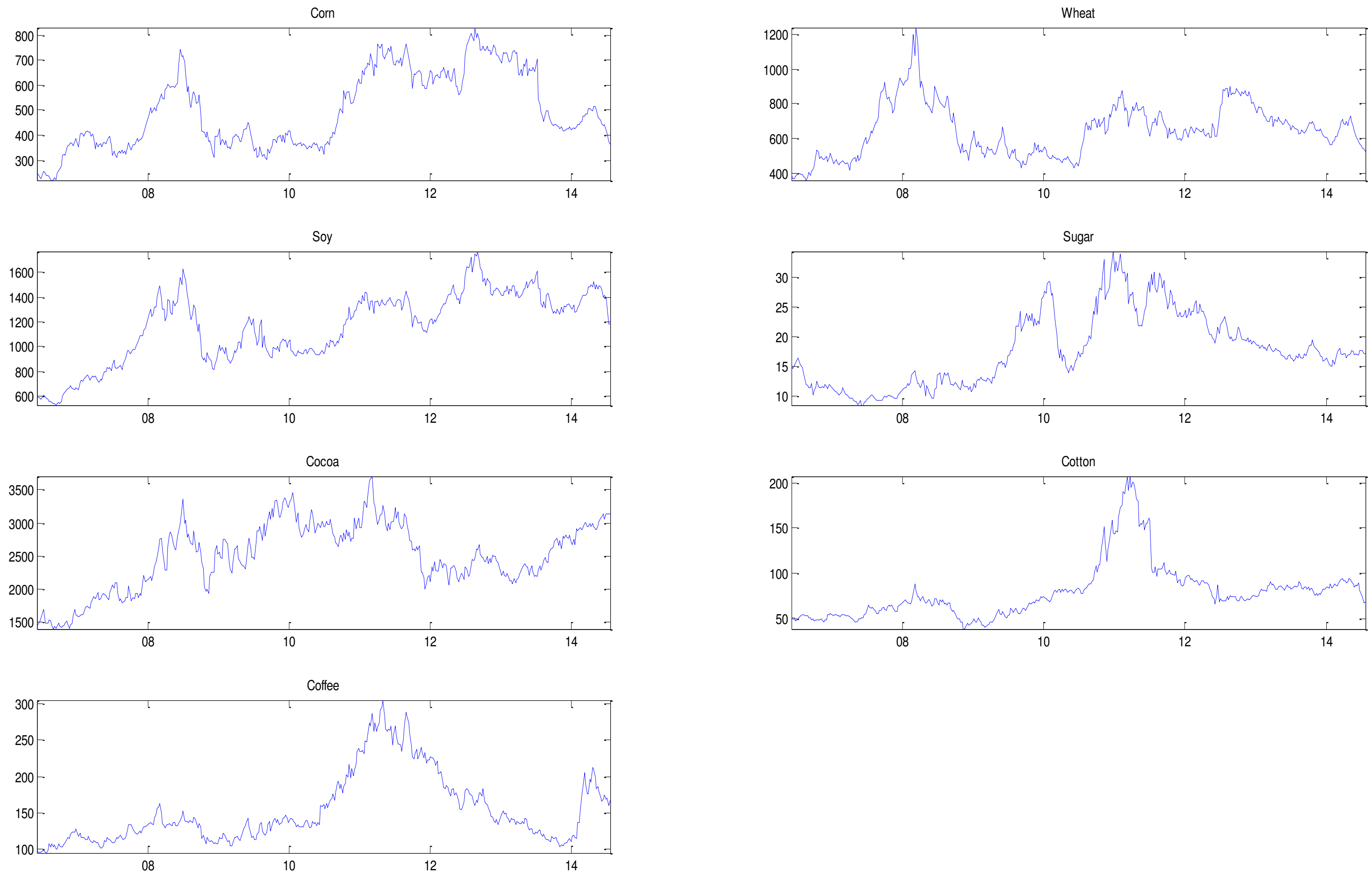
The other financial and macroeconomic variables included in the analysis are: a) light sweet crude oil futures, also known as West Texas Intermediate oil (WTI) futures; b) ethanol futures; c) the Standard & Poor's 500 index (S&P 500); d) the dollar effective exchange rate index; e) the Baltic dry freight index; f) the CBOE volatility index (VIX); g) the MSCI emerging markets index, h) the US generic govt. 10 year yield; i) the US three month T-bill (short rate); j) the Treasury–Eurodollar (TED) spread, k) the spread of Moody's AAA corporate bond over the T-bill (yield spread), l) the spread of Moody's BAA corporate bond over the 10-year constant maturity Treasury yield (credit spread). They are also considered for every Tuesday to be consistent with the CFTC data. A detailed data description is reported in **Table 1**.

Table 1 Data

Commodity futures prices	**Bloomberg Ticker**
Generic 1st Cocoa futures contract (ICE formerly NYBOT)	CC1 Comdty
Generic 1st Coffee futures contract (ICE formerly NYBOT)	KC1 Comdty
Generic 1st Corn No. 2 Yellow futures, US$ (CME GROUP)	C 1 Comdty
Generic 1st Cotton futures contract (ICE formerly NYBOT)	CT1 Comdty
Generic 1st Soybean No. 2 Yellow futures, US$ (CME GROUP)	S 1 Comdty
Generic 1st Sugar No. 11 futures, US$ (ICE formerly NYBOT)	SB1 Comdty
Generic 1st Wheat futures, US$ (CME GROUP)	W 1 Comdty
Macro and financial variables	**Bloomberg Ticker**
Generic 1st WTI Crude Oil futures, US$ (CME GROUP/NYMEX)	CL1 Comdty
Generic 1st Ethanol futures, US$ (CME GROUP)	DL1 Comdty
Standard & Poor's 500 (CME GROUP)	SPX Index
Dollar Index – Spot[1] (NYBOT)	DXY Curncy
Baltic Dry Freight	BDIY Index
CBOE Volatility Index	VIX Index
MSCI Emerging Markets Index	MXEF Index
US generic 10-year Treasury yield	USGG10YR Index
US three month T-Bill	USGG3M Index
TED Spread	BASPTDSP Index
Moody's AAA Corporate Bond yield	MOODCAAA Index
Moody's BAA Corporate Bond yield	MOODCBAA Index

[1] US effective exchange rate index tracks the performance of a basket of leading global currencies versus US dollar.

Figure 1 Commodity futures prices



4. Empirical Analysis

In this section we first filter each raw return series to control for the exposure of agricultural futures to common risk factors and to avoid serial correlation in agricultural returns. By adopting a GARCH approach, the volatility becomes conditional on past volatility and returns. This allows us to better capture the serial clustering of extreme events and volatilities which characterizes most price series. We then turn to the identification of extreme returns located in the 10% tails of the distribution. As GARCH-filtered returns are used to calculate the tails of the distribution, the GARCH approach basically ensures that only "new" extreme events (out of periods with relatively low volatility) will be considered. Finally, we use a multinomial logit model to evaluate the joint occurrences of large absolute value returns and the drivers of each state.

4.1 Filtering procedure: the GARCH approach

We begin with an analysis of the statistical properties of our agricultural price data in **Table 2**, to motivate the use of a filtering procedure. First, results of the Augmented–Dickey–Fuller (ADF) tests (Panel A) suggest taking first differences to obtain stationary time series at conventional significance levels in all cases. Consequently, weekly prices are transformed into continuously compounded weekly returns (**Figure 2**) by taking natural logarithms, differencing and multiplying by 100. Second, the descriptive statistics reveal skewed, fat-tailed returns as well as significant serial correlation and ARCH effects in returns (Panel B). More precisely, the Ljung-Box autocorrelation tests reject the null of no serial correlation for four of the seven commodities (at the 10% significance level). The ARCH LM tests based on Engle (1982) suggest that five return series exhibit signs of volatility clustering (at the 10% significance level).

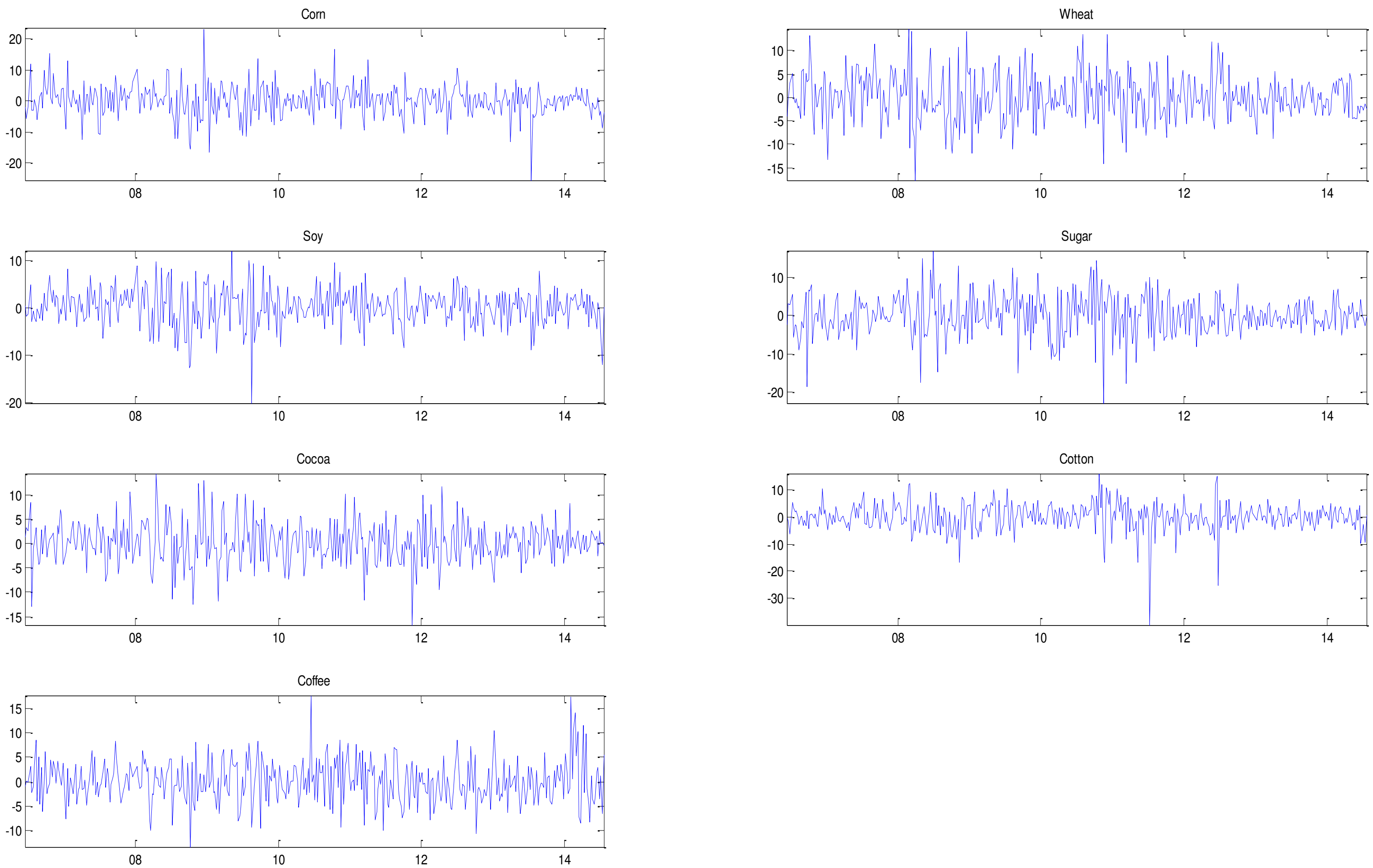
Table 2 Summary statistics of raw weekly agricultural futures returns

	Cocoa	Coffee	Corn	Cotton	Soy	Sugar	Wheat
Panel A: Stationarity							
Level							
ADF statistic	-2.02	-1.70	-2.28	-1.82	-2.31	-1.84	-2.77
p-value	0.28	0.43	0.18	0.37	0.17	0.37	0.07
1st log-difference							
ADF statistic	-11.38	-5.17	-5.16	-20.19	-21.27	-10.59	-20.73
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Descriptive Return Statistics							
Mean	0.18	0.13	0.09	0.07	0.17	0.03	0.07
Std. Dev.	4.24	4.30	5.08	5.19	3.93	5.28	4.96
10% quantile	-4.75	-5.06	-5.82	-5.14	-4.49	-5.76	-6.07
90% quantile	4.99	5.46	5.61	5.78	4.70	6.50	6.26
Min	-16.72	-13.30	-25.55	-39.99	-20.05	-22.99	-17.63
Max	14.31	17.66	23.25	16.15	12.03	17.13	14.65
Skewness	-0.02	0.29	-0.19	-1.37	-0.48	-0.32	0.07
Kurtosis	4.06	3.96	5.84	12.63	4.81	4.56	3.48
Ljung-Box statistic	14.45**	17.20***	9.62*	3.26	2.64	9.45*	4.45
ARCH LM statistic	19.74**	14.12	14.20	18.53**	16.56*	27.19***	15.90*

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The indication of autocorrelation and volatility clustering for several return series motivate our approach of filtering the original return series with AR-GARCH processes and using the residuals in the analysis. This pre-filtering should remove the serial clustering of extreme events that is due to serial correlation and/or periods of heightened volatility. In a period of strongly changing returns one expects that the variance of the following returns will also be high. A strong price change becomes, therefore, less surprising compared to the same price change in calm periods. Using GARCH models, to obtain a time-series for which extreme observations are not

Figure 2 Commodity futures price returns



serially clustered, should thus be suitable to identify the tail in the return distribution. Similar approaches have been proposed in the risk management literature in applications of extreme value theory (e.g. McNeil et al., 2005). In addition, we adopt the filtering procedure to reduce the possibility that we attribute the clustering of extreme price changes to commonly known risk factors (e.g. Dungey et al., 2005). To control for this exposure to common risk factors, we include in our AR-GARCH models a set of exogenous variables known to predict commodity returns.[2]

More specifically, for each raw return series, we estimate an AR(1)-GARCH(1,1) model containing five common risk factors motivated by asset pricing theories. First, to control for broad market exposure, we use the S&P 500 equity index to proxy the market portfolio (Dusak, 1973). Changes in the equity index can also signal shifts in economic activity and real demand for commodities (Tang and Xiong, 2012). In addition, we include the US dollar index as risk factor to control for the exposure of energy futures (priced in US dollars) to exchange rate risk, based on Erb and Harvey (2006). Finally, we include the weekly change in the short rate, yield spread and credit spread, based on Bessembinder and Chan (1992) and Hong and Yogo (2010).

The regression results (**Table 3)** indicate that common aggregate market factors can be relevant in explaining the returns of individual agricultural futures. In particular, the S&P 500 returns and dollar index returns turn out to be important determinants for all commodities with the notable exception of corn. In contrast, we find no clear-cut evidence that risk factors related to bond markets are reflected in agricultural returns. Altogether, the explanatory power of the AR-GARCH models remains modest as witnessed by the adjusted R^2 ranging from 2% for sugar to 14% for wheat and cocoa. Unreported Ljung-Box tests on residuals from the models indicate that using AR(1)-GARCH(1,1) processes is sufficient to remove serial correlation in all return series.

Table 3 Summary of filtering procedure

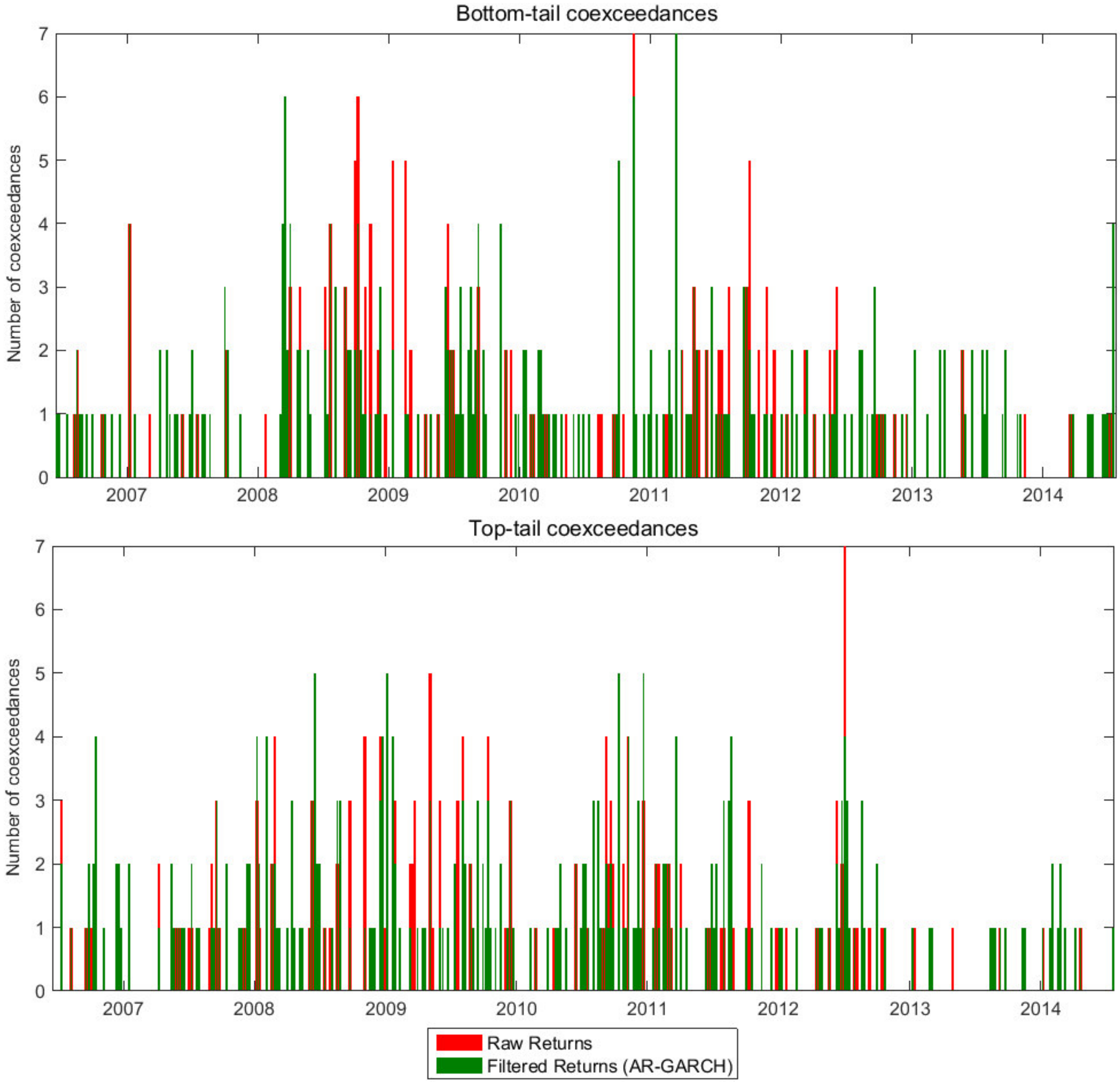
	Cocoa	Coffee	Corn	Cotton	Soy	Sugar	Wheat
Mean equation							
Constant	0.201	0.014	0.045	0.089	0.220*	-0.119	-0.125
	(0.27)	(0.95)	(0.96)	(0.71)	(0.07)	(0.49)	(0.67)
AR term	-0.074	0.019	-0.052	0.033	-0.083*	-0.077	-0.011
	(0.13)	(0.76)	(0.65)	(0.62)	(0.09)	(0.11)	(0.85)
S&P 500 return	0.137	0.393***	0.284	0.378***	0.333***	0.198**	0.267**
	(0.26)	(0.00)	(0.39)	(0.00)	(0.00)	(0.04)	(0.01)
Dollar index return	-1.237***	-0.641*	-0.850	-0.550**	-0.421**	-0.444**	-1.203**
	(0.00)	(0.05)	(0.40)	(0.02)	(0.01)	(0.02)	(0.01)
Δ Short rate	-0.004	0.000	0.000	0.004	0.001	0.003	0.001
	(0.11)	(0.91)	(0.87)	(0.11)	(0.77)	(0.18)	(0.73)
Δ Yield spread	0.030*	-0.003	0.031	0.005	-0.006	-0.029	0.039
	(0.09)	(0.84)	(0.67)	(0.80)	(0.68)	(0.11)	(0.10)
Δ Credit spread	-0.039	-0.005	-0.029	0.043	-0.031	0.076	0.003
	(0.66)	(0.94)	(0.81)	(0.67)	(0.62)	(0.31)	(0.97)
GARCH equation							
Constant	0.051	1.000*	1.000	0.753	1.000***	0.401*	0.972
	(0.77)	0.07	0.77	0.14	0.00	0.05	0.18
ARCH term	0.045***	0.047**	0.013	0.142**	0.224***	0.136***	0.099**
	(0.00)	(0.04)	(0.92)	(0.02)	(0.00)	(0.00)	(0.01)
GARCH term	0.951***	0.892***	0.943***	0.845***	0.725***	0.854***	0.855***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R2	0.14	0.09	0.08	0.07	0.07	0.02	0.14

Note: p-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[2] For robustness, we have also implemented a filtering procedure using a VAR model containing one lag and our set of common risk factors. The VAR framework can also account for the possibility that return dynamics depend on their own characteristics and those of economically related agricultural futures. Results remain qualitatively similar, but are not presented here due to space limitations. They are available upon request. We believe the reported main results based on a GARCH framework are more conservative, since they control for volatility clustering.

We subsequently use the residuals from the regression models to identify extreme returns for each agricultural market. To this end, we define an extreme return – or exceedance – as one that lies either below the 10% or above the 90% quantile of the filtered return distribution. Since there are 417 observations, the 10% cut-off yields 42 positive return ("top-tail") exceedances and 42 negative return ("bottom-tail") exceedances for each agricultural commodity.[3]

Figure 3 Number of agricultural commodity markets experiencing extreme returns



Note: The graphs show the number of joint occurrences of extreme agricultural commodity returns, referred to as co-exceedances, across the seven agricultural markets within a given week. A negative (positive) extreme return lies in the bottom (top) 10% tail of the return distribution. The co-exceedances are plotted separately for (i) bottom tails (upper panel) and top tails (lower panel) and (ii) raw returns (red) and filtered returns (green).

Next, we count the number of agricultural markets that simultaneously experience an extreme return within a given week – referred to as co-exceedances. **Figure 3** shows the top-tail and bottom-tail co-exceedance counts over time. We have plotted the co-exceedances separately for raw returns (red) and filtered returns (green) to illustrate the importance of filtering the return data. Indeed, a comparison indicates that serial correlation, volatility clustering and the risk factors used in the filtering procedure account for some of the clustering in extreme price changes across markets. However, the co-exceedance patterns, based on filtered returns, still provide evidence of clustering in extreme agricultural returns. A cluster of worst agricultural returns appears during the financial crisis at the turn of the year 2008-09. The extent of clustering in top-tail co-exceedances seems to be pronounced in periods of unfolding crises, i.e. in the first half of 2008 (subprime

[3] A 5% cut-off as in Bae et al. (2003) gives too few observations (only 21) for a meaningful analysis.

crisis) and the second half of 2010 (European sovereign debt crisis). Another episode of top-tail clustering is the year 2009, when commodity prices recovered from the financial crisis. We subsequently seek to explain this extreme dependence among agricultural commodities.

4.2 Multinomial logit model

To estimate the probabilities associated with the joint emergence of extreme price events among agricultural commodities, we implement a multinomial logistic model following Koch (2014) and Bae et al. (2003). The major advantage of this model class, especially relative to those based on extreme value theory grounded on a copula function, is that it can condition the likelihood of observing (co-)exceedance events on attributes of relevant economic variables. Most important, the conditioning on covariates offers an econometrically efficient way of exploring which factors help explaining the propagation of tail events across agricultural markets.

Formally, the multinomial logit model can be written as:

$$\ln\Omega_{j|b}(x) = \ln\frac{\Pr(y=j\,|\,x)}{\Pr(y=b\,|\,x)} = x\beta'_{j|b} \quad \text{for } j = 0,1,\ldots,\text{n} \tag{1}$$

Where *ln Ω* is the log of the odds, *j* is one category of *n+1* possible categories, *b* is the base category, which is referred as comparison group, *x* is a vector of covariates (or explanatory variables), *y* is the dependent polytomous variable, Pr (*y* = *j*) is the predicted probability of belonging to category *j*, and β_j is the vector of coefficients associated with the explanatory variables that is estimated by maximum likelihood. Since $\ln\Omega_{b|b}(x) = \ln 1 = 0$, it holds that $\beta_{b|b}$ =0. That is, the log odds of an outcome compared to itself is always 0, and thus the effects of any independent variables must also be 0. The log of the odds ranges from $-\infty$ to ∞.

The *n* equations can be solved to compute predicted probabilities:

$$\Pr(y=j\,|\,x) = \frac{e^{x\beta'_{j|b}}}{\sum_{k=0}^{n} e^{x\beta'_{k|b}}} \quad \text{j} = 0,1,\ldots,\text{n} \tag{2}$$

In general, with *n+1* categories, only *n* binary logits need to be estimated. This is because the multinomial logistic regression compares the probability of being in each of *n* categories to the baseline or reference category *b*. It is noteworthy that the estimation results are contingent on the choice of the threshold required for defining extreme events (here 10% tail). In addition, the focus on large return shocks, by definition, decreases the sample size.

To perform this analysis, we choose to restrict the dependent variable to four categories (0, 1, 2, 3) in order to balance the need of having a model that is parsimonious and yet one that elaborately captures the range of possible categories (0, 1, 2, 3, 4, 5, 6, 7 markets experiencing an extreme event). We, therefore, differentiate between four tail event scenarios: the categorical variable *y* is set equal to 0 when no extreme returns are observed during the week (this is the baseline, "calm" time case); *y* is set equal to1 if one exceedance is observed during the week ("slightly agitated" time case), *y* is set equal to 2, if two or three co-exceedances are observed during the week ("agitated" time case); and *y* is set equal to 3, if four or more co-exceedances are observed during the week ("turbulent" time case). **Table 4** presents a frequency table of our dependent variable reflecting the four different tail event scenarios.

Table 4 Summary of dependent variable

		Bottom tails		Top tails	
		Frequency	Per cent	Frequency	Per cent
y=0	Calm (0 tail event)	236	56.59%	243	58.27%
y=1	Slightly Agitated (1 tail event)	112	26.86%	103	24.70%
y=2	Agitated (2-3 tail events)	45	10.79%	39	9.35%
y=3	Turbulent (4-7 tail events)	24	5.76%	32	7.67%

The choice of explanatory variables in our specifications is motivated by the existing literature (e.g. Algieri, 2014b; Tadesse et al. 2014; Tang and Xiong, 2012). We therefore distinguish between three conduits: (1) The "macroeconomic conduit" reflects fundamental demand factors and captures the possibility that the synchronized extreme price events are triggered by business-cycle driven demand shock mainly from emerging economies. (2) The "energy conduit" accounts for possible spillover effects due to oil price shocks and the demand for biofuels. (3) The "financial conduit" refers to the financialization and speculation in commodity market and captures potential links between extreme returns and the increasing flow of speculative money into agricultural futures markets.

Specifically, the "macroeconomic" conduit includes:

- The Baltic Dry Freight Index. The log return of this variable is used as proxy for the real economic activity in line with Kilian (2009) who argues that fluctuations in freight rates are a leading indicator of changes in the global real economic activity and a measure for changes in global demand.
- The MSCI Emerging Market Index. The log return of this index is considered as proxy for the strength of economic growth in emerging economies that determines the commodity demand from emerging markets as in Tang and Xiong (2012) and Koch (2014).

The "energy conduit" comprises:

- The WTI crude oil futures price (log returns). A rise in oil prices exerts an upward pressure on input costs such as fertilizers, irrigation, and transportation costs, which in turn lead to a decline in profitability and production, with a consequent rise in commodity prices.
- Ethanol futures price (log returns). Biofuels impact commodity prices through the demand side. This is because the demand for corn, soybeans and other grains increases in order to produce more biofuels, resulting in higher prices of these grains. The demand for biofuels has been further facilitated by subsidies and biofuel mandates.

The "financial conduit" includes:

- An indicator variable for extreme stock market shocks (set to one if the S&P 500 has a return in the 10% tails of the return distribution, and zero otherwise). This dummy variable accounts for possible spillover effects from the stock market to commodity markets due to portfolio-reallocation in times of flight-to-quality (e.g., Caballero et al., 2008).
- CBOE Volatility Index (VIX). The VIX captures the implied volatility in the S&P 500 and reflects stock market expectations of volatility. It is a popular barometer of investor sentiment and often referred to as the *fear index*. This inclusion is motivated by evidence that tail events are more likely in a high volatility environment. We use stationary log returns of the VIX in the empirical analysis.
- The scalping index. Scalping is known as an intraday activity made up of instant transactions by traders which open and close contract positions within a very short period of time to make profits. The scalping index is a proxy for short-term speculation and computed as the ratio of trading volume (TV) to open

interest (OI)[4] in future contracts (Peck, 1982; Du et al., 2011; Manera et al., 2013). Formally, it is given by: [5]

$$scalping\ index = \frac{TV}{OI} \tag{3}$$

- The relative change of Managed Money (MM) trading position. Managed money represents professional fund managers and is a good proxy for hedge funds speculators. The inclusion is motivated by the common concern that a "small bet" by large hedge funds using leverage can overwhelm relatively small markets resulting in large price changes (Fung and Hsieh, 2000). The managed money index[6] is calculated as change in net long positions of managed money traders relative to its total size (i.e. the sum of short, long and spread open interest):

$$MM\ net\ long = \frac{\Delta OI_{netlong}^{MM}}{OI_{long}^{MM} + OI_{short}^{MM} + OI_{spread}^{MM}} \tag{4}$$

- The relative change of Commodity Index Traders (CIT) trading position. This category of traders identified by CFTC corresponds to index investors (Guilleminot et al. 2014, Verleger, 2007; Commodity Futures Trading Commission, 2008), who track a given commodity index. They can invest through OTC derivative instruments or exchange-traded-funds. These traders can take long or short exposure to the index and the CFTC separately releases the short and long position for each commodity. Our CIT index is computed as change in net long positions of index traders relative to the total open interest of index traders:[7]

$$CIT\ net\ long = \frac{\Delta OI_{netlong}^{CIT}}{OI_{long}^{CIT} + OI_{short}^{CIT}} \tag{5}$$

It is worthwhile noting that each of the considered financial indices (scalping, managed money and index traders) has been constructed aggregating data over the seven agricultural commodities and each commodity enters the index with a specific weight. In particular, we used the following weighted index:

$$\mathrm{X_w} = \sum_{i=1}^{7} \lambda_i\ \mathrm{X}_i \tag{6}$$

Where X_i is a specific financial index for commodity i and λ_i is the weighting factor, that is calculated as the share of the market value of the open interest of commodity i of the market value of the open interest of all commodities, i.e., $\lambda_i = \frac{p_i * TOT\_OI_i}{\sum_k p_k * TOT\_OI_k}$. The price of the contract, p_i, is converted from the reported market price (which refers to a specified unit of the commodity) to the price of contract (using the contract size). For

[4] Open interests refer to the number of futures contracts outstanding.

[5] Volume and OI refer to all contracts of the commodity – i.e. all contracts with different maturities, not only active contracts.

[6] Different managed money indices were also computed and used in a battery of regressions but the results across indices are very similar. These alternative indices are summed up as follows:

(1) $CIT\ net\ long = \Delta\ OI_{long}^{MM} - \Delta\ OI_{short}^{MM}$

(2) $CIT\ net\ long = \frac{\Delta OI_{netlong}^{MM}}{TOT_{long} + TOT_{short}}$

(3) $CIT\ net\ long = \frac{\Delta OI_{netlong}^{MM}}{OI_{long}^{MM} + OI_{short}^{MM}}$

[7] Alternative CIT measures have been also considered, they are highly correlated and the results are quite similar across estimations. Specifically, the two alternative considered indices are:

(1) the absolute change in net long positions of index traders: $\Delta\ OI_{long}^{CIT} - \Delta\ OI_{short}^{CIT}$

(2) change in net long positions of index traders relative to total market open interest: $\frac{\Delta OI_{netlong}^{CIT}}{TOT_{long} + TOT_{short}}$

open interest all contracts of a commodity (not only the active one) are used. Note that all change variables and log returns are multiplied by 100 to consider percentage values.

4.2.1 Multinomial logit analysis: empirical results

The estimates of the multinomial logit model are reported separately for bottom tails and top tails in **Table 5.**

Calm time is the most frequently occurring state and it is, therefore, employed as reference group. We estimate the model for three scenarios: a model for a slightly agitated scenario relative to calm state, a model for an agitated state relative to calm state, and a model for turbulent time relative to calm state. Since the parameter estimates are relative to the reference group, the standard interpretation of the multinomial logit is that for a unit change in the predictor variable, the logit of outcome j relative to the reference group is expected to change by its respective parameter estimate (which is in log-odds units) given the variables in the model are held constant.

Table 5 Results of Main Specification

	Bottom Tails			Top Tails		
	Slightly agitated	Agitated	Turbulent	Slightly agitated	Agitated	Turbulent
Macroeconomic conduit						
Baltic dry	-0.0269 **	-0.0187	0.00634	0.0193	-0.00951	0.0109
	(0.045)	(0.291)	(0.783)	(0.140)	(0.621)	(0.610)
MSCI emerging mkt.	-0.0410	0.0422	0.0714	0.0361	-0.0645	-0.0943
	(0.353)	(0.489)	(0.345)	(0.417)	(0.326)	(0.201)
Financial conduit						
MM net long	-0.346 **	-0.860 ***	-1.165 ***	0.247	0.581 ***	0.825 ***
	(0.022)	(0.000)	(0.000)	(0.105)	(0.009)	(0.001)
CIT net long	-0.0180	-0.218	-0.609 ***	-0.0117	0.148	0.0885
	(0.872)	(0.158)	(0.002)	(0.914)	(0.373)	(0.634)
Scalping index	-0.0206	0.0117	0.0257	0.0187	0.0109	0.0410
	(0.365)	(0.715)	(0.556)	(0.406)	(0.746)	(0.261)
VIX volatility	-0.00223	-0.0126	-0.0202	0.00803	-0.0124	-0.0205
	(0.843)	(0.451)	(0.363)	(0.482)	(0.480)	(0.273)
Extreme S&P 500	0.222	0.0770	0.594	0.169	0.133	0.962 **
	(0.462)	(0.860)	(0.273)	(0.579)	(0.777)	(0.048)
Energy conduit						
WTI oil	0.00649	-0.0670	-0.0255	0.0145	0.0244	0.0625
	(0.833)	(0.123)	(0.639)	(0.633)	(0.610)	(0.245)
Ethanol	-0.0533 **	-0.0491	-0.0963 ***	0.00381	0.0577	0.160 ***
	(0.032)	(0.150)	(0.009)	(0.870)	(0.158)	(0.001)
_cons	-0.333	-2.128 ***	-3.662 ***	-1.302 ***	-2.190 ***	-3.661 ***
	(0.502)	(0.003)	(0.000)	(0.009)	(0.003)	(0.000)
N		416			416	
pseudo R^2		0.097			0.068	
AIC		872.2			896.2	
BIC		993.1			1017.1	
ll_0		-449.7			-448.4	
ll		-406.1			-418.1	
chi2		87.26			60.66	

Note: Base category: calm times; p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Bottom tails refer to extreme events with negative signs (price falls), top tails refer to extreme events with positive signs (price surges). Three (bottom and top) tail event scenarios are differentiated: The "slightly agitated" scenario if one exceedance occurs, the "agitated" scenario if two or three co-exceedances take place in a week, and the "turbulent" scenario if four or more co-exceedances occur during the week.

The coefficient of the Baltic variable in the first column of **Table 5**, for example, allows calculating the log-odds ratio of a slightly agitated market (one bottom tail event) relative to the calm state based on Equation

(1). This applies to the other estimated coefficients in column (1), too. Hence, the negative coefficient of the Baltic variable in column (1) implies that if the real economic activity were to increase by one unit, the multinomial log-odds for having slightly agitated times – when there is only one extreme price drop – relative to calm time would be expected to decrease by 0.027 units, holding the other variables constant.[8] Considering the variable managed money in the first, second, and third column of **Table 5**, it emerges that if net long positions were to increase by one unit, the multinomial log-odds for observing extreme price busts instead of "tranquil" times would decrease from 1.16 to 0.35 units.

Caution is indicated when transferring the interpretation of the estimated coefficients from the log-odds ratio equation (1) to the actual probabilities of observing a specific event (equation 2): Because the probabilities of the complementary categories – i.e. the denominator in (1) – also change, the sign of the estimated coefficient β does not always translate to the same sign for the marginal effect on the probability. Marginal effects at the mean of the explanatory variables are calculated in order to get a better interpretation of qualitative and quantitative results of the multinomial logit regression (**Table 6**). Marginal effects indicate the change in probability if one explanatory variable changes marginally at the mean, holding all other variables constant.[9] It can be quickly verified that the signs of those coefficients that are statistically significant at the 10% level do not change compared to the sign of their marginal effects.[10] In some rare cases significance levels change. The marginal effects can be interpreted easily. Take again the case of the Baltic dry index: when the variable is at its mean value, a reduction of one percentage point, increases the probability of observing one bottom tail event by 0.5 percentage points. The largest marginal effects can be found for Managed Money (MM) positions: Considering top-tail events, a one percentage point increase of the relative MM positions, increases the probability of observing agitated and turbulent markets by 3.8 and 3.0 percentage points, respectively (**Table 6**). Likewise, for the top tail, the relative probability of having calm periods decreases by 9 percentage points for every percentage point of increase in managed money.

To sum up, the considered channels have a different impact on tail events. Specifically, with reference to the macroeconomic channel, economic shocks in emerging economies (proxied by the MSCI emerging markets) do not cause tail events in either direction. Likewise, the Baltic Dry index is statistically insignificant except for the occurrence of single bottom tail events: a drop in freight costs, for example due to lower global demand, is only associated to isolated extreme price drops in agricultural commodity markets, but not to synchronous tail events. Thus, business-cycle driven demand factors provide virtually no explanatory power for the propagation of tail events across agricultural markets. This finding is not in contrast with the view that shifts in demand shape commodity prices (Krugman, 2008; Kilian and Hicks, 2013), but highlights that demand shocks have not triggered *extreme* price events. The finding is rather consistent with the theoretical predictions that fundamentals have much less explanatory power on extreme price movements in time of large inflows of speculative money (Liu et al., 2011).

Turning to the financial conduit, we find strong evidence that managed money positions help explaining the transmission of joint extreme price changes. In fact, this variable seems to have the strongest impact on tail events in either direction and in particular for synchronous tail events. More specifically, a reduction (increase) of managed money net long position is significantly related to an increasing probability of large price falls (rises) across at least two agricultural markets. The significance for the agitated (2-3 tail events) and turbulent (4-7 tail events) scenarios may reflect that managed money traders hold positions across many agricultural futures markets (Cheng et al., 2014) and, thus, changes in trading positions affect various markets at the same time. This finding corroborates the evidence presented in Büyüksahin and Robe (2014) which indicates that increased hedge fund activity strengthens cross-market linkages.

[8] Another way to interpret the results of **Table 5** is to exponentiate the estimated logit coefficients which gives relative risk ratios (RRR). The RRR of a coefficient indicates how the risk of the outcome falling in the comparison group (e.g., turbulent state) compared to the risk of the outcome falling in the reference group (calm state) changes with the variable in question. An RRR>1 indicates that the comparison outcome is more likely. Vice-versa with RRR<1, the outcome is more likely to be in the reference group.

[9] Technically, for a continuous variable, marginal change at the mean is the partial derivative or instantaneous rate of change in the estimated quantity with respect to its mean. For a factor variable, marginal change is the difference in the prediction when the factor variable is 1 compared with the prediction when the variable is 0.

[10] This does, however, not hold for all of the statistically insignificant coefficients due to the non-linearity of the model.

Table 6 Marginal Effects

	Bottom Tails				Top Tail			
	Slightly agitated	Agitated	Turbulent	Calm	Slightly agitated	Agitated	Turbulent	Calm
dy/dx	**y=1**	**y=2**	**y=3**	**y=0**	**y=1**	**y=2**	**y=3**	**y=0**
Macroeconomic conduit								
Baltic dry	-0.0050**	-0.0009	0.0005	0.0055*	0.0038	-0.0012	0.0003	-0.0028
MSCI emerging mkt.	-0.0101	0.0045	0.0024	0.0033	0.0095	-0.0056	-0.0042	0.0004
Financial conduit								
MM net long	-0.0376	-0.0601***	-0.0290***	0.1267***	0.0244	0.0378**	0.0303***	-0.0925***
CIT net long	0.0075	-0.0163	-0.0172***	0.026	-0.0066	0.0118	0.0034	-0.0085
Scalping index	-0.0047	0.0015	0.0009	0.0024	0.0029	0.0003	0.0015	-0.0046
VIX volatility	0.0001	-0.001	-0.0005	0.0014	0.0021	-0.0011	-0.0009	-0.00003
Extreme S&P 500°	0.0379	-0.0016	0.0179	-0.0542	0.0145	0.0017	0.0506	-0.0668
Energy conduit								
WTI oil	0.0033	-0.0058*	-0.0006	0.0030	0.0015	0.0014	0.0024	-0.0053
Ethanol	-0.0087*	-0.0025	-0.0022**	0.0134**	-0.0024	0.0039	0.0066***	-0.0081
Pr(y|x)	0.2861	0.0932	0.0305	0.5902	0.2572	0.088	0.045	0.6098

Note: This table provides estimates of the partial derivatives of the exceedance probabilities with respect to the regressors, evaluated at their means. They need to be multiplied by 100 to get the marginal effects of the exceedance probabilities in percentages.
Mean values x: Baltic dry -0.30% ; MSCI emerging mkt. 0.11%; MM net long 0.2%; CIT net long -0.6%; Scalping index 21.72; VIX volatility -0.16%;
Extreme S&P 500 0.20; WTI oil 0.09%; Ethanol -0.15%.
(°) dy/dx is for discrete change of dummy variable from 0 to 1

In contrast, our results suggest that index traders have only little impact on tail events: Their net long position changes are only significant for bottom-tail events for four or more commodities. As index traders follow typically a (long-term oriented) portfolio diversification strategy rather than short-term speculation purposes, positions change hardly over time. Nevertheless, massive financial outflows might have contributed to extreme price drops. Contrary to the trading positions of the two financial traders, short-term oriented speculation, measured by the scalping index, is statistically not relevant to the likelihood of observing joint extreme returns in agricultural markets. Besides studying the impact of speculative trading, the inclusion of the VIX and extreme stock market dummy allow investigating whether shocks from financial markets transmit to agricultural markets. We find no evidence that tail events are more likely in a high volatility environment: The VIX estimates are insignificant and the mostly negative signs rather indicate that tail events are less likely when stock market expectation of volatility is high. There is also little evidence of shock spillover effects from the stock market to agricultural markets. The indicator variable is only significant for top tail events in the turbulent scenario. The positive coefficient estimate suggests that large price rises in four or more agricultural markets coincide with tail events in the stock market. However, it is important to note that the marginal effects at the mean remain statistically insignificant (**Table 6**). Therefore, we should not over-interpret the spillover effect that could be explained by portfolio-reallocation of investors moving from stocks to agricultural futures in line with Caballero et al. (2008), who argue that the collapse of US asset markets during the subprime crisis triggered the creation of a bubble in commodity markets.

Finally, regarding the energy conduit, oil price returns do not trigger any tail events in agricultural market, while ethanol returns are highly significant for synchronous tail events of multiple agricultural commodities: High (low) ethanol returns are indeed associated with the occurrence of top (bottom) tail events that occur simultaneously for at least three commodities. This result indicates that the demand aspect of the energy circuit (agricultural commodities can be used for energy generation) has a stronger role for tail events as the input cost aspect (energy prices affect production, transportation and fertilizer costs). It thus testifies that ethanol and agricultural prices have become increasingly interwoven, in line with McPhail and Babcock (2012), Algieri (2014a).

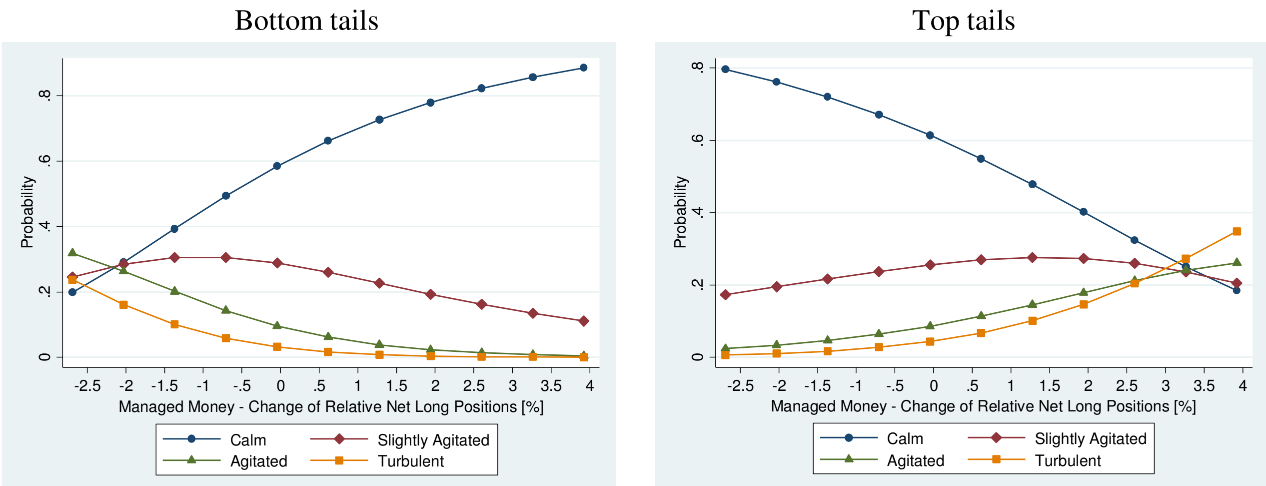
A battery of diagnostic tests to validate our baseline specification is reported in detail in section S.1 of the supplementary material. Additionally, we show the results of an extended multinomial model that controls also for the T-bill, the TED-spread and the Bid-Ask spread in commodity markets to capture additional financial market and liquidity indicators. The estimated coefficients and significance levels of our main specification are hardly affected when these variables are added. The additional variables turn out to be all insignificant (except for T-bill and TED-spread that are statistically significant at the 10% level in two individual cases). Furthermore, we examine the appropriateness of using a multinomial logit model by testing it against an ordered logit model.

4.2.2 Graphical analysis of predicted probability

To complete our analysis we have computed the response of our probability estimates to the full range of value associated with the significant covariates holding all other variables constant at their mean. Plotting the probabilities of exceedances, as a function of a regressor over the whole relevant range of the regressors, enables us to better gauge how changes in the covariates affect the probabilities of exceedance. We report two co-exceedance response curves for each significant covariate: one with the probability of different states for the bottom tail and one for the top tail (**Figure 4**; **Figure 5**).

Clearly, the probability of having two or more co-exceedances in the bottom tails falls with increasing managed money net position, in a non-linear form (**Figure 4**). This probability ranges from a minimum of 0% (when the largest increase in the net long position occurs) to a maximum of approximately 24% (when the largest decrease in the net long position occurs). On the contrary, the probability of observing the calm state with respect to bottom-tail events increases with managed money net positions; and the probability of observing slightly agitated markets reaches its maximum around a 1 percent reduction in managed money net long positions.

Figure 4 Co-exceedance response curves: Probability of different states against managed money net positions

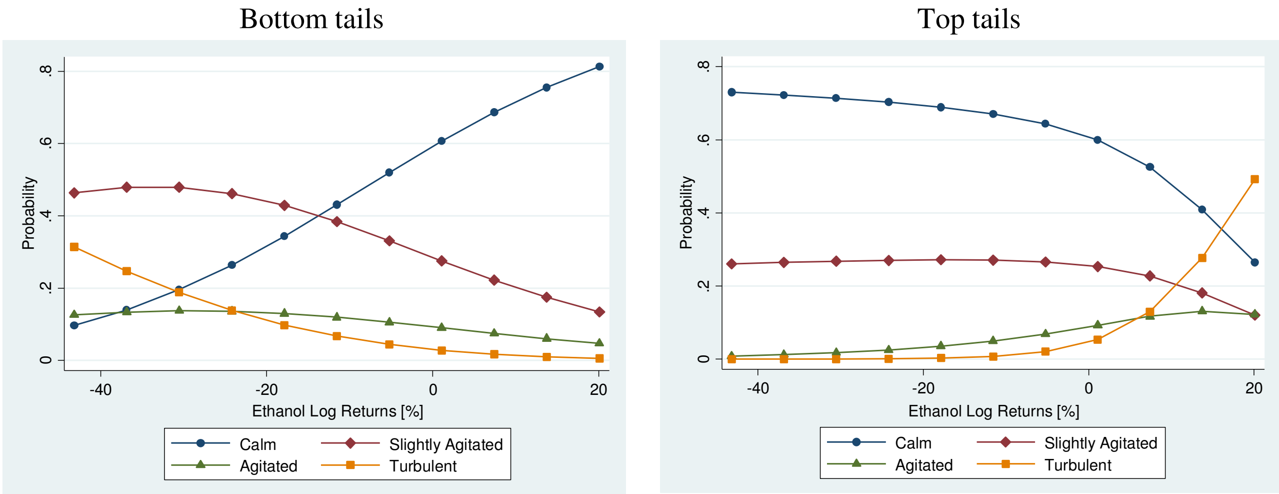


Note: The panels illustrate the sensitivity of implied conditional probabilities of the four different tail event scenarios to changes in managed money net long positions.

The probability of observing one or more extreme events in top tails rises with managed money net positions and it increases significantly for the turbulent state's probability. Instead, the probability to experience the calm state decreases with an increasing net long position of managed money traders. For example, the strongest increase of the net long position results in a probability of extreme price rises in two or three (four or more) markets equal to about 26% (35%).

The same type of behavior appears for ethanol returns (**Figure 5**). Therefore, we can conclude that price upsurges in commodity market are more likely to materialize when returns in ethanol are increasing. Additionally, the slope of the response curve for top-tails is relatively flat, unless a large rise in ethanol prices occurs. When an ethanol return of 20% per week occurs, for example, the probability of the turbulent scenario rises to approximately 49%.

Figure 5 Co-exceedance response curves: Probability of different states against ethanol returns



Note: The panels illustrate the sensitivity of implied conditional probabilities of the four different tail event scenarios to ethanol returns.

4.2.3 Limitations of our analysis

In drawing lessons for the future, some important caveats apply to our empirical design. While the multinomial logit approach offers an econometrically efficient way of providing valuable information about the typical market conditions associated with tail events in one or more markets, the model may suffer from an endogeneity problem. Most important, we treat managed money and index trader position changes as exogenous. In particular, we implicitly assume that the observed position changes of traders stem from shifts in their demand. Yet, we cannot rule out that the financial traders also trade to accommodate other traders (i.e. hedgers) in the market. Thus, we face a classical simultaneity bias: Position changes initiated by financial traders should be positively correlated with price changes, whereas those coming from accommodating producers' hedging needs should be negatively correlated with price changes (Cheng et al., 2014). In this respect, our study may suffer from downward-biased estimates of price impacts for position changes of managed money traders and index traders.

In addition, the estimated price impact may be biased if the correlation of position changes and price changes is due to omitted variables. This can in particular be problematic if commodity traders consider information on omitted market fundamentals for their trading decisions. We seek to alleviate this further source of endogeneity by introducing a set of control variables (such as VIX, demand fundamentals, market liquidity proxies). As the considered commodities are in most cases highly imperfect substitutes (with the exception of corn and soybean for feed demand and corn and sugar for ethanol demand) and we control for common demand shocks, other omitted demand factors are unlikely to explain the occurrence of *synchronous* tail events in four or more commodity markets. Supply shocks, e.g. due to harvest and trade policy shocks, are difficult to control for in high frequency time series analysis. Although discretionary trade policies affected food prices in 2008 and 2010 substantially, they were only implemented for wheat and rice (Martin and Anderson, 2012). Hence, trade shocks are for only one of our considered commodities relevant and again unlikely to cause synchronous tail events across commodities. Regarding the harvest shocks, we expect again little simultaneous impact of weather events on the commodities due to different growing seasons and regions. Correlation of annual yield shocks is only for two commodity pairs higher than 0.5 – for the corn-soybean pair (0.61) and wheat-sugar beet pair (0.59) (see the Supplementary Material for the complete correlation table). Hence, omitted supply shocks are unlikely to bias the impact of managed money position for synchronous tail events in four or more markets.

Still, position changes of financial traders may come from other factors that influence price expectations. Therefore, we caution against an over-interpretation of our estimated results as true estimates of the cause and effect relationship between position changes and price changes.

5. Conclusions

This study has investigated the occurrence of extreme price events and boom–bust processes in agricultural markets during the period 2006-2014.

First, we have found that extreme price changes, located in the 10% tails of the distribution, cluster across agricultural markets. We have then characterized the tail events, with calm, slightly agitated, agitated and turbulent states and investigated which factors contribute to the propagation of extreme scenarios, when returns have been extraordinarily high or low. Then, we have disentangled three transmission channels: (1) the macroeconomic conduit which captures the possibility that the synchronized extreme price events are driven by the increasing importance of commodity demands from rapidly growing emerging economies; (2) the energy conduit that accounts for possible spillover effects due to oil price shocks and the demand for biofuels; (3) the financialization conduit which refers to potential links between extreme returns and the increasing flow of money from financial participants into agricultural futures markets.

Our results indicate that managed money positions and ethanol prices have a key role in triggering extreme price booms and busts. Indeed, the strongest increase of the net long position results in a probability of extreme price rises in two or three (four or more) markets equal to about 26% (35%). As well, when an ethanol return of 20% per week occurs, the probability of the turbulent scenario rises to approximately 49%. At the same time, extreme returns in the US stock market appear to trigger top tail events that affect at least three agricultural commodities. This could be an indication that stock market shocks lead to an exaggerated appreciation of agricultural commodities through spillover effects. Index traders have only little impact on tail events: They are only significant for bottom-tail events for four or more commodities. As index traders follow typically a (long-term oriented) portfolio diversification strategy rather than short-term speculation purposes, positions change hardly over time. The dominant role of ethanol prices compared to oil prices suggests that the agricultural markets are increasingly linked to energy markets through the demand side (biofuel use), rather than the production cost side. Finally, the real demand channel remains mostly insignificant which indicates that traditional market fundamentals have little role in explaining *extreme* price changes despite their undisputed general impact on prices (Tadesse et al. 2014). Specifically, economic shocks in emerging economies do not cause tail events in either direction. Likewise, the Baltic Dry index is statistically insignificant except for the occurrence of single bottom tail events.

Further research employing clear identification strategies is necessary to provide robust evidence on the price impact of speculative trading. In this regard, recent work of Henderson et al. (2014) and Mou (2011) that exploit different trading motives at different times open up promising avenues for future research. A related research direction pertains to the ability of instrument variables to deal with endogeneity as proposed in Guilleminot et al. (2014). Specifically, it would be interesting to investigate whether capital market theory may guide the selection of appropriate instrument variables that explain speculative activity due to systematic market shocks.

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