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Wave after Wave: Contagion Risk from Commodity Markets

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Abstract

The aim of this study is to investigate the possible contagion risk coming from energy, food and metals commodity markets and to assess risk spillovers from biofuel to food commodity markets and from crude oil to food markets. To this purpose, we use the delta Conditional Value-at-Risk *ΔCoVaR*) approach recently proposed by Adrian and Brunnermeier (2016) based on quantile regression. This novel methodology allows us first to identify a measure of contagion risk for energy, food and metals commodity markets, then to detect whether the risk contribution for a given market is significant, while distinguishing between tail events driven by financial factors, economic fundamentals or both, and finally, to assess whether the contagion effect of one market is significantly larger than the one of another market. The results show that energy, food and metals commodity markets transmit contagion within markets and there are spillovers from crude oil and biofuel to food markets. In particular, oil is systemically riskier than the other markets in causing economic instability. Oil is also more important than biofuel in affecting food markets. It emerges that contagion risk is mainly triggered by financial factors for energy and metal markets, while financial and economic fundamentals are relevant for food markets.

Keywords: Commodity markets, Contagion risk, *ΔCoVaR*

JEL codes: F37, G15, Q14, Q43

Content

1. Introduction

Systemic risk and the spreading of contagion have attracted considerable attention among researchers and policy makers since the outburst of the global financial crisis in 2008. Generally, systemic risk describes the vulnerability of the financial sector in which adverse consequences of internal shocks can spread and even magnify within the entire sector and then spill over in a wave-like manner to the rest of the economy. The global financial crisis has, indeed, demonstrated that breakdowns in individual parts or components of the financial system could have disruptive effects for the entire financial network and contagion effects could spread out to the economy at large.

Starting from this background, the present study aims to move the attention from the traditional financial sectors to commodity markets by assessing the drivers of contagion risk and the existence of spillovers across markets. Differently from the extant literature, that has extensively investigated the transmission of risks from one institution (bank or financial company) to another within the same sector (financial or banking), we focus on whether and to which extent the risk of distress in one market, namely energy, food and metals commodity, transmits across markets and to the whole economy. We further assess whether financial determinants, economic fundamentals or both factors drive contagion risk and if risk spillovers take place from energy to food commodity futures markets distinguished in their main components: maize, rapeseed, soybean, soybean-oil, sugar and wheat.

In our analysis, the risk of contagion coming from commodity markets is caused by extreme price shocks (i.e., abnormal price rises and price falls located on the far tails of the return distribution) of a given commodity that can spill over across markets and affect negatively the entire economy. Technically, the risk of extreme commodity prices and their impact on the economy are identified by the *ΔCoVaR* measure of risk, recently proposed by Adrian and Brunnermeier (2016). Thus, *ΔCoVaR* captures the potential for the propagation of specific market distress across the economy by gauging the increase in tail co-movements.

The rationale for examining the contribution to contagion risk coming from energy, food and metals sectors is driven by the fact that commodity trading could cause an analogous degree of risk as that one caused by traditional financial markets. For instance, with the new European market infrastructure regulation (EMIR) package, the EU has highlighted that systemic risk can be channelled from energy and food sectors to the traditional financial sector through the use of derivatives, thus the EU has envisaged that the scope of financial regulation could be expanded towards commodity markets. In addition, there is a certain similarity between commodity and traditional financial markets. Both are crucial to all the sectors of the economy through production, consumption and financial contracts, and the scarcity in one of them is susceptible to trigger serious damage to the economy. Indeed, demand for energy and food is usually inelastic, showing evidence of the strong dependence of the economy on these commodity prices. Integration of commodity market and conventional asset markets may further allow shocks to easily propagate and trigger waves of contagion.

The study provides several contributions to the extant literature. It explicitly examines how commodity markets contribute to contagion risk. In this sense, contagion risk quantifies the extent to which a tail event in a particular commodity market can generate and spread out a tail event to another market and to the rest of the economy.

The focus on how commodity markets can induce contagion risk has hardly been the subject of research. To our knowledge, the studies by Raynaud and Lautier (2012) and by Pierret (2013) have flagged the possibility of a systemic risk in the energy markets, but a thorough analysis that involves contagion risks of energy, food and metals markets and transmission of abnormal price ups and downs across markets has so far not been undertaken. This is important given the interlinkages between oil, biofuels and food commodity markets and their effects on the whole economy. Such an analysis is, in fact, crucial as it makes possible to take into account the eventuality that a price shock occurring in a specific market can spread, not only through its own market, but also to other markets, and vice-versa. A further novelty is that we try to establish which of the commodity market contributes the most to contagion risk and which factors drive it. An additional novelty of the study relates to the use of the *ΔCoVaR* risk measure to detect impacts and interactions between energy and food markets, and to examine dependence during extreme market events generated by economic fundamentals, financial factors or a combination of the two. This methodology has been recently proposed in the systemic risk literature, but applied only to financial institutions or to the financial sector (Bernal et al. 2014). We extend it to commodity markets with some differences to account for their specificity. It should be mentioned that studying contagion risk associated to commodity markets is particularly relevant since, quoting Serra and Gil (2012), commodity "price increases are the most likely to have relevant negative economic impacts".

The remainder of the study is organized as follows: Section 2 reviews the existing literature on risk measures, Section 3 depicts the adopted methodology, Section 4 describes the data used in the study and sketches their descriptive statistics, Section 5 presents the empirical analysis and discusses the results, and Section 6 concludes.

2. Literature Review

Contagion occurs when extreme price shocks materializing in one specific commodity market become so widespread to reach a systemic dimension. Put differently, strong spillover and ripple effects operate during turbulent times so that the distress in a particular market transmits to other commodity markets and ultimately to the whole economy.

In order to detect contagion and its determinants we draw from the literature of systemic risk[1] measures[2]. Well-known examples of risk measures include: 1. the Systemic Risk (SRISK) Index (Acharya et al. 2012; Acharya et al. 2010; Brownlees and Engle 2012), 2. the Game theoretic 'Shapley Value' (Tarashev et al. 2010; Drehmann and Tarashev 2013), 3. the ΔCoVaR measure (Adrian and Brunnermeier 2016).

The SRISK index of an individual firm is determined by the expected capital shortage a financial firm would experience in case of a significant market decline over a given time horizon. The shortage depends on the firm's degree of leverage, its size and its equity loss conditional on a market decline, which is also known as Marginal Expected Shortfall (MES). This risk measure can be considered as a 'top-down measure' given that it tries to assess the impact of distress occurring at the level of the financial system on an individual financial institution.

The Shapley value (SV) is a very general methodology developed in the context of cooperative games, which consists in allocating the output (gains or losses, i.e., 'the shared value') produced by a group, among its members (players) in a way that reflects fairly their individual contributions. The share of the aggregated value attributed to a particular player is the SV of this player. Applied to the financial system, the SV methodology allocates the total risk of the aggregated financial system (the shared value) to individual institutions (the players). The allocations are based on each institution's marginal contribution to the overall risk. The systemic importance of each institution is hence its Shapley value. Institutions with higher systemic importance will have a higher SV than others.

A rather different approach underpins the *ΔCoVaR* measure, which has been suggested by Adrian and Brunnermeier (2016) as a way to measure the systemic importance of institutions and possible contagion effects. Indeed, the prefix 'Co' stands for Conditional, Contagion or Co-movement. *ΔCoVaR* gauges, thus, the severity of distress in the system, conditional on distress in a given institution or in a group of institutions. In this sense, it can be considered as a 'bottom-up measure' of risk.

There is no perfect methodology that precisely measures the contributions of individual commodity market shocks to contagion risk. However, we adopt the *ΔCoVaR* approach since

[1] Systemic risk arises if the distress in one a bank or group of financial institutions threatens the functioning of the entire financial system and then spills over to the rest of the economy (Hellwig1998).
[2] See Bisias et al. (2012) for a comprehensive survey.

it can be seen as a measure more closely capturing contagion risks, while SRISK is a measure that more closely captures the exposure to common shocks that affect the whole financial system. In addition, the *ΔCoVaR* approach offers great flexibility for evaluating risk spillovers and interconnectedness across markets, and, given that it relies on high-frequency data, it is a highly reactive risk measure.

In what follows, we will first describe the use of *ΔCoVaR* in the context of financial systemic risk and then adapt it to commodity markets and to the case of biofuel/crude oil-related price transmission.

3. $\Delta CoVaR$ Methodology

Let $\{R_t^{system}\}_t$ and $\{R_t^i\}_t$ denote the time-series of log- price returns[3] of the financial *system* (measured by the stock market returns) and the log-returns of a financial institution *i*, respectively

Given some critical level τ, the $CoVar^{system|i}$ is the Value-at-Risk (*VaR*) of the financial system *conditional* (*Co*) on an event affecting institution *i*, which is materialized by the log-returns for this institution (R^i) being equal to its level of *VaR* for a τ_i^{th} quantile (i.e., $R^i = VaR_{R^i}(\tau_i)$). The Value-at-Risk is a probabilistic measure that evaluates the potential loss in value/returns of a risky asset or portfolio over a defined period (e.g., one day) for a given confidence interval (e.g., 95%). For instance, if 1 day-*VaR* on an asset is 1 million with 95% confidence level, there is a only a 5% chance that the value of the asset will drop more than 1 million over any given day. The *VaR* is the maximum loss of value, which statistically corresponds to the lower (left) tail of the unconditional value/return distribution with a 5% cumulative value (Figure 1).

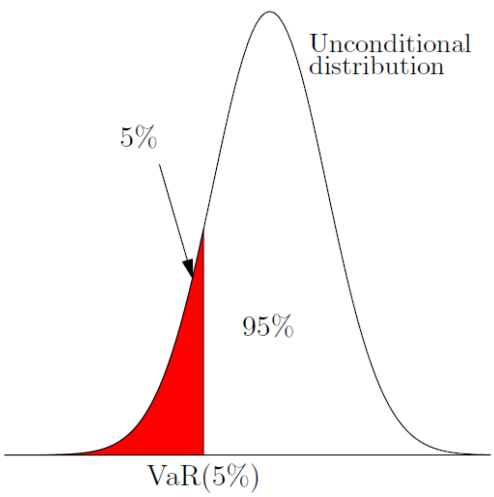


Figure 1: The Value-at-Risk

The $CoVar^{system|i}(\tau)$ is, thus, defined by the τ^{th} quantile of the conditional probability distribution of log-returns of the system (R^{system}) (Figure 2). Formally,

$$\mathbb{P}\left(R^{system} \leq CoVaR^{system|i}(\tau) | R^i = VaR_{R^i}(\tau_i)\right) = \tau$$

and

$$\mathbb{P}\left(R^i \leq VaR_{R^i}(\tau_i)\right) = \tau_i$$

[3]Price returns R_t are daily logarithm price differential, i.e., $R_t = ln\ S_t - ln\ S_{t-1}$ where S_t is the price of the stock at time *t*.

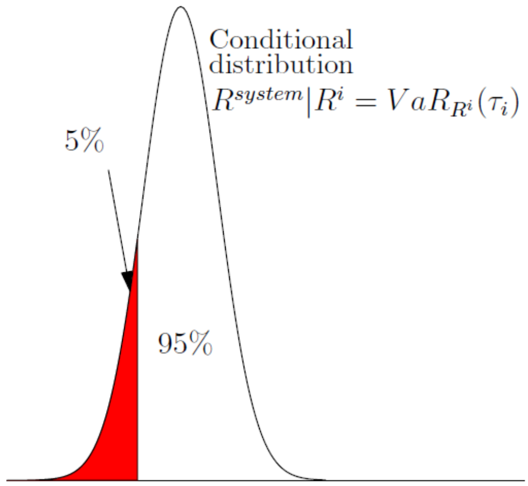


Figure 2: $CoVar$

The actual measure gauging the effect of an extreme event on the financial system is given by the difference between the $CoVaR$ of the *system* when a given financial institution *i* is in distress – i.e., when it is at a critical tail level τ_i – and the $CoVaR$ of the same financial system when the institution *i* is at a 'normal' or uncritical level, such as 50%, i.e., when *i* is at his median state. Hence, the measure in question is defined as:

$$\Delta CoVaR^{system|i}(\tau) = CoVaR^{system|R^i = VaR_{R^i}(\tau_i)}(\tau) - CoVaR^{system|R^i = VaR_{R^i}(50\%)}(\tau)$$

In short, the $\Delta CoVaR^{system|i}(\tau)$ measures the risk materializing at the complete system when the institution i is in distress relative to a situation where i is at its median (or normal state). We can think the $\Delta CoVaR^{system|i}(\tau)$ as the 'systemic risk contribution' of the financial institution *i* since, intuitively, it quantifies the increase in the risk of the financial system when the institution *i* experiences extreme events.

We transpose the *ΔCoVaR* methodology applied in the financial sector to commodity markets with three main differences.

First, we consider in our application the whole economy as 'the system' proxied by the Standard & Poor's 500 (*S&P*), since, as described in Section 4, it mirrors the global economic activity. Crude oil (*O*), food (*F*), biofuels (*B*), all metals (*M*) play the role of 'institution *i*'. In this sense, we assess the impact on the whole economy of adverse shocks (or the risk of distress) affecting one of the different commodity markets.

Second, for each 'institution *i*' we look at both the left and right tail of each commodity distribution (rather than just the left tail used in financial applications), while we still consider the left tail of the system (Figure 3). The reason stems from the fact that in our setting distress in commodity markets occurs when prices are extremely high or extremely low, while in financial applications a crisis takes place when a bank (or a financial institution) records extreme losses. For our system (the S&P 500 index), distress (or economic instability) occurs when it registers losses, as in the case of financial application, therefore we are interested in the left tail of its distribution.

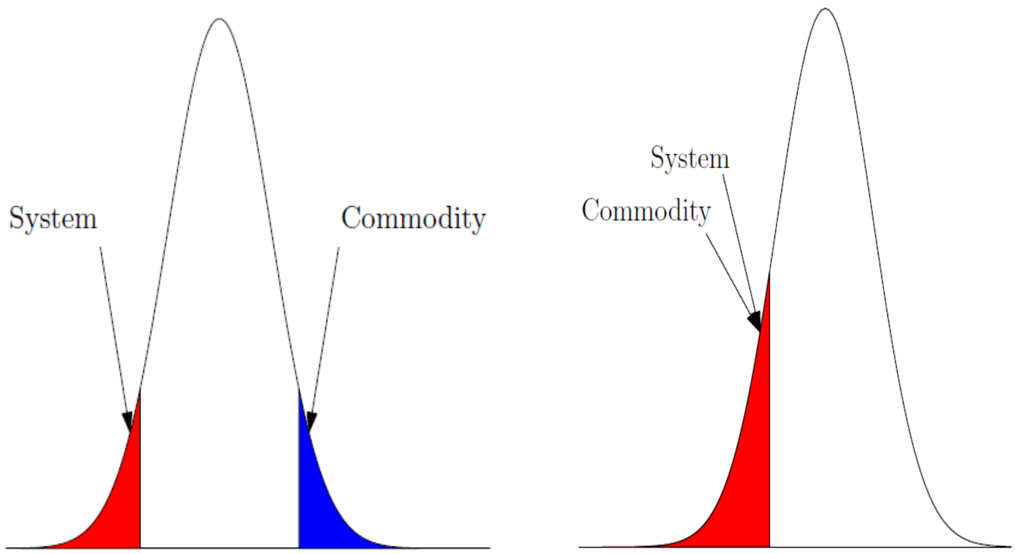


Figure 3: $CoVar$ for commodity market analysis

Third, we distinguish between $\Delta CoVaR$ measures driven by financial variables, $\Delta CoVaR$ measures driven by economic fundamentals and $\Delta CoVaR$ measures triggered by both factors to establish which factors explain tail dependence between the system and institutions. Hence, the finding that commodities price shocks driven by financial factors are significant could have relevant policy implications in terms of regulating commodity futures markets.

We develop our analysis in few stages. Initially, we evaluate energy, food and metals markets contagion risk via $\Delta CoVaR$, so that we build four risk measures: $\Delta CoVaR^{system|O}$, $\Delta CoVaR^{system|F}$, $\Delta CoVaR^{system|B}$, and $\Delta CoVaR^{system|M}$, with *system*={*S*&*P*}. In this phase, we distinguish tail dependence driven by financial contagion vs. economic fundamentals factors.

We then evaluate whether extreme prices in energy, food and all metals market can affect the entire system, i.e., we test whether energy, food and all metals markets contagion risk is statistically significant. Technically, this implies running a formal test of *significance* with null hypothesis:

$$H_0: \quad \Delta CoVaR^{system|i}(\tau) = 0, \qquad i \in \{F, O, B, M\}, \qquad \tau \in \mathcal{T} \subset (0,1) \tag{1}$$

We proceed with a formal test of *dominance* to rank the most risky markets in terms of contagion. The test of *dominance* has the following null hypothesis:

$$H_0: \quad |\Delta CoVaR^{system|i}(\tau)| \leq |\Delta CoVaR^{system|j}(\tau)|, \quad i \in \{F, O, B, M\}, \quad \tau \in \mathcal{T} \subset (0,1) \tag{2}$$

In other words, this test enables us to establish which market among crude oil, food, biofuel and all metals, has the major impact on the entire economy.

Given the interlinkages between energy and food markets, we further evaluate if risk spillovers exist from energy to food markets. In particular, we assume that the single food commodity plays the role of the system and energy commodities are the 'institutions'[4]. It is worthwhile noticing that, this time for both system and 'institutions', we look at the *right* tail of their return distributions, given that abnormal increases in energy prices can lead to extreme price upswings in each food commodity market (Figure 4).

Again, we run significance tests for disaggregated food products with null hypotheses:

$$H_0\text{: } \Delta CoVaR^{k|O}(\tau) = 0, \tag{3}$$

$$H_0\text{: } \Delta CoVaR^{k|B}(\tau) = 0, \tag{4}$$

with

$k \in \{maize,\ rapeseed,\ soybean,\ \ soybean-oil,\ sugar,\ wheat\},\ \ \tau \in \mathcal{T} \subset (0,1)$

Rejection of such hypotheses means that crude oil and/or biofuel markets have an impact on specific food markets (i.e., there are risk spillovers from *O* to commodity market *k* or from *B* to commodity market *k*).

Besides, we implement dominance tests with the null hypothesis:

$$\mathrm{H_0}\text{:}\quad |\Delta\mathrm{CoVaR}^{\mathrm{k|O}}(\tau)| \leq |\Delta\mathrm{CoVaR}^{\mathrm{k|B}}(\tau)|,\quad \tau \in \mathcal{T} \subset (0,1)$$

The latter test is useful to determine whether crude oil returns have a larger impact than biofuel returns on food commodity *k*, with $k \in$ {*maize*, *rapeseed*, *soybean*, *soybean–oil*, *sugar*, *wheat*}.

[4]We consider maize, rapeseed, soybean, soybean-oil, sugar, and wheat since they fuel the production of biofuels. We do not consider the aggregate food commodity index as it includes also products such as coffee and cocoa that are not used in biofuel production.

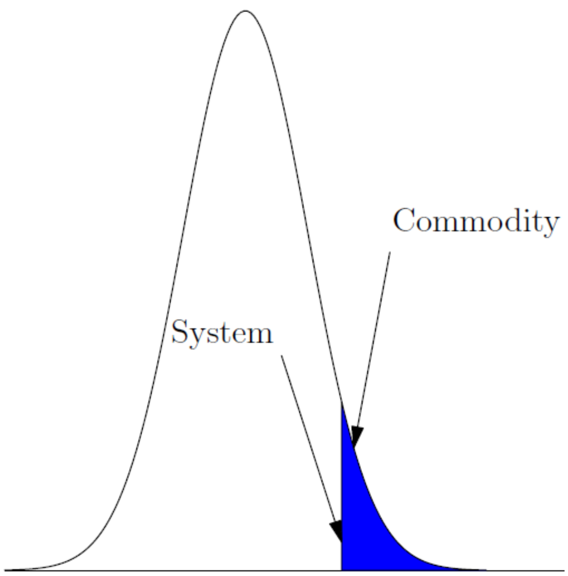


Figure 4: $CoVar$ for food and energy spillover market analysis

3.1 Estimation of $\Delta CoVaR$

In order to construct the $\Delta CoVaR$ risk measures for the system conditioned on each market we implement a six-step procedure.

Step 1. We run the τ_i-quantile regression

$$R_t^i = \alpha_i + \gamma_i N_t + e_t^i \tag{5}$$

where R_t^i refers to daily price returns of one of the four markets of interest (oil, food, ethanol, all metals), α_i is the constant, N_t is a set of explanatory variables, which reflect common market conditions that may drive individual commodity market's returns, and the error term e_t^i is assumed to be i.i.d. with zero mean and constant variance, and independent of N_t. Specifically, we have estimated three return series models: in the first one, N_t contains only common financial risk factors, labelled $N_t^{financials}$; in the second model, N_t includes only economic fundamentals, labelled $N_t^{fundamentals}$; in the third one, N_t comprises both financial and fundamentals factors, labelled N_t^{all}. In this way, we have been able to disentangle tail dependence determined by financial drivers (financial contagion), economic triggers (fundamentals-based contagion) and both factors taken together (mixed contagion). The confidence level τ_i is set at 5% when we look at the left tail of the institution's return distribution and at 95% when we examine the right tail.

Step 2. We obtain the τ_i -VaR for institution or market *i* as the predicted value

$$\widehat{VaR}_t^i\,(\tau_i) = \hat{\alpha}_i + \hat{\gamma}_i N_t \tag{6}$$

Here $\hat{\alpha}_i$ and $\hat{\gamma}_i$ represent the estimated parameters from eq. (5).

Step 3. We repeat the first two steps replacing τ_i by 50% to obtain 50%-*VaR* for market *i*.

Step 4. We run the τ-quantile regression

$$\mathrm{R}_t^{\text{system}} = \mathrm{a} + \mathrm{b}\,\mathrm{R}_t^{\mathrm{i}} + \mathrm{c}\,\mathrm{Z}_t + \varepsilon_t \tag{7}$$

where R_t^{system} denotes log-returns of the S&P 500 index at time *t*, the error term ε_t is assumed to be i.i.d. with zero mean and constant variance and independent of R_t^i, and the set of explanatory variables Z_t.

Step 5. We compute the following $CoVaR$ measures, which are the *VaR* of the system conditional on a situation of distress within oil, food, biofuel and all metals markets (i.e., τ_i is fixed at 5% (95%) level, which corresponds to the left (right) tail of the 'institutions' distribution), and the *VaR* of the system conditional on a normal situation within oil, food, biofuel and all metals markets (represented by a 50% quantile regression):

$$\widehat{\mathrm{CoVaR}}_t^{\mathrm{system}|\mathrm{R}^{\mathrm{i}}=\mathrm{VaR}_{\mathrm{R}^{\mathrm{i}}}(\tau_{\mathrm{i}})}(\tau) = \hat{\mathrm{a}} + \hat{\mathrm{b}}\,\widehat{\mathrm{VaR}}_t^{\mathrm{i}}(\tau_{\mathrm{i}}) + \hat{\mathrm{c}}\,\mathrm{Z}_t$$

$$\widehat{\mathrm{CoVaR}}_t^{\mathrm{system}|\mathrm{R}^{\mathrm{i}}=\mathrm{VaR}_{\mathrm{R}^{\mathrm{i}}}(50\%)}(\tau) = \hat{\mathrm{a}} + \hat{\mathrm{b}}\,\widehat{\mathrm{VaR}}_t^{\mathrm{i}}(50\%) + \hat{\mathrm{c}}\,\mathrm{Z}_t$$

Here â, b, ˆ, and ĉ indicate the estimated parameters from eq.(7).

Step 6. The estimated $\Delta CoVaR$ measure can finally be obtained as the difference

$$\Delta\widehat{\mathrm{CoVaR}}_t^{\mathrm{system}|\mathrm{i}}(\tau) = \widehat{\mathrm{CoVaR}}_t^{\mathrm{system}|\mathrm{R}^{\mathrm{i}}=\mathrm{VaR}_{\mathrm{R}^{\mathrm{i}}}(\tau_{\mathrm{i}})}(\tau) - \widehat{\mathrm{CoVaR}}_t^{\mathrm{system}|\mathrm{R}^{\mathrm{i}}=\mathrm{VaR}_{\mathrm{R}^{\mathrm{i}}}(50\%)}(\tau).$$

The $\Delta\widehat{CoVaR}_t^{system|i}(\tau)$ represents the marginal contribution of oil, food, biofuel, or all metals market to contagion risk and, when τ_i = 95%, a $\Delta CoVaR$ different from zero can be interpreted as an increase in extreme market losses for the system (economic instability) when a given market is in distress.

The six-step procedure is also implemented to assess risk spillovers from energy to food markets. In this case, R_t^i refers to daily price returns of oil and ethanol, while R_t^{system} denotes daily price returns of disaggregated food commodities.

3.2 Testing Procedures

To implement the significance and dominance tests, we consider the testing procedure proposed by Bernal et al. (2014). For a fixed value of τ, the authors test whether or not the cumulative distribution functions (CDFs) of $CoVaRs$ at a the τ_i level and at the 50% level are different from each other. This is achieved by bootstrapping the Kolmogorov-Smirnov (KS) test statistic using the procedure proposed by Abadie (2002). The KS test cannot be used directly because the estimated distributions introduce an unknown nuisance parameter that jeopardizes the distribution-free character of the KS test. Hence, Bernal et al. (2014) use the method of Abadie (2002) that allows to obtain critical values by resampling the test statistic under conditions consistent with the null hypothesis. The method of Abadie (2002) consists in a nonparametric i.i.d. block bootstrap in stochastic dominance tests, in which data are divided into blocks that are resampled to replicate the time-dependent structure of the original data.

The two-sample Kolmogorov-Smirnov statistic they use is hence defined as:

$$\mathrm{K_{mn}}(\tau) = \sup_{\mathrm{u}} |\, \mathrm{F_m}(\mathrm{u}) - \mathrm{G_n}(\mathrm{u})| \tag{8}$$

where m and n are the size of the two samples and $F_m(u)$ and $G_n(u)$ are the CDFs of the $\widehat{CoVaR}_t^{system|R^i=VaR_{R^i}(\tau_i)}(\tau)$ and $\widehat{CoVaR}_t^{system|R^i=VaR_{R^i}(50\%)}(\tau)$, respectively.

For the dominance hypothesis with a fixed value of τ, the test statistic to bootstrap is given by:

$$\mathrm{G_{mn}}(\tau) = \sup_{\mathrm{u}} |\, \mathrm{A_m}(\mathrm{u}) - \mathrm{B_n}(\mathrm{u})| \tag{9}$$

Where $A_m(u)$ and $B_m(u)$ are the CDFs of the absolute values of $\Delta CoVaR^{system|i}(\tau)$ and $\Delta CoVaR^{system|j}(\tau)$ and *m* and *n* are the size of the two samples. Again, bootstrap-based methods are needed to calculate the p-values for the dominance test.

4. Data Description

To estimate the contribution of commodity market to contagion risk and risk spillovers across markets, we consider daily trading data from 16 May 2005 to 19 June 2013, for a total of 2041 observations. All data are taken from Bloomberg database (Table 1).

Table 1: List of Variables and Bloomberg Tickers

Variables	Bloomberg Ticker
S&P GSCI Commodity Agricultural index	SPGSAG Index
S&P GSCI Commodity All Metals index	SPGSAM Index
Generic 1st WTI Crude Oil futures, US$ (NYMEX)	CL1 Comdty
Generic 1st Ethanol futures, US$ (CBOT)	DL1 Comdty
S&P GSCI Commodity index	SPGSCI Index
Baltic Dry Freight	BDIY INDEX
Standard & Poor's 500	SPX Index
Generic 1st Corn No. 2 Yellow futures, US$ (CBOT)	C 1 Comdty
Generic 1st Rapeseed, € (EURONEXT)	IJ1 Comdty
Generic 1st Soybean No. 2 Yellow futures, US$ (CBOT)	S 1 Comdty
Generic 1st soybean-oil, US$ (CBOT)	BO1 Comdty
Generic 1st Sugar No. 11 futures, US$ (ICE)	SB1 Comdty
Generic 1st No. 2 Soft Red Winter Wheat futures, US$ (CBOT)	W 1 Comdty
Dollar effective exchange rate	DXY Curncy
Federal fund rate (overnight interest rate)	FEDL01 Index
Market Volatility Index (20-day ahead implied volatility of S&P 500 index options)	VIX INDEX
Moody's BAA Corporate Bond yield	MOODCBAA Index
Moody's AAA Corporate Bond yield	MOODCAAA Index
TED spread	BASPTDSP Index
Libor	US0003M Index

The variable used as *system* is the S&P 500 (S&P) index given that it is a well-established measure used in the literature to quantify global economic activity on daily basis[5]. The S&P 500 index comprises the 500 largest U.S. firms and is also a benchmark indicator of the overall stock market conditions and a leading indicator of the global economy. This is because the stock market usually begins to decline before the economy as a whole declines, and usually starts to improve before the general economy begins to recover from a slump.

The variables used as *institution* are the daily closing futures prices[6] of energy, agricultural and all metals markets. We focus on commodity futures prices mainly because they are

[5]Other variables that could be used as proxies of economic activity, such as GDP or industrial production, are not available at high frequency.

[6]We have used the first generic futures contracts series (which considers at each date the price of the contract with the closest maturity).

important price signals to guide commodity demand and spot prices (e.g., Antoniou and Foster 1992; Yang et at. 2005). In addition, given that the volume of trade is larger in futures markets than spot markets (e.g., Roehner 2009), it is reasonable to expect that the dynamics in futures markets could have a stronger effect on the whole economy since price patterns are more reliable. Furthermore, we are interested in knowing how the higher speculative influence in commodity futures markets impacts the entire economy.

Oil data refers to daily futures prices of West Texas Intermediate, also known as Texas Light Sweet, which is a type of crude oil used as a benchmark in oil pricing and the underlying commodity of the New York Mercantile Exchange's oil futures contracts.

As a proxy of the price of biofuels, we consider ethanol futures prices. Ethanol futures trading was newly introduced at the Chicago Board of Trade (CBOT) in May 2005, this is the reason why our dataset starts in that period.

We have then collected two aggregated indices for food products and all metals, explicitly, the S&P GSCI Agriculture Index and the S&P GSCI All Metals index.

The S&P GSCI Agriculture Index and the S&P GSCI All Metals Index are sub-indices of the S&P GSCI[7] and provide investors with a reliable and publicly available benchmark for investment performance in the agricultural and metal commodity markets. The S&P GSCI Agriculture Index comprises the following commodities in order of weighting importance: wheat, maize, soybeans, cotton, sugar, coffee and cocoa. The S&P GSCI All Metals Index includes industrial metals, – namely aluminium, copper, lead, nickel and zinc – and precious metals – namely, gold and silver.

The set of N_t and Z_t variables entering the *CoVaR* measure, when the *institutions* are commodity markets and the system is S&P 500, includes those factors identified by the literature (Fama and French 1989; Ferson and Harvey 1994) as possible drivers of commodity and stock market's returns. We restrict ourselves to a small set of *N* and *Z* factors to avoid overfitting the data. Specifically, $N_t^{financials}$ comprises:

- the CBOE Volatility Index (VIX), which captures the implied volatility of the S&P500 index and reflects stock market expectations of volatility. It is a popular barometer of investor sentiment and often referred to as the 'fear index' (Koch 2014; Bae et al. 2003);

[7]The S&P GSCI index was originally developed by Goldman Sachs (GS). In 2007, ownership transferred to Standard & Poors, who currently own and publish it. It is a tradable index that is readily available to market participants of the Chicago Mercantile Exchange. The S&P GSCI contains as many commodities as possible, with rules excluding certain commodities to maintain liquidity and investability in the underlying futures markets. The index currently comprises 24 commodities from all commodity sectors - energy products, industrial metals, agricultural products, livestock products and precious metals. In particular, its composition as of February 2013 is given by 78.65% of energy products, 6.12% of industrial metals, 1.81% of precious metals, 10.42% of agriculture, and 3.01% of livestock. The index contains a much higher exposure to energy than other commodity price indices such as the Dow Jones-UBS Commodity Index.

- the conditional volatility within each market, which controls for specific market exposure. Conditional volatility is the standard deviation of a future return that is conditional on known information such as the history of past returns. It has been calculated via a GARCH(1,1) model as developed by Bollerslev (1986).

$N_t^{fundamentals}$ includes:

- the Baltic Dry Index (BDI) proxy for global demand[8] (Kilian 2009);
- the MSCI Emerging Market Index proxy for the strength of economic growth in emerging economies that determines the commodity demand from emerging markets (Koch 2014; Tang and Xiong 2012);
- the returns on dollar effective exchange rate (DXY), which controls for the exposure of commodity futures (priced in US dollars) to exchange rate risk (Algieri 2014a; Erb and Harvey 2006);
- the US three month T-bill (short-term interest rate) used as barometer of global changes in the international monetary policy (Manera et al. 2013; Chevallier 2009; Bae et al. 2003; Bessembinder and Chan 1992);

N_t^{all} includes all the aforementioned variables, i.e. both financial variables and fundamental factors.

The set of state variables Z_t used in the quantile regression to explain R^{system}, in addition to the CBOE Volatility Index, the Baltic Dry Index and the returns on dollar effective exchange rate, comprises:

- the spread between Moody's BAA and Moody's AAA Corporate Bond yields – i.e., yield returns of bonds rated BAA and AAA by Moody's – which represents the default risk premium (sometimes called the junk bond yield) (Manera et al. 2013; Chevallier 2009; Sadorsky 2002);
- TED spread (i.e., the difference between the 3-Month London Interbank Offered Rate (LIBOR) and 3-Month Treasury Bill), which provides a measure of stress (or not) in credit markets and, therefore, it is an indicator of world financial and economic health (Manera et al. 2013; Bae et al. 2003);

[8]The Baltic Dry index has been published daily by the Baltic Exchange in London since May 1985. Based on daily quotes for booking vessels of various sizes and across multiple maritime routes (about 50), the Baltic Dry Index is an indicator of transportation costs for raw materials and is considered as a leading indicator (forward looking) of economic activity since it involves events taking place at the earlier stages of global commodity chains. Given that the supply structure of the shipping industry is generally predictable and relatively inflexible, changes in shipping costs reflect changes in the worldwide demand for raw materials. A high Baltic Dry Index is an indication of a tight shipping supply due to high demand and is likely to create inflationary pressures along the supply chain. A sudden and sharp decline of the Baltic Dry Index is likely to foretell a recession since producers have substantially curtailed their demand leaving shippers to substantially reduce their rates in an attempt to attract cargo. Shortly, a high Baltic Dry Index growth rate is positively associated with industrial production growth and vice-versa.

- the term spread[9], which is calculated as the spread between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity[10].

To evaluate risk spillover across energy and food markets we further consider the futures price returns for single energy products and for those agricultural products used to produce the first generation of biofuels, namely maize, rapeseed, soybeans, soybean-oil, sugar, and wheat. The set of N_t and Z_t variables entering the *CoVaR* measure, when the *institutions* are energy markets and the system is mirrored by each single agricultural product, consists of those factors that might drive energy and food commodity market's returns. We employ the same regressors N_t^{all} used in the previous analysis for the institutions, i.e., both financial variables and economic fundamentals factors, while the factors explaining the system, Z_t, encompass:

- the Baltic Dry Index;
- the MSCI Emerging Market Index;
- the returns on dollar effective exchange rate;
- the VIX Index;
- the Southern Oscillation Index anomalies (SOI). This index measures the fluctuations in air pressure occurring between the western and eastern tropical Pacific during El Niño and La Niña episodes[11] and it is used to proxy global weather conditions. Indeed, although the events described by the SOI index arises in the Pacific Ocean, they have strong effects on the world's weather and an important influence on the world's production and price of primary non-oil commodities[12] (Brunner 2002; Algieri 2014b).

[9]Several studies find that term spread is a good predictor of output growth and recessions. See Wheelock and Wohar (2009) for a review.

[10]Yield on long-term securities typically exceeds those on otherwise comparable short-term securities, reflecting the preference of most investors to hold instruments with shorter maturities. Therefore, the yield curve is typically upward sloping. Analysts have noted that in recessions the yield curve is inverted (i.e., short-term yields are above those on long-term securities).

[11]It is a standardised index based on the observed sea level pressure differences between Tahiti, French Polynesia and Darwin, Australia. In general, a negative phase of the SOI represents below-normal air pressure at Tahiti and above-normal air pressure at Darwin. SOI data are taken from the National Oceanic and Atmospheric Administration National Climatic Data Center.

[12]Prolonged periods of positive SOI values coincide with La Niña events during which water becomes cooler than normal; vice-versa, SOI values below zero mirror El Niño episodes during which water becomes warmer than normal. La Niña events are associated with increasing droughts throughout the mid-latitudes, where much of wheat and other relevant grains such as maize and soybeans are produced, thus suppressing their yield (Hurtado and Berri 1998) and driving up prices. For this reason, La Niña episodes have historically been associated with global food crises. El Niño is associated with an increased likelihood of droughts in tropical land areas, which mainly affects crops such as sugar.

Descriptive statistics

The evolution of logarithmic commodity returns and descriptive statistics are reported in Figure 5 and Table 2 respectively.

Daily returns have average values close to zero and differing high standard deviations, indicating dispersion in volatility behaviour across markets and products. Oil and biofuel show higher volatility than food and metals commodities. The maximum (minimum) value achieved by oil and biofuel is larger (smaller) than the one recorded for food and metals. Within food commodities, sugar, wheat and maize exhibit higher volatility than soybean and rapeseed. All series are skewed (with the exception of maize) and display significant excess kurtosis (fat tails). The evidence provided by Jarque-Bera test suggests that all series have not-normal distributions (all return series strongly reject the normality hypothesis) which is consistent with the presence of fat tails and skewness.

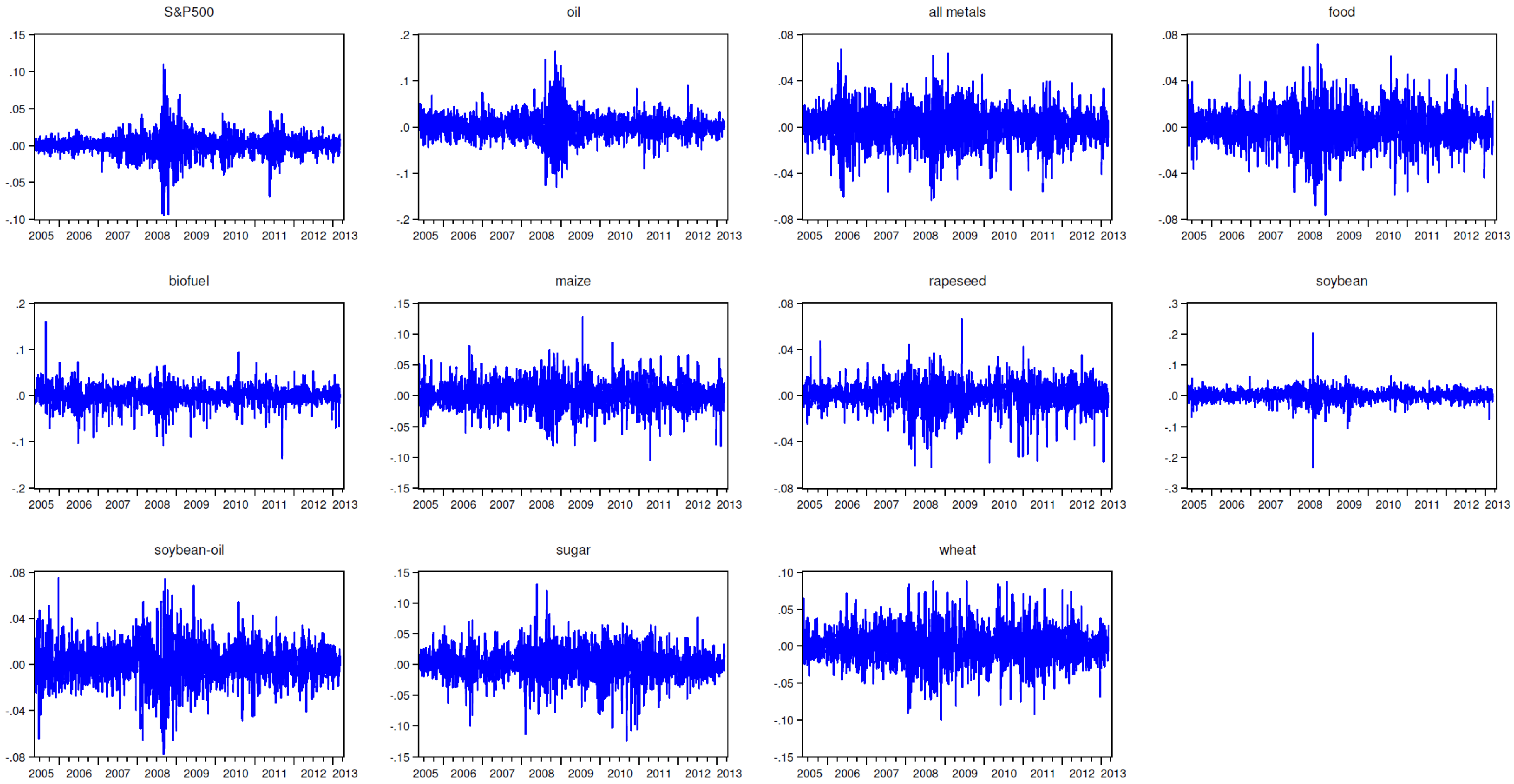


Figure 5: Time Series Plots of Logarithmic Commodity Returns.

Table 2: Descriptive Statistics for Logarithmic Commodity Returns

	S&P500	O	M	F	B	maize	rapeseed	soybean	soybean-oil	sugar	wheat
Mean	1.62E-04	3.61E-04	3.00E-04	3.85E-04	3.67E-04	5.76E-04	3.25E-04	4.25E-04	3.86E-04	3.46E-04	3.97E-04
Maximum	0.11	0.164	0.067	0.072	0.16	0.128	0.066	0.203	0.075	0.131	0.088
Minimum	-0.095	-0.131	-0.064	-0.076	-0.137	-0.104	-0.062	-0.234	-0.078	-0.124	-0.100
Std. Dev.	0.014	0.024	0.015	0.015	0.02	0.021	0.012	0.019	0.016	0.024	0.023
Skewness	-0.309	0.126	-0.213	-0.203	-0.473	0	-0.704	-0.807	-0.046	-0.251	0.026
Kurtosis	12.704	8.245	4.546	4.802	8.843	4.906	6.931	24.076	5.48	5.801	4.413
Jarque-Bera	8028.971	2341.326	218.531	289.648	2974.785	308.327	1480.49	37939.25	522.942	687.725	169.775
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

We report in Table 3 a number of measures of dependence between the 'system' and the 'institutions' to describe co-movement between different price returns. In particular, Table 3 displays the classical linear Pearson correlation index (ρ), the Spearman's (ρ_S) and Kendall's (ρ_τ) rank correlation indices. While the simple Pearson correlation fails to capture the important tails behaviour of the joint probability distribution, the other measures are more robust given that they account for non-linearities and the existence of dependence inside extreme values of data sets.

Specifically, the Spearman's and Kendall's tests are nonparametric measures of statistical dependence between two variables, are measured as ordinal numeric and allow one to analyse the concordance between two rankings. However, while the former merely considers the two sets of ranks, the latter also shows whether the components of the vector have a tendency to move together. The results for both coefficients are similar, the values obtained with Spearman's rank correlation coefficient being higher (Table 3). The results show that there are co-movements between the system and the institutions. The highest coefficients appear between the system and oil, followed by the system and metals, the system and food, and the system and ethanol. Co-movements are more evident from the analysis of food and energy markets (Table 3, Panel B). The measures of dependence indicate, in fact, that maize and wheat tend to co-move more with ethanol than oil, while soybean, soybean-oil and sugar tend to co-move more with oil than ethanol, rapeseed instead co-move with oil and ethanol in a similar way. To evaluate extreme phenomena (or extreme co-movements) more in detail we examine the $\Delta CoVaR$ risk measures.

Table 3: Measures of dependence between the 'system' and the 'institutions'

Panel A: System = S&P 500				
	O	M	F	B
ρ	0.335	0.294	0.241	0.136
ρ_S	0.293	0.293	0.176	0.094
ρ_τ	0.293	0.293	0.176	0.094

Panel B: System = Food Commodity												
Commodity	maize		rapeseed		soybean		soybean-oil		sugar		wheat	
	O	B	O	B	O	B	O	B	O	B	O	B
ρ	0.311	0.477	0.339	0.318	0.376	0.338	0.504	0.385	0.26	0.208	0.282	0.391
ρ_S	0.282	0.487	0.299	0.297	0.35	0.338	0.466	0.355	0.242	0.202	0.244	0.368
ρ_τ	0.193	0.356	0.205	0.204	0.24	0.235	0.326	0.247	0.163	0.137	0.167	0.257

Note: ρ denotes Pearson linear correlation, ρ_S is Spearman's rank correlation coefficient, ρ_τ is Kendall's rank correlation coefficient.

5. Empirical Analysis

5.1 Results of $\Delta CoVaR$ and the Significance Tests

Descriptive statistics and the graphical plot of our estimated risk measures ($\Delta CoVaR$) obtained from using quantile regressions when the system is the *S*&*P* 500, the institutions are commodity markets and τ is set at the 5% level, are reported in Table 4 and Figure 6, respectively. We look at both the left tail (τ_i=0.05) and the right tail (τ_i=0.95) of the commodity market return distribution. The regressors used in all the quantile regressions include both economic fundamentals and financial variables. Recalling that $\Delta CoVaR_t^i$, quantifies the marginal contribution of market *i* to overall contagion risk, we observe that in the oil market $\Delta CoVaR$ is more volatile and, on average, it is larger than $\Delta CoVaR$ for the other markets (Table 4). It is also evident that commodity markets move strongly together and the contagion risk for oil market shot up dramatically during the crisis while slowed down with the other indices after it (Figure 6). The dynamics of $\Delta CoVaR$ point to the presence of pro-cyclicality which occurs because risk measures tend to be low in booms and high in crises.

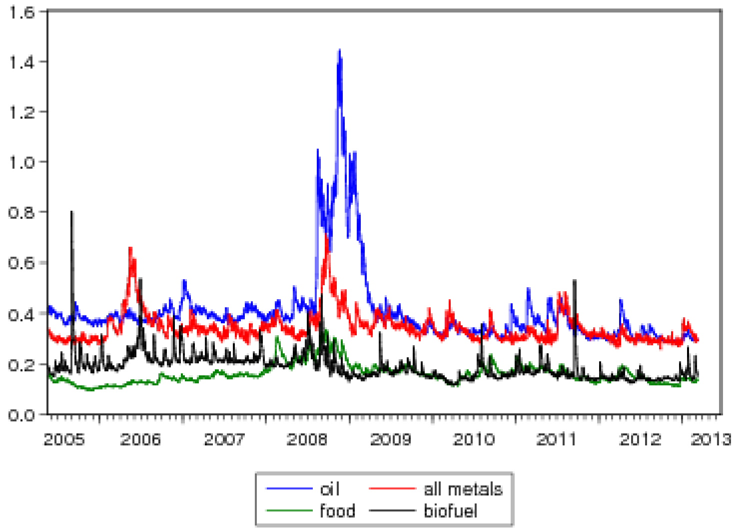
Table 4: Descriptive Statistics of the $\Delta CoVaR$ measures (in percentage) with S&P500 index as the system and N_t fundamentals and financial variables.

	$\lvert\Delta CoVaR\rvert, \tau_i = 0.05$				$\lvert\Delta CoVaR\rvert, \tau_i = 0.95$			
	O	M	F	B	O	M	F	B
Mean	0.407	0.343	0.16	0.187	0.495	0.216	0.155	0.077
Maximum	1.443	0.712	0.335	0.803	1.848	0.565	0.34	0.678
Minimum	0.276	0.258	0.094	0.114	0.252	0.076	0.056	0.026
Std. Dev.	0.152	0.06	0.041	0.052	0.206	0.064	0.038	0.048
Skewness	3.477	2.381	1.382	2.873	3.371	1.199	1.093	3.446
Kurtosis	16.64	10.541	5.381	22.129	15.791	5.68	4.774	27.384
Jarque-Bera	19946.85	6771.304	1132.691	33949.57	17792.17	1101.076	674.967	54640.34
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

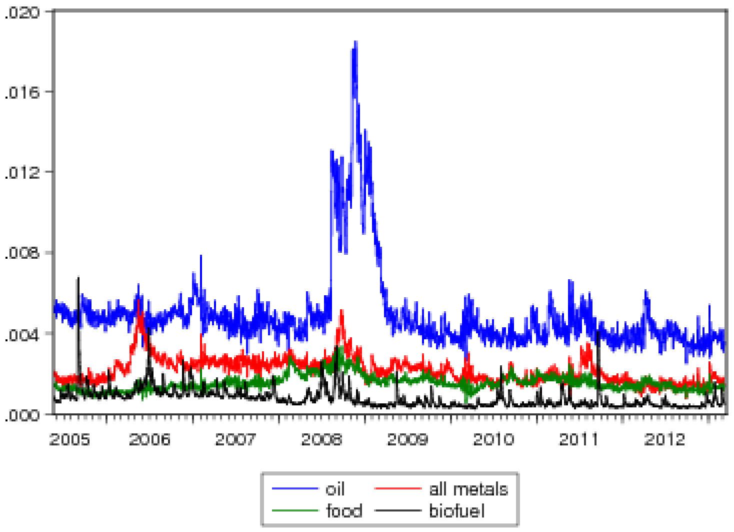
Panel B: Correlation matrices

	$\lvert\Delta CoVaR\rvert, \tau_i = 0.05$					$\lvert\Delta CoVaR\rvert, \tau_i = 0.95$			
	O	M	F	B		O	M	F	B
O	1				O	1			
M	0.487	1			M	0.401	1		
F	0.583	0.431	1		F	0.511	0.42	1	
B	0.127	0.262	0.151	1	B	0.148	0.401	0.039	1

Note: The table reports descriptive statistics (Panel A) and the correlation matrix (Panel B) for the $\Delta CoVaR$ risk measure referred to oil (O), all metals (M), food (F), and biofuel (B). τ is set at the 5% level. τ_i is set at the 95% level (right tail of the institution's distribution) or at the 5% level (left tail of the institution's return distribution).



(a) | $\Delta CoVaR$ |, τ_i=0.05



(b) $\boldsymbol{\Delta CoVaR}$, τ_i=0.95

Figure 6: Time Series Plots of $\Delta CoVaR$ (in percentage)

The significance test, eq. (1), allows us to identify if a given market is significantly risky for the system. For this test we distinguish between risk measures driven by economic fundamentals (Table 5), financial variables (Table 6) and both factors (Table 7), with the objective to evaluate which driver makes a given commodity market significantly risky for the whole economy.

In detail, Tables 5-7 show the observed test statistics in eq. (8) and the associated p-values assuming the $S\&P500$ index as the system and oil, food, ethanol, all metals as institutions.

We consider $\mathcal{T}$ ={0.01,0.05,0.1}[13] and set $\tau_i = 0.05$ and $\tau_i = 0.95$ in all the $\Delta CoVaR$ considered. Put simply, we consider for the 'institutions' both the right tails ($\tau_i = 0.95$) – which mirror a situation of extremely high prices – and the left tails ($\tau_i = 0.05$) – which correspond to a situation of extremely low prices. For the system, we look at the left tails – which refer to abnormal drop in prices, i.e., a marked slowdown in the whole economy.

The rejection of the null hypothesis, given by a very low p-value, indicates that a given 'institution' *i* (i.e., oil, food, ethanol, all metals) produces contagion risk.

Table 5: Significance Tests with the S&P500 index as the system and fundamental variables (BDI, MSCI, DXY, T-Bill) in the quantile regressions.

		$\tau_i = 0.05$					$\tau_i = 0.95$			
		O	M	F	B		O	M	F	B
τ =0.01	Test Stat	0.003	0.003	0.088	0.205	Test Stat	0.004	0.101	0.213	0.015
	Pval	1.000	1.000	0.000	0.000	Pval	1.000	0.000	0.000	0.960
		O	M	F	B		O	M	F	B
τ =0.05	Test Stat	0.002	0.002	0.087	0.173	Test Stat	0.004	0.12	0.195	0.014
	Pval	1.000	1.000	0.000	0.000	Pval	1.000	0.000	0.000	0.985
		O	M	F	B		O	M	F	B
τ =0.1	Test Stat	0.002	0.002	0.067	0.079	Test Stat	0.003	0.085	0.152	0.008
	Pval	1.000	1.000	0.000	0.000	Pval	1.000	0.000	0.000	1.000

Note: The table reports the observed test statistics in eq. (8) and the associated p-values. O, M, F, and B denote log-returns for the WTI oil index, S&P GSCI All Metals index, S&P GSCI Agriculture index, and ethanol CBOT index, respectively. Data covers the period May 2005-June 2013.

Table 5 shows that when the $CoVaR$ and $\Delta CoVaR$ measures are explained by economic fundamentals, ethanol and oil markets do not generate contagion risk[14] when extremely high energy prices materialize. Similarly, when abnormal oil and metal price drops are generated by economic fundamentals, the underlying markets do not tend to trigger any contagion risk. Conversely, when $CoVaR$ and $\Delta CoVaR$ measures are explained by financial factors (Table 6), all markets contributes to contagion risk both when commodity prices surge and when they fall abnormally. This holds true also when the $CoVaR$ and $\Delta CoVaR$ measures are explained by both financial drivers and economic fundamentals (Table 7).

[13] τ can be interpreted as a measure of economic instability, we have therefore a general definition of economic instability when τ=0.05, a broader definition of economic instability when τ=0.1, and a narrower definition of economic instability when τ=0.01.

[14] The same result was obtained when the broader energy commodity index was used instead of oil. For reason of space this finding has not been reported but it is available from the authors upon request.

Table 6: Significance Tests with the S&P500 index as the system and financial variables (VIX, conditional volatility) in the quantile regressions.

		$\tau_i = 0.05$					$\tau_i = 0.95$			
		O	M	F	B		O	M	F	B
τ =0.01	Test Stat	0.171	0.097	0.082	0.119	Test Stat	0.162	0.098	0.084	0.108
	Pval	0.000	0.000	0.000	0.000	Pval	0.000	0.000	0.000	0.000
		O	M	F	B		O	M	F	B
τ =0.05	Test Stat	0.150	0.115	0.083	0.105	Test Stat	0.148	0.120	0.082	0.094
	Pval	0.000	0.000	0.000	0.000	Pval	0.000	0.000	0.000	0.000
		O	M	F	B		O	M	F	B
τ =0.1	Test Stat	0.117	0.083	0.063	0.051	Test Stat	0.111	0.086	0.067	0.046
	Pval	0.000	0.000	0.000	0.009	Pval	0.000	0.000	0.000	0.022

Note: The table reports the observed test statistics in eq. (8) and the associated p-values. O, M, F, and B denote log-returns for the WTI oil index, S&P GSCI All Metals index, S&P GSCI Agriculture index, and ethanol CBOT index, respectively. Data covers the period May 2005-June 2013.

These results highlight three interesting points. First, the economic system fragility is conditioned by what happens in commodity markets, i.e., there are risk spillover effects from commodity markets to the whole economy. Second, while positive or negative shocks to economic fundamentals do not always lead to contagion risk, financial drivers contribute to make all commodity markets risky for the economy. This is confirmed when both financial and economic drivers are considered together. In short, there is a certain evidence of financial and mixed contagion. Third, only for food sector both positive and negative shocks driven either by economic fundamentals or financial variables or both, can lead to economic instability. All these results hold for different significance levels. A small exception is recorded for biofuel. Indeed, when a broader definition of economic instability is considered ($\tau = 0.1$), extreme hikes in biofuel prices are not significant in generating any contagion risk (Table 7).

Table 7: Significance Tests with the S&P500 index as the system and fundamentals and financial variables (BDI, MSCI, DXY, T-Bill, VIX, conditional volatility)

		$\tau_i = 0.05$					$\tau_i = 0.95$			
		O	M	F	B		O	M	F	B
τ =0.01	Test Stat	0.213	0.143	0.085	0.113	Test Stat	0.249	0.092	0.079	0.054
	Pval	0.000	0.000	0.000	0.000	Pval	0.000	0.000	0.000	0.004
		O	M	F	B		O	M	F	B
τ =0.05	Test Stat	0.185	0.163	0.085	0.100	Test Stat	0.231	0.106	0.079	0.047
	Pval	0.000	0.000	0.000	0.000	Pval	0.000	0.000	0.000	0.023
		O	M	F	B		O	M	F	B
τ =0.1	Test Stat	0.141	0.118	0.064	0.047	Test Stat	0.172	0.078	0.064	0.023
	Pval	0.000	0.000	0.001	0.023	Pval	0.000	0.000	0.001	0.642

Note: The table reports the observed test statistics in eq. (8) and the associated p-values. O, M, F, and B denote log-returns for the WTI oil index, S&P GSCI All Metals index, S&P GSCI Agriculture index, and ethanol CBOT index, respectively. Data covers the period May 2005-June 2013.

5.2 Results of the Dominance Tests

For the dominance test we consider only $CoVaR$ and $\Delta CoVaR$ measures explained in terms of economic and financial drivers, given that only in this case all the $\Delta CoVaR$s are statistically significant. Specifically, this test shows the importance of the contributions of each commodity market to contagion risk, i.e., which market tends to propagate the highest distress (or shock) across the economy.

In detail, Table 8 reports the observed test statistics in eq. (9) and the associated p-values assuming the S&P500 as the system for the critical levels in $\mathcal{T}$={0.01,0.05,0.1}. To establish a ranking in terms of contagion for commodity markets, each of the six matrices of Table 8, corresponding to the possible pairs (τ, τ_i), has to be read as follows: market *j* dominates market *i,* i.e. has a greater impact in terms of contagion, only if the p-value in the *i*th row–*j*th column is large (e.g., larger than 5%) *and* the p-value in the *j*th row–*i*th column is small (e.g., smaller than 5%). Thus, in order to establish whether one market dominates another, the two cells in Table 8, corresponding to the two markets, have to be examined together. As an example, take oil (*O*) as market *j* and food (*F*) as market *i*, for $\tau = 0.01$ and $\tau_i = 0.95$. In this case, the observed test statistic, for the null that $\Delta CoVaR^{system|i}$ is smaller than $\Delta CoVaR^{system|j}$, is equal to 0.000 with a p-value of 99.9%, thereby not rejecting the null hypothesis. Furthermore, the observed test statistic for the null that $\Delta CoVaR^{system|j}$ is smaller than $\Delta CoVaR^{system|i}$ is equal to 0.995 with a p-value of 0, which implies a rejection of the null. Combining the two results, we conclude that market *j*, i.e., oil, dominates market *i*, i.e., food. This means that oil is riskier than food in threatening the stability of the whole economic system.

The results in Table 8 indicate that it is possible to identify a specific rank among the four indices for each tail, that means it is possible to order commodity markets on the basis of their contribution to contagion. For the right tail, which captures extreme price increases, the ranking is:

- (1) oil dominates all the remaining markets;
- (2) all metals dominate food and ethanol markets;
- (3) food dominates ethanol;
- (4) ethanol is dominated by all the remaining markets.

For the left tail, that mirrors extreme price drops, the contribution of each market to contagion risk can be ranked as follows:

- (1) oil dominates all the remaining markets;
- (2) all metals dominate food and ethanol markets;
- (3) ethanol dominates food;
- (4) food is dominated by all the remaining markets.

This denotes that when prices skyrocket and when they reduce significantly, the marginal contribution of oil to the overall risk is higher than the contribution of metal, food and ethanol. The only difference between the two tails occurs for the ethanol and food markets when $\tau = 0.01$ and $\tau = 0.05$. Specifically, while food dominates ethanol when prices boost, the opposite situation takes place when prices fall. This can be due to the fact, that extreme food price drops are less dangerous than sharp increases. For τ=0.1, instead, the two tails show the same ranking. This reveals the fact that extreme hikes and drops in price generate the same commodity classification, when a broader definition of system instability is considered. It is interesting to notice that the results of the dominance tests are in line with the measures of dependence showed in Table 3.

To sum up, combining the results of the significance and dominance tests, we can establish that any perturbation occurring in a given commodity market becomes important in the sense that it finishes to affect the whole economy. Some commodity markets tend to have a significantly larger propagation effect of shocks. Indeed, the degree of the impact is larger when oil market registers distress, because oil may exert influence also on the dynamics of the other markets via different channels. Moreover, it emerges that contagion effects are more pronounced when the distress in food market is caused by extreme prices surges. In this latter case, the spread of market disturbances can be a potential risk mainly for poor countries that spend a large percentage of their income on food. The contagion effect increases the vulnerability of the poor consumer in periods of high prices, hurting thus food and nutrition security.

Table 8: Dominance Tests with S&P5000 index as the system and fundamentals and financial variables (BDI, MSCI, DXY, T-Bill, VIX, conditional volatility) in quantile regressions.

		$\tau_i = 0.05$					$\tau_i = 0.95$			
	i\j	O	M	F	B	i\j	O	M	F	B
	O	-	0.872 (0.000)	0.983 (0.000)	0.944 (0.000)	O	-	0.982 (0.000)	0.995 (0.000)	0.991 (0.000)
τ =0.01	M	0.000 (0.999)	-	0.885 (0.000)	0.609 (0.000)	M	0.000 (0.999)	-	0.151 (0.000)	0.714 (0.000)
	F	0.000 (0.999)	0.000 (1.000)	-	0.000 (0.999)	F	0.000 (0.999)	0.027 (0.208)	-	0.723 (0.000)
	B	0.000 (0.999)	0.002 (0.980)	0.395 (0.000)	-	B	0.000 (0.999)	0.002 (0.979)	0.005 (0.931)	-
	i\j	O	M	F	B	i\j	O	M	F	B
	O	-	0.395 (0.000)	0.975 (0.000)	0.956 (0.000)	O	-	0.936 (0.000)	0.993 (0.000)	0.992 (0.000)
τ =0.05	M	0.000 (0.999)	-	0.972 (0.000)	0.946 (0.000)	M	0.000 (0.999)	-	0.469 (0.000)	0.871 (0.000)
	F	0.000 (0.999)	0.000 (0.999)	-	0.000 (0.999)	F	0.000 (0.999)	0.000 (0.999)	-	0.768 (0.000)
	B	0.000 (0.999)	0.000 (0.998)	0.256 (0.000)	-	B	0.000 (0.999)	0.001 (0.996)	0.004 (0.964)	-
	i\j	O	M	F	B	i\j	O	M	F	B
	O	-	0.533 (0.000)	0.975 (0.000)	0.998 (0.000)	O	-	0.953 (0.000)	0.993 (0.000)	0.999 (0.000)
τ =0.1	M	0.000 (1.000)	-	0.948 (0.000)	0.995 (0.000)	M	0.000 (0.999)	-	0.353 (0.000)	0.966 (0.000)
	F	0.000 (0.999)	0.000 (0.999)	-	0.728 (0.000)	F	0.000 (1.000)	0.000 (1.000)	-	0.951 (0.000)
	B	0.000 (0.999)	0.000 (1.000)	0.001 (0.995)	-	B	0.000 (1.000)	0.000 (1.000)	0.000 (0.998)	-

Note: The table reports the observed test statistics in eq. (9) and the associated p-values (in parenthesis). O, M, F, and B denote log-returns for the WTI oil index, S&P GSCI All Metals index, S&P GSCI Agriculture index, and ethanol CBOT index, respectively. Data covers the period May 2005 - June 2013.

5.3 Risk Spillovers between Energy and Food Markets

Table 9 reports significance tests in the context of the risk spillovers analysis between energy and food markets. Explicitly, we have disaggregated the food commodity market in its main components and evaluated if energy market risks affect each food commodity.

The system, this time, is given by each single agricultural commodity, while oil and ethanol are the two 'institutions'. Hence, $\Delta CoVaR^{j|i}$ captures the increase in risk of individual food markets *j* when energy markets *i* falls into distress.

For testing the presence of risk spillovers, we look at the right tails of the distributions (i.e., prices upsurges) for both the system and 'institutions'. We compute both the significance and dominance tests for the case $\tau_i = 0.95$ and $\mathcal{T}$={0.9,0.95,0.99}.

Given that for both oil and ethanol we always reject the null hypothesis that $\Delta CoVaR$ is equal to zero, the energy sector has a significant impact on each food commodity during a period of distress. Put differently, oil and ethanol markets significantly contribute to food market distress.

Table 10 reports dominance tests in the context of the risk spillovers analysis. This test establishes whether ethanol has a larger impact than oil on a given food commodity. We conclude that oil dominates ethanol for a given commodity if the corresponding p-value in the left column is small *and*, at the same time, the one in the right column is large. Hence, for all food commodities oil strongly dominates ethanol. This means that spillovers from oil market to food commodity markets are larger than those coming from ethanol market. It is interesting to highlight that for maize and wheat, the dominance results differ from those regarding the dependence measures of Table 3.

From a policy perspective, predicting sudden changes in risk spillovers from crude oil to agricultural commodities prices can help to design and implement possible subsidy measures for specific commodities in poor countries. During the periods of turbulence in crude oil prices, indeed, risk spillovers increase. Knowing these risks can be helpful to design appropriate policy interventions to mitigate the impact of increasing commodity prices especially on the poor and vulnerable.

Table 9: Significance Tests for Risk Spillovers.

	τ =0.90											
	maize		rapeseed		soybean		soybean-oil		sugar		wheat	
	O	B	O	B	O	B	O	B	O	B	O	B
Test Stat	0.741	0.490	0.704	0.234	0.828	0.365	0.861	0.263	0.687	0.156	0.608	0.429
Pval	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	τ =0.95											
	maize		rapeseed		soybean		soybean-oil		sugar		wheat	
	O	B	O	B	O	B	O	B	O	B	O	B
Test Stat	0.870	0.397	0.705	0.186	0.868	0.367	0.891	0.241	0.685	0.168	0.599	0.406
Pval	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	τ =0.99											
	maize		rapeseed		soybean		soybean-oil		sugar		wheat	
	O	B	O	B	O	B	O	B	O	B	O	B
Test Stat	0.838	0.204	0.881	0.182	0.856	0.354	0.879	0.239	0.795	0.034	0.598	0.281
Pval	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.169	0.000	0.000

Note: The table reports the observed test statistics in eq. (8) and the associated p-values

Table 10: Dominance Tests for Risk Spillovers.

	τ =0.90		τ =0.95		τ =0.99	
Commodity	Test 1	Test 2	Test 1	Test 2	Test 1	Test 2
maize	0.756 (0.000)	0.001 (0.995)	0.849 (0.000)	0.000 (0.997)	0.976 (0.000)	0.000 (1.000)
rapeseed	0.975 (0.000)	0.000 (0.999)	0.982 (0.000)	0.000 (1.000)	0.989 (0.000)	0.000 (0.999)
soybean	0.960 (0.000)	0.000 (0.999)	0.971 (0.000)	0.000 (0.999)	0.983 (0.000)	0.000 (1.000)
soybean-oil	0.982 (0.000)	0.000 (1.000)	0.988 (0.000)	0.000 (0.999)	0.985 (0.000)	0.000 (0.999)
sugar	0.990 (0.000)	0.000 (1.000)	0.988 (0.000)	0.000 (0.999)	1.000 (0.000)	0.000 (0.999)
wheat	0.720 (0.000)	0.001 (0.994)	0.755 (0.000)	0.001 (0.994)	0.916 (0.000)	0.000 (1.000)

Note: The table reports the observed test statistics in eq. (9) and the associated p-values (in parenthesis). Left column is for the test with null hypothesis H_0: $|\Delta CoVaR^{k|O}(\tau)| \leq |\Delta CoVaR^{k|B}(\tau)|$ (Test 1) and right column for the test with null hypothesis H_0: $|\Delta CoVaR^{k|B}(\tau)| \leq |\Delta CoVaR^{k|O}(\tau)|$ (Test 2) where k denotes one of the food commodity maize, rapeseed, soybean, soybean-oil, sugar, and wheat.

6. Conclusions

In this study we have assessed the contribution of commodity market to contagion risk. To this purpose, we have first constructed a $\Delta CoVaR$ measure of risk within each market, and run a significance and dominance test starting from the original $CoVaR$ developed by Adrian and Brunnermeier (2016). In our analysis market i is in 'distress' when it registers an abnormal rise or drop in commodity prices, i.e., extremely high or low returns, which are susceptible to trigger serious damages to the whole economy.

The significance test has allowed us to determine whether the $\Delta CoVaR$ related to a specific market is different from zero, meaning that this market has an impact on the economic system (i.e., the market can generate contagion risk and spillover effects). The dominance test has permitted us to gauge whether a given market is systemically riskier than another in transmitting the effects of extreme price shocks to the entire economy.

Our results indicate that all commodity markets generate significant contagion risks, i.e., tail events tend to propagate from commodity markets to the rest of the economy. This is true both when contagion risk measures are explained in terms of financial factors alone and when they are explained by financial and economic fundamentals taken together. This means that we find evidence of financial and mixed contagion. Conversely, when contagion risk measures are explained by economic fundamentals, only food commodity markets can lead to economic instability. This reveals that while financial shocks materializing in each commodity market, including food, are likely to trigger economic instability, shocks to economic fundamentals can produce economic distress only in the case of food commodity markets. In addition, the analysis shows that risk measures tend to be high during crises and low during booms, suggesting that the dynamics of $\Delta CoVaR$s are pro-cyclical. Based on the results of the dominance tests, it is possible to sketch a likely rank of commodity markets which contribute most to contagion risk. In detail, oil's risk contribution is found to dominate the other markets both when prices experience significant increases and when they dramatically fall. Furthermore, all metals market dominates agricultural and ethanol markets, and agricultural dominates ethanol market when there are price-ups. In the case of price-downs food is dominated by ethanol. From an economic point of view, this means that a distress occurring in oil market has the largest negative consequences for the whole economy, followed by a distress in metals, agricultural and ethanol markets.

We have also found that spillover effects take place from energy to food commodity market, that oil is systemically riskier than ethanol in pushing distress in maize, wheat, rapeseed, soybean and soybean-oil markets, thus price spillovers from oil to food markets are more relevant than those coming from ethanol to food.

From a policy perspective, given that we find evidence of financial contagion from commodity market to the rest of the economy it would be desirable that legal infrastructures for financial markets were sound and clear, so to avoid that completely free markets without any oversight could lead to dangerous situations.

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