Realized correlations, betas and volatility spillover in the commodity market: What has changed?

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Abstract

This papers adopts the recently proposed realized Beta GARCH model of Hansen et al. (J. Appl. Econ. (2014)) to examine the changes in price and return dynamics that affected the commodity market during the 2007-2008 boom and bust. We provide evidence that, starting from 2006, realized correlations between agricultural commodities within the same group significantly increased. Moreover, the observed increase in correlations between agriculturals and oil was greater still. The dynamics of the volatility spillover across commodities are also investigated. It is found that spillover effects became more evident prior to the commodity price crash. However, this increase in volatility transmission tended to anticipate the increase in correlations. To conclude, it is shown that the size of a short position in oil required to hedge a long agricultural commodity position , given by the realized beta, therefore increased significantly.

Keywords: Commodities; Correlation; Beta; Volatility Spillover; Realized Measures

1   Introduction

In the recent years, the availability of different type of commodity futures indices has made investing in the commodity market widely accessible to new players seeking a capital allocation which offered diversification with respect to the equity, currency and fixed income markets and which is also positively correlated with changes inflation (Schofield, 2007).

As a consequence, commodity futures have emerged, starting from early 2000, as popular asset class as investors turned to commodities as a means to diversify their portfolios (Cheng and Xiong, 2014). The large fluctuations in commodity prices observed amid the latest financial crisis and the crash which occurred in late 2008 have contributed to attract a considerable level of academic attention. A set of stylized empirical facts characterizing the commodity prices has emerged, see Cheng and Xiong (2014) for a comprehensive review.

First, a proper commodity 'super-cycle' has been experienced in the last 10 years with the resulting boom and bust of futures prices. This had as a consequence an extreme increase in commodity returns volatility, which is more pronounced for index commodities than for off-index commodities.

Secondly, an increase in cross-commodity correlations has also been observed. As evidences suggest before the early 2000s, commodity market were partially segmented from outside financial

markets and from each others. Erb and Harvey (2006) showed that commodities had only low positive return correlations with each other. Gorton and Rouwenhorst (2006) did not find evidences of correlations between commodity returns and the S&P 500 returns, especially at short horizons (daily and monthly). This segmentation does no longer hold. The correlations of different sectors of the Goldman Sach Commody Index (GSCI) with the GSCI Energy index rose from a pre-2004 range between $\pm$ 20% to reach 70% in 2008. This phenomenon is observed also within the same sector. Furthermore, the correlation of commodity returns with returns on other asset classes has also increased, e.g. increasing correlations between GSCI Total Return Index and MSCI Emerging Market Index, DXY US Dollar Index [1], 10-year US Treasury yield and CRSP Value-weighted Index.

Last, along with increasing volatility and correlation, volatility spillover effects have been found between commodities and between commodities and other assets.

In this paper we present a novel set of analyses whose goal is to provide further evidences of the changes in price and return dynamics in the commodity market around the 2007-2008 boom&bust. We focus our attention on three main statistics which describe the linkage between commodities: correlations, volatility spillovers and optimal hedging ratios (or betas).

Asset correlation dynamics are crucial in portfolio management and risk hedging as investors seek to diversify their allocations by targeting lowly correlated assets. Our results show that starting from 2005, correlations between commodities started to significantly increase, therefore wiping out the diversification benefit for which commodities were chosen in first place. This feature, first noted in Tang and Xiong (2012), is also confirmed in a recent paper by Dorman and Karali (2014). Examining commodity data from 1990 through 2011 they find that simple correlation coefficients between futures prices and the probability of nonstationarity of the series have increased over time, therefore signaling that the commodity market is shown to become more efficient after 2004.

Along with correlations, spillovers effect are also an important aspect to be considered when dealing with a portfolio of assets. Indeed, a surge in assets volatility, together with an increase in volatility transmission, affects optimal portfolio allocations and can result in greater costs for managing risks (e.g. higher hedging costs). It is therefore crucial to understand and possibly anticipate changes in volatility relationships in order to develop appropriate risk management strategies. Volatility spillovers have been studied abundantly in the financial literature. See for example Baele (2005), Bekaert and Harvey (1997), Bekaert et al. (2002), Christiansen (2007), Ng (2000). For applications on high-frequency data see Bonato et al. (2013) and Fengler and Gisler (2014). While these works all focus on the equity, currencies or bond markets, only recently has the academic literature started to investigate this topic in the commodity market, and especially between oil and agricultural commodities or oil and the stock market; see the seminal paper of Wu et al. (2010) and Chang et al. (2013), Arouri et al. (2011), Mensi et al. (2013) also amongst others.

We conclude the empirical analyses by showing how hedging strategies have also been affected by the latest development of the commodity market dynamics. Particular attention will be given to the interaction between oil and agricultural commodities.

Within our analyses we focus in particular on the interaction between oil and agricultural commodities. In the academic literature, particular attention has been given the the interaction between energy commodities (specifically oil) and agricultural commodities. The rise of energy prices along with the boom in agricultural commodity prices - which led to the so called 'food crisis' - raised the question of whether energy markets have any explanatory power on the observed upward movement in agricultural food prices. The political implications of such nexus would indeed very important.

Different hypothesis to link oil and agricultural prices have been suggested. First, the relation between oil and agricultural prices is motivated by oil being a production cost. Baffes (2007) analyzed how crude oil prices spill on the price of 35 internationally traded primary commodities and found that

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[1]Multiplied by -1

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the pass-through of crude oil shocks to the overall non-energy commodity index, the fertilizer index, agriculture and metals are 0.16, 0.33, 0.17, respectively.

The positive comovement between oil and agricultural commodities can be also motivated using the substitutive effect between biofuels and fossil fuel. An increase in oil prices inspire people to develop alternative sources of energy: the bioethanol and biodiesl extracted from corn and soybean, respectively, are considered the appropriate substitute of crude oil. Thus, increase in oil prices can result in the increase of corn and soybean prices and finally lead to the surge in prices of the other agricultural commodities as the planting acreage is limited in a certain period of time (Chang and Su, 2010). In terms of volatility spillover, Wu et al. (2010) show that spillover intensies from crude oil prices onto corn prices (spot and futures) have increased significantly since the Energy Policy Act of 2005. This act established the Renewable Fuel standard requiring that transportation fuels sold in the United States contain a minimum amount of renewable flues. Subsequent tax incentives, federal and state mandates and the progressive elimination of Methyl Tertiary Butyl Ether as an additive in many states have quickly increased the demand for biofuels, particularly corn-based ethanol.

A third hypothesis argues that global economic activity, rather than increases in oil prices, is the main driver of higher agricultural commodity prices, see Krugman (2008), Hamilton (2009), Kilian (2009). The development of emerging economies (China and India in particular) in the past decade has stimulated unprecedented demands for a broad range of commodities in sectors like energy and metal. This may have led to a joint price boom for commodities.

A last explanation presented by Tang and Xiong (2012), which is alternative to both the biofuel and global economic activity hypothesis, links the increase correlation between oil and non-energy commodity prices to the financialization of the commodity market. The authors argue that, as a result of the financialization process, the price of an individual commodity is no longer determined solely by its demand and supply. Instead, prices are also determined by the aggregate risk appetite for financial assets and the investment behavior of diversified commodity index investors.

From the methodological side we rely in the realized beta GARCH model of Hansen et al. (2014). The realized beta GARCH is a multivariate volatility model which incorporates both generalized autoregressive conditional heteroskedasticity (GARCH) and realized measures of variances and covariances. Realized measures are important as they extract information about the current levels of volatilities and correlations from high-frequency data. This is particularly useful for modeling financial returns during periods of rapid changes in the underlying covariance structure. The model has a hierarchical structure: the 'market' return is modeled with a univariate realized GARCH model (Hansen and Huang, 2012; Hansen et al., 2012)). In principle, other approaches based on multivariate GARCH (DCC, BEKK) could be employed in order to estimate dynamic correlations and assess the spillover effects. We decided instead to adapt the realized beta GARCH to the commodity case. On the one hand, this enables us to consider the price and return information available at intra-day frequency. On the other hand the mode lends itself well to represent fit the commodity market composition. In the realized beta GARCH model the multivariate structure is constructed by modeling 'individual' returns conditional on the past and contemporary market variables (return and volatility). This makes it feasible to extract the 'betas' but also account for contemporaneous volatility spillover between the market and the single asset. In our setup, for each agricultural commodity class (Grains and Softs), we impose the most material single-name commodity to be the market variable. This enables us to measure the changes in correlations within a same class. Then, following the approach of Tang and Xiong (2012), we make use of oil as the market variable thus allowing to assess how correlations between Agriculturals and oil developed.

Our work contributes to the literature studying the interaction between oil and agricultural commodities by presenting an innovative approach based on a recently introduced multivariate model for realized measures. This model combines the information contained in the high frequency intra-day price observations with a conditional heteroskedasticity model. It also possess a hierarchical structure

in which each single commodity return is modeled as function of the 'market' return, in a CAPM-like fashion. This setup adapts itself very well to our purposes as we use one commodity (the most represented in the commodity indices) as proxy for the market and extrapolate the model realized correlation between this commodity and each single commodities along with the (contemporaneous) spillover effect.

Our results confirm that agricultural commodities belonging to the same sector (Softs or Grains) experience an increase in correlations staring from 2006. Correlations between oil and those commodities has also significantly increased. Additionally, we find that, along with increased correlations, spillover effects of oil on agricultural commodities became more prominent, especially around the raise and fall of the commodity market. To conclude, we show how these changes affected the optimal hedging ratios, defined in term of realized betas. The optimal hedging ratio is the amount of dollars to be invested in a short position in an asset in order to hedge a 1$ long position in an other asset. In our setting, the representative investor is assumed to hedge a long position in an agricultural future with a short position in oil. Our results show a marked increase in optimal hedging ratios. A consequence of this is that hedging costs have also increased. This is coherent with our previous findings since an increase in correlations results in lower diversification benefits and increase in spillover effect induces higher volatility risk. This obviously drives the cost of protecting against risk higher.

The paper is structured as follows: Section 2 introduces the econometric approach adopted, i.e. the realized Beta modes of Hansen et al. (2014) and its adaptation the the case of commodities; Section 3 presents the dataset used; empirical results are reported in Section 4: realized correlations, spillover effects and optimal hedging ratios; Section 5 concludes.

2 Econometric methodology

2.1 Realized Beta GARCH

The realized beta GARCH proposed by Hansen et al. (2014) is a multivariate volatility model which incorporates both generalized autoregressive conditional heteroskedasticity (GARCH) and realized measures of variances and covariances. Realized measures are important as they extract information about the current levels of volatilities and correlations from high-frequency data. This is particularly useful for modeling financial returns during periods of rapid changes in the underlying covariance structure. The model has a hierarchical structure: the 'market' return is modeled with a univariate realized GARCH model (Hansen and Huang, 2012; Hansen et al., 2012)). A multivariate structure is constructed by modeling 'individual' returns conditional on the past and contemporary market variables (return and volatility). The resulting model has the structure of a dynamic capital asset pricing model (CAPM) that makes it feasible to extract the 'betas' but also account for contemporaneous volatility spillover between the market and the single asset.

Let $r_{0,t}$ and $x_{0,t}$ denote the market return and a corresponding realized measure of volatility, respectively. Similarly, the notation $r_{1,t}$ and $x_{1,t}$ denote the same variable associated with an individual asset returns. Realized measures of volatility are constructing using the information available at intra-day frequency. This approach was pioneered by Andersen and Bollerslev (1998). The classical estimator of the realized volatility reads

$$x_{0,t} = \sum_{i=1}^{I} r_{0,t-1+ih,h}^2 \tag{1}$$

where $r_{0,t-1+ih,h} \equiv p_{0,t-1+ih} - p_{0,t-1+(i-1)/h}$ denotes the vector of returns for the i-th intraday period on day t, for $i = 1, \ldots, I$. I refers to the number of intraday intervals, each of length $h \equiv 1/I$. Under

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the assumption that the process is continuous and no market microstructure noise is present, this estimator provides an accurate measures of the process integrated variance.

Define the conditional variance $h_{0,t} = var(r_{0,t}|\mathcal{F}_{t-1})$ and $h_{1,t} = var(r_{1,t}|\mathcal{F}_{t-1})$. Define also the conditional correlation $\rho_{1,t} = corr(r_{0,t}, r_{1,t}|\mathcal{F}_{t-1})$; it follows directly that the realized version of the 'beta'

$$\beta_{1,t} = cov(r_{1,t}, r_{0,z}|\mathcal{F}_{t-1})/var(r_{0,t}|\mathcal{F}_{t-1}) \tag{2}$$

is given by

$$\beta_{1,t} = \rho_{1,t}\sqrt{\frac{h_{1,t}}{h_{0,t}}}. \tag{3}$$

The model for the market return and realized measures of volatility takes the form of an exponential GARCH. It is described by the following three equations

$$r_{o,t} = \mu_0 + \sqrt{h_{0,t}}z_{0,t} \tag{4}$$
$$\log h_{0,t} = a_0 + b_0 \log h_{0,t-1} + c_0 \log x_{0,t-1} + \tau_0(z_{0,t-1}) \tag{5}$$
$$\log x_{0,t} = \xi_0 + \phi_0 \log h_{0,t} + \delta_0(z_{0,t}) + u_{0,t}, \tag{6}$$

where $z_{o,t} \overset{i.i.d.}{\sim} N(0,1)$ and $u_{o,t} \overset{i.i.d.}{\sim} N(0,\sigma_{u,0}^2)$. The functions $\tau(z)$ and $\delta(z)$ are called leverage functions because they model aspects related to the leverage effects, which refers to the dependence between returns and volatility. They are defined as $\tau(z) = t_1z + t_2(z^2-1)$ and $\delta(z) = \delta_1 z + \delta_2(z^2-1)$. Equations (5) and (6) are referred to as the return equation and the GARCH equation, respectively. The third equation, ((6)), is called the measurement equation and completes the specification of the density $f(r_{0,t}, x_{0,t}|\mathcal{F}_{t-1})$.

To conclude, a model for the time series associated with the individual asset needs to be formulated, conditional on the contemporaneous 'market' variables. This reads

$$r_{1,t} = \mu_1 + \sqrt{h_{1,t}}z_{1,t} \tag{7}$$

where the dependence on $(r_{0,t}, x_{0,t})$ operates through $\rho_{1,t} = cov(z_{0,1}, z_{1,t}|\mathcal{F}_{t-1})$, the conditional correlation. The factor structure is then revealed:

$$z_{1,t} = \rho_{1,t}z_{0,t} + \sqrt{1 - \rho_{1,t}^2}\omega_{1,t} \tag{8}$$

where $\omega_{1,t} = (z_{1,t} - \rho_{1,t}z_{0,t})/\sqrt{1 - \rho_{1,t}^3}$ has mean zero, unit variance and it is uncorrelated with $z_{0,t}$. This implies that the studentized returns for the individual asset is a linear combination of the studentized market return and the idiosyncratic component $\omega_{1,t}$, where the relative weight, defined by $\rho_{1,t}$ is time varying. The model concludes by specifying the dynamics for $h_{1,t}$ and $\rho_{1,t}$. For $h_{1,t}$ the GARCH equation is used

$$\log h_{1,t} = a_1 + b_1 \log h_{1,t-1} + c_1 \log x_{1,t-1} + d_1 \log h_{0,t} + \tau_1(z_{1,t-1}). \tag{9}$$

The parameter d_1 can be interpreted as contemporaneous *spillover effect*, measuring the extent to which the market's volatility affects the volatility of the individual asset while accounting for the asset-specific volatility dynamics. The model is formulated in a way that $h_{0,t}$ is $\mathcal{F}_{t-1}$-measurable, so the presence of $h_{0,t}$ on the right-hand side of the equation does not contradict the definition of $h_{1,t}$.

For the dynamics of $\rho_{1,t}$ a Fisher transformation is adopted, $\rho \to F(\rho) = \frac{1}{2}\log\frac{1+\rho}{1-\rho}$ which is a one-to-one mapping from (-1, 1) into $\mathbb{R}$. The GARCH equation for the transformed correlation is given by

$$F(\rho_{1,t}) = a_{10} + b_{10}F(\rho_{1,t-1}) + c_{10}F(y_{1,t-1}).$$

Finally, the following measurement equations specify the conditional densities for the two realized measures

$$\log x_{1,t} = \xi_1 + \psi_1 \log h_{1,t} + \delta_1(z_{1,t}) + u_{1,t} \tag{10}$$

$$F(y_{1,t}) = \xi_{10} + \psi_{10} F(\rho_{1,t}) + \nu_{1,t}. \tag{11}$$

The model is estimated via maximum likelihood. The marginal model for the market variables closely follow that of Hansen et al. (2012) and can be further decomposed into the conditional densities of $r_{0,t}$ and of $x_{0,t}|r_{0,t}$. The likelihood contribution for the conditional model for individual assets also permits a further decomposition into the conditional densities of $r_1|r_{0,x_0}$ and $(x_1, y_2|r_1, r_0, x_0)$.

2.2 Market model for commodities

The realized beta GARCH model described above lends itself well not only to situations in which one is interesting in a dynamic CAPM framework, but it provides a very flexible tool to asses the dynamics of the correlations, spillovers effects and optimal hedge ratios between two individual assets belonging to the same class.

In this paper we focus in particular on the commodity market. Our goal is to investigate the behavior of correlations, changes in spillover effects and optimal hedge ratios within agricultural commodities and between oil and agricultural commodities as effect of the recent boom & bust (also referred by some as 'food crisis', see Wang et al., 2014) the commodity market experienced in starting from 2005.

We use two major commodities, corn and sugar, as representative of the market commodity for the Grains and Softs sector, respectively. We chose corn and sugar as they are the commodities with the largest weight per sector in the three major commodity indices in Table 1. In a next step, we use oil as proxy for the commodity market index in order to describe the commodity market as a whole. The choice of oil as commodity market index proxy follows Tang and Xiong (2012) and is motivated by the fact that oil is the commodity receiving the largest weights in two important commodity indices: S&P Goldman Sachs and the Dow Jones UBS.

As a consequence of the financialization of the commodity market, Tang and Xiong (2012) show how prices of non-energy commodity futures in the United States have become increasingly correlated with oil prices. Following the lines of Barberis et al. (2005), Bonato and Taschini (2015) confirm that this increase in comovement across commodities and with oil cannot be explained as only driven by fundamentals and provide new evidences supporting the friction or sentiment based view explanations.

3 Data

A total of 28 commodity futures are traded in the US market. Table 1 considers, out of these 28, 4 Grain commodities (corn, soy beans, chicago wheat and soybean oil), 4 Soft commodities (coffee, cotton, cugar and cocoa) and oil. For each of this commodity we also report the weight associated with three major commodity indices: S&P GSCI, UBS-DJ CI and Thomson-Reuters CI.

Data are provided by *disktrading.com* and are at 1-minute frequency covering the trading hour of the CME and ICE. Globex trading information (i.e. outside the markets trading hours) is at our disposal for major commodities only and is therefore not used. Futures data are in continuous format containing price data of the most actively traded contracts. Close to expiration of a contract, the position is rolled over to the next available contract, provided that activity has increased. In order to guarantee that our results are based on overlapping time periods, we only considered trades that occurred between 10.30 and 14.00. Our data set spans the period going from Jan 2, 2002 to March

24, 2011, for a total of 2,281 trading days. Daily prices of the commodities under analyses are plotted in Figure 1

Commodity	Ticker	Exchange	S&P GSCI	DJ-UBSCI	Thomson Reuters
WTI crude oil	CL	NYMEX	40.6	15	5.88
Corn	C	CME Group	3.6	6.9	5.88
Soya beans	S	CME Group	0.9	7.4	5.88
Chicago wheat	W	CME Group	3.7	3.4	5.88
Soybean oil	BO	CME Group	-	2.9	5.88
Coffee	KC	ICE	0.5	2.7	5.88
Cotton	CT	ICE	0.7	2.2	5.88
Sugar	SB	ICE	2.1	2.8	5.88
Cocoa	CC	ICE	0.2	-	5.88

Table 1: List of commodities used in the analysis along with future ticker, market in which they are traded and weight given by the three major commodity indices as of 2008.

In the next step we compute the series of realized covariance matrices using the classical estimator presented in Andersen et al. (2003) and Barndorff-Nielsen and Shephard (2004) de Pooter et al. (2008):

$$\Sigma_t = \sum_{i=1}^{I} r_{t-1+ih,h} r'_{t-1+ih,h} \tag{12}$$

with an intra-day frequency of 15-minute prices. $r_{t-1+ih,h} \equiv p_{t-1+ih} - p_{t-1+(i-1)/h}$ denotes the $(n \times 1)$ vector of returns for the i-th intraday period on day t, for $i = 1, \ldots, I$, and with $n = 4$ as the number of assets. I refers to the number of intraday intervals, each of length $h \equiv 1/I$.

One shortcoming of the covariance matrix estimator we adopted is that it is not efficient in the presence of market microstructure noise and asynchronous trading (see for example Sheppard, 2006, Lunde and Voev, 2007, Barndorff-Nielsen et al., 2011a, Mancino and Sanfelici, 2008, Barndorff-Nielsen et al., 2011b among others). We think this does not represent an issue since we consider the most active trading part of the day, use assets that are traded in the same markets (NYMEX for oil and CME Groups for the Grains and ICE for Softs) and compute correlation within sector or with respect to oil, the most traded and liquid commodity future. This should reduce the distortion induced by stale prices, non-homogenous trading times, irregularly spaced data points, asynchronism, different institutional features using different trading platforms or exchange systems. A comparison with the more sophisticated multivariate realized kernels of Barndorff-Nielsen et al. (2011a) did not show significant difference in terms of realized correlations.

4   Empirical results

4.1   Estimation results

Estimation results of the realized beta GARCH for Grain and Soft commodities are displayed in Table 2. Recall that corn and sugar are used as market return for Grains and Softs, respectively. The parameter c_1, which captures the effect of the lagged realized measure on the conditional variance, is positive and significant, although not as large as observed in Hansen et al. (2014) in the case of stocks. The GARCH parameter b_1 is smaller than is usually the case for conventional GARCH models. This is partially explained by the fact that some persistency in volatility is captured by the realized measure. More importantly, the parameter d_1 is large and significant. This parameter measures the spillover effect from market (i.e. corn and sugar) volatility to individual (Grains and Softs) commodity
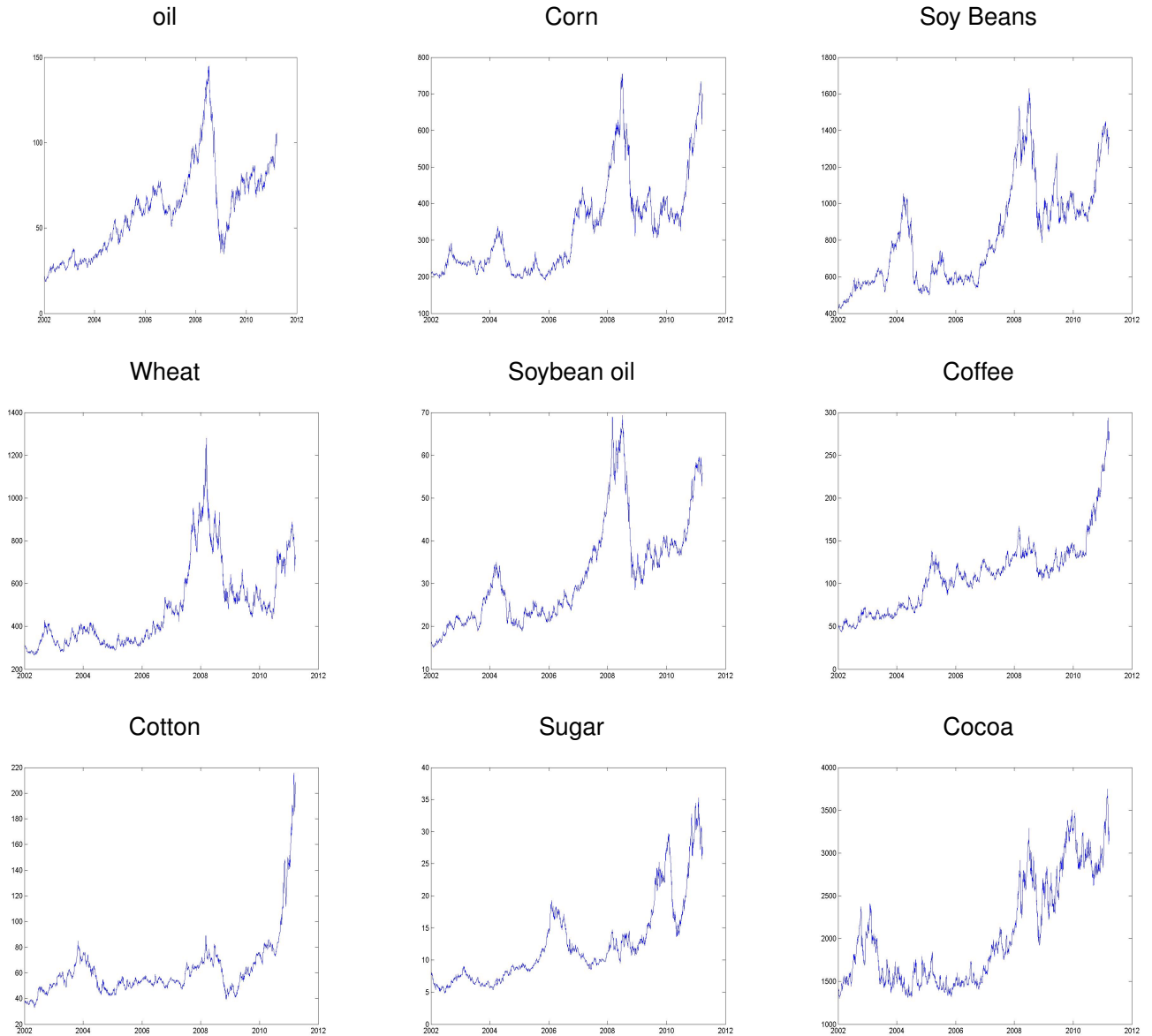
Figure 1: Commodity futures daily prices.

volatilities. The observed value of d_1 is much larger than what was observed for stocks. This highlights the importance of the spillover components in the commodities under investigation. Note also that this result shows that market volatility tends to have a positive contemporaneous effect on individual commodity volatility. Volatility is generally a very persistent process and unreported results indicate that replacing the contemporaneous term $\log h_{0,t}$ with its lagged counterpart $\log_{h_{0,t-1}}$ in Eq. (9) does not materially change the result. The estimate for τ_1 is generally not significant, whereas the estimate of τ_2 is positive and significant. Hence there is no clear evidence of leverage effect. ξ, the parameter of the measurement equation, is always negative. This is to be expected since the realized measures are computed over the open-to-close period, which only captures a fraction of the daily (close-to-close) volatility.

Very similar conclusions hold when oil is employed as market commodity. Results are reported in Table 3. Note, however, how the coefficient c is now higher whereas the spillover parameter d

Commodity	μ_0	a_1	b_1	c_1	d_1	τ_1	τ_2	ξ	δ_1	δ_2
Soy beans	-0.062	0.040	0.393	0.063	0.530	**0.005**	0.011	-0.292	**0.002**	0.872
	(0.008)	(0.012)	(0.036)	(0.009)	(0.043)	(0.005)	(0.002)	(0.018)	(0.000)	(0.014)
Chicago Wheat	-0.032	0.127	0.773	0.112	0.104	**-0.002**	0.014	-0.702	0.016	0.046
	(0.010)	(0.006)	(0.013)	(0.005)	(0.016)	(0.004)	(0.001)	(0.016)	(0.004)	(0.002)
Soybean oil	-0.060	0.070	0.377	0.057	0.540	**0.001**	**0.002**	-0.348	**-0.007**	0.027
	(0.011)	(0.012)	(0.035)	(0.009)	(0.041)	(0.002)	(0.002)	(0.018)	(0.004)	(0.002)
Coffee	-0.070	0.109	0.598	0.061	0.293	**0.001**	0.008	-0.600	-0.013	**0.004**
	(0.017)	(0.022)	(0.106)	(0.009)	(0.100)	(0.004)	(0.002)	(0.021)	(0.006)	(0.002)
Cotton	-0.033	0.080	0.641	0.068	0.245	0.014	0.003	-0.530	**-0.004**	**0.001**
	(0.017)	(0.012)	(0.103)	(0.008)	(0.097)	(0.004)	(0.002)	(0.019)	(0.006)	(0.003)
Cocoa	-0.032	-0.066	0.678	0.065	0.229	**0.004**	0.008	-0.119	-0.019	**0.001**
	(0.014)	(0.038)	(0.112)	(0.009)	(0.112)	(0.004)	(0.002)	(0.020)	(0.006)	(0.002)

Table 2: Realized Beta GARCH estimation results for Grains and Softs when corn and sugar are used as market commodity, respectively. Numbers in bold denote coefficient not significant at 5% level.

is lower than what is observed in Table 2. Therefore the spillover effect is much more pronounced within commodity sector than it is between agricultural commodities and oil. Again, there is no clear evidence of leverage effect and, as before, the parameter ξ of the measurement equation is negative and significant.

Commodity	μ_0	a	b	c	d	τ_1	τ_2	ξ	δ_1	δ_2
Corn	**-0.019**	**-0.003**	0.648	0.156	0.166	0.005	0.005	0.016	-0.011	0.006
	(0.011)	(0.004)	(0.072)	(0.019)	(0.088)	(0.003)	(0.001)	(0.013)	(0.003)	(0.002)
Soya beans	**-0.012**	-0.041	0.561	0.144	0.258	-0.012	**-0.001**	0.088	-0.013	0.005
	(0.009)	(0.010)	(0.070)	(0.018)	(0.084)	(0.003)	(0.001)	0.028)	(0.003)	(0.002)
Chicago wheat	**0.008**	0.099	0.646	0.153	0.173	0.005	0.005	-0.277	**-0.003**	**0.002**
	(0.007)	(0.010)	(0.043)	(0.013)	(0.054)	(0.002)	(0.001)	(0.018)	(0.002)	(0.002)
Soybean oil	-0.040	**-0.019**	0.474	0.114	0.379	**-0.001**	0.004	**0.015**	-0.010	0.008
	(0.018)	(0.012)	(0.118)	(0.031)	(0.145)	(0.002)	(0.002)	(0.009)	(0.004)	(0.002)
Coffee	-0.104	0.057	0.642	0.160	0.170	0.009	**0.000**	-0.154	-0.013	0.002
	(0.016)	(0.008)	(0.043)	(0.012)	(0.054)	(0.002)	(0.000)	(0.018)	(0.003)	(0.001)
Cotton	-0.073	0.067	0.476	0.113	0.380	0.000	**0.001**	-0.153	-0.010	**0.002**
	(0.017)	(0.015)	(0.114)	(0.031)	(0.143)	(0.000)	(0.001)	(0.020)	(0.003)	(0.001)
Sugar	**0.028**	0.133	0.695	0.153	0.122	**0.000**	0.004	-0.416	**-0.001**	**-0.001**
	(0.027)	(0.011)	(0.030)	(0.009)	(0.038)	(0.000)	(0.001)	(0.018)	(0.001)	(0.001)
Cocoa	**-0.012**	-0.108	**0.318**	**0.071**	**0.578**	0.019	0.004	0.119	**-0.001**	0.001
	(0.014)	(0.054)	(0.484)	(0.123)	(0.597)	(0.006)	(0.002)	(0.069)	(0.001)	(0.001)

Table 3: Realized Beta GARCH estimation results with oil used as market commodity, respectively. Numbers in bold denote coefficient not significant at 5% level.

4.2   Realized correlations

We present now the realized beta GARCH model correlations. As done above, we consider two cases. First, in order to compute correlation within commodity sector, we employ corn and sugar as market commodity for Grains and Softs, respectively. Secondly, we analyze the interaction between oil and the agricultural commodities by using oil as market commodity.

Within-sector correlations are displayed in Figure 2. For Grains, correlations with corn are generally high and show a inverse 'U' shape. Correlations increase from 2002 and reach the maximum in 2007. They then decrease to values lower than in 2002 but again pick up after 2010. For Softs,

correlation with sugar is generally very low and starts spiking starting from late 2007/early 2008. For Coffee and Cotton this correlation reaches its maximum in late 2008 and then decrease. For Cocoa this pattern is somehow delayed as it is seen starting only from 2009.

Our results show that the so-called 'food-crisis' affected in a greater way Softs commodities, which were not significantly correlated before 2008. For Grains, which display large positive correlation across the sample, the super-cycle of commodities is less visible but still present.
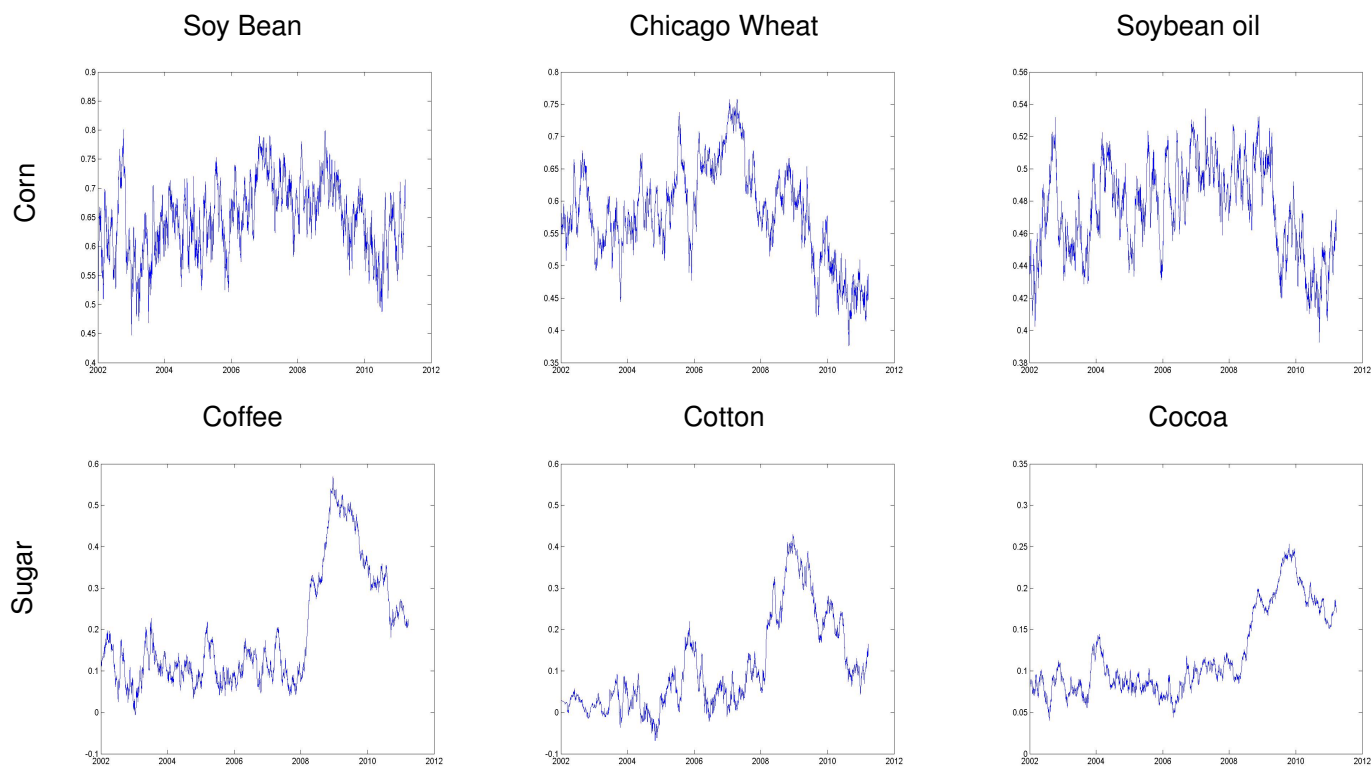

Figure 2: Model realized futures returns correlations for each agricultural sector. 'Market' commodities are corn and sugar for Grains, Soft, respectively

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This sections concludes with the analysis of correlations between oil and agricultural commodities. Results are shown in Figure 3. Clearly, the correlation between oil and agricultural commodities was negligible in the beginning of our sample. It then started to increase and jumped in early 2008 to finally decrease after the bursting of the commodity bubble. Note, however, that differently from the correlation within Grains and Softs, correlations with oil remain at levels which are much higher than 2002. There are therefore evidences of a regime shift in the levels of correlation between agricultural commodities and oil. These results corroborate the findings of Tang and Xiong (2012). They noted increased correlations between oil and agricultural commodities amid the 2007-2008 boom and bust and motivated this finding as a result of the massive increase in index investing experienced in the commodity markets starting from 2004.

4.3 Spillover effects

Along with correlations, a very important aspect requiring attention when holding a portfolio of commodities is related to the risk embedded in the volatility transmission across its components. That is, the volatility risk spillover. Understanding and modeling spillover effects is crucial to provide accurate predictions of assets volatilities. This has an impact in the construction of optimal portfolios but also
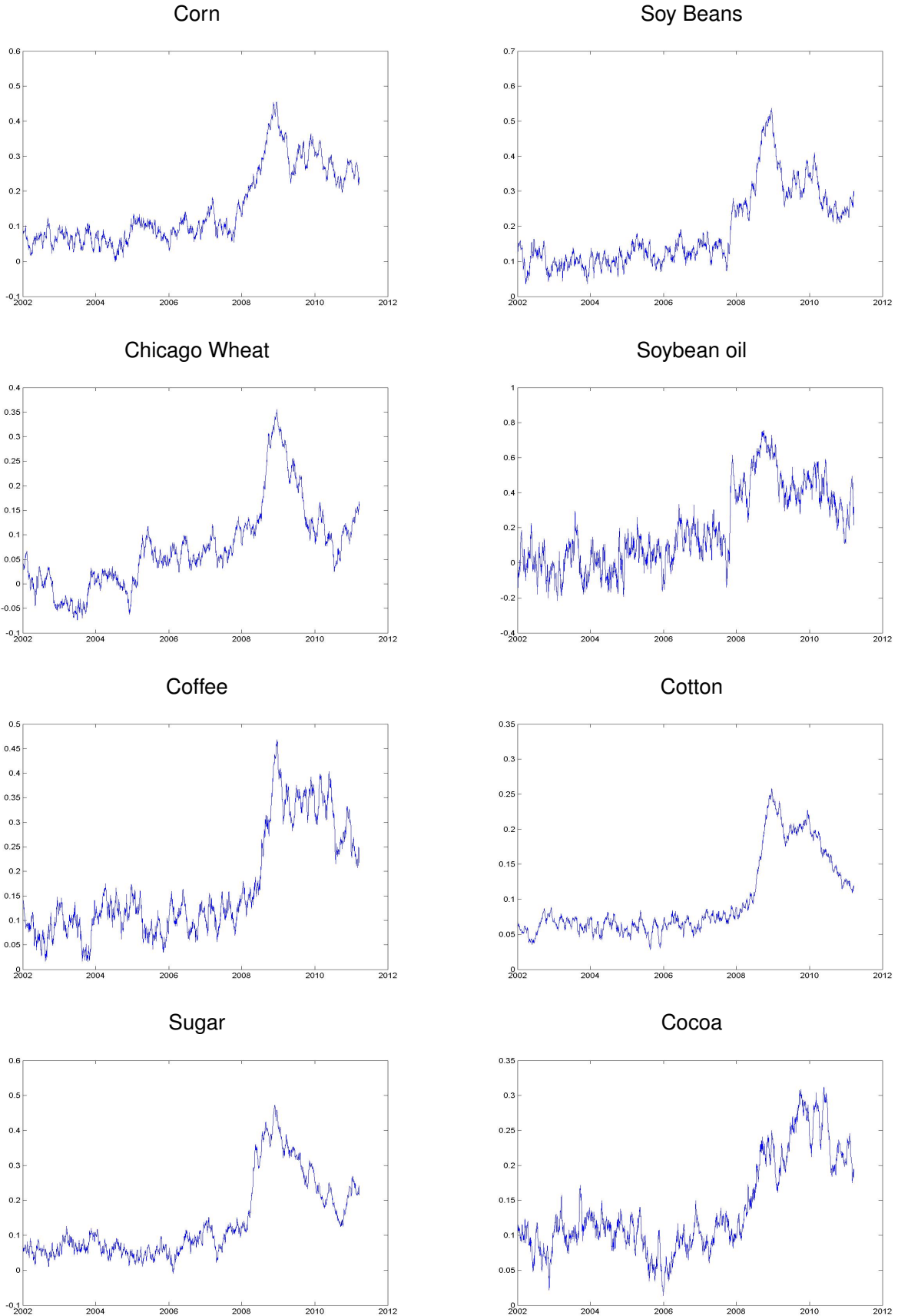
Figure 3: Model realized futures returns correlations between oil and Grains and Softs commodities.

in the development of appropriate risk management strategies. In this model, risk spillover is defined as the dependence of a given asset variance on the contemporaneous variance of the market (or on the commodity that acts as market). An increase in asset volatility, together with an increase in volatility transmission can result in greater costs for managing risks (e.g. higher hedging costs). It is therefore crucial for risk management purposes to understand and possibly anticipate changes in volatility relationships. Volatility spillovers have been studied abundantly in the financial literature. See for example Baele (2005), Bekaert and Harvey (1997), Bekaert et al. (2002), Christiansen (2007), Ng (2000). For applications on high-frequency data see Bonato et al. (2013) and Fengler and Gisler (2014). While these works all focus on the equity, currencies or bond markets, only recently has the academic literature started to investigate this topic in the commodity market, and especially between oil and agricultural commodities or oil and the stock market, see the seminal paper of Wu et al. (2010) and Chang et al. (2013), Arouri et al. (2011), Mensi et al. (2013) also amongst others.

As shown in Equation (9), the realized beta GARCH models lends itself well to the measurement of the volatility spillover between the market commodity and each single commodity. Differently from the literature on volatility spillover (see for example Chang et al., 2013; Arouri et al., 2011; Wu et al., 2010; Nazlioglu et al., 2013; Fengler and Gisler, 2014 or Bonato et al., 2013) which assumes a lagged volatility transmission effect, the model we use assumes a contemporaneous effect. As already mentioned in this paper, given the persistency typical of the volatility, using a lagged or contemporaneous variable should not affect particularly the result.

In order to account for time variation in the volatility spillover effect, we followed Fengler and Gisler (2014) and Diebold and Yilmaz (2009, 2012, 2014), and use a rolling window approach. Using 500-day rolling windows, we recursively estimate the parameters of the realized beta GARCH model and store the values of d_1, the coefficient associated to the $\log h_{0,t}$ term. Results are presented in graphical form in Figure 4.

Although not as evident as for correlations, the spillover of oil volatility shocks onto the major agricultural commodities is seen to get larger starting from around 2004. Spillovers then start to decrease roughly between 2006 and 2008. This results show that the transmission of volatility shocks from oil to agricultural commodities actually started before the increase in correlations. Also, the peak in volatility transmission is experienced earlier than the peaks in correlation values. While reckoning that such result are specific of the model adopted in this paper, it is worthwhile noting that they shows that changes in the dynamic of the volatility transmission, although not extremely distinct, have anticipated the changes in dependency structure between commodities. This finding is very important if one considers the loss in diversification of a portfolio of commodities associated with an increase in returns correlations.

4.4 Hedging ratios

Correlations and volatility spillovers are key elements to build appropriate portfolio hedging strategies. We conclude this empirical section by showing how hedging strategies have also been affected by the latest development of the commodity market dynamics. Again, the focus will be directed to the interaction between oil and agricultural commodities.

Consider a two-asset portfolio composed of corn and oil futures. In order to minimize the risk of a hedged portfolio, a long position in one-dollar on corn must be hedged by a short position of $\beta CO, t$ dollars in oil. This optimal hedge ratio is given in Kroner and Sultan (1993) and reads

$$\beta_{CO,t} = \frac{h_{CO,t}}{h_{O,t}}. \tag{13}$$

Now, note how $\beta_{CO,t}$ coincides with the realized beta specification in Eq. (3), where corn is the individual asset and oil is interpreted as the 'market'. Hence, by employing the realized GARCH
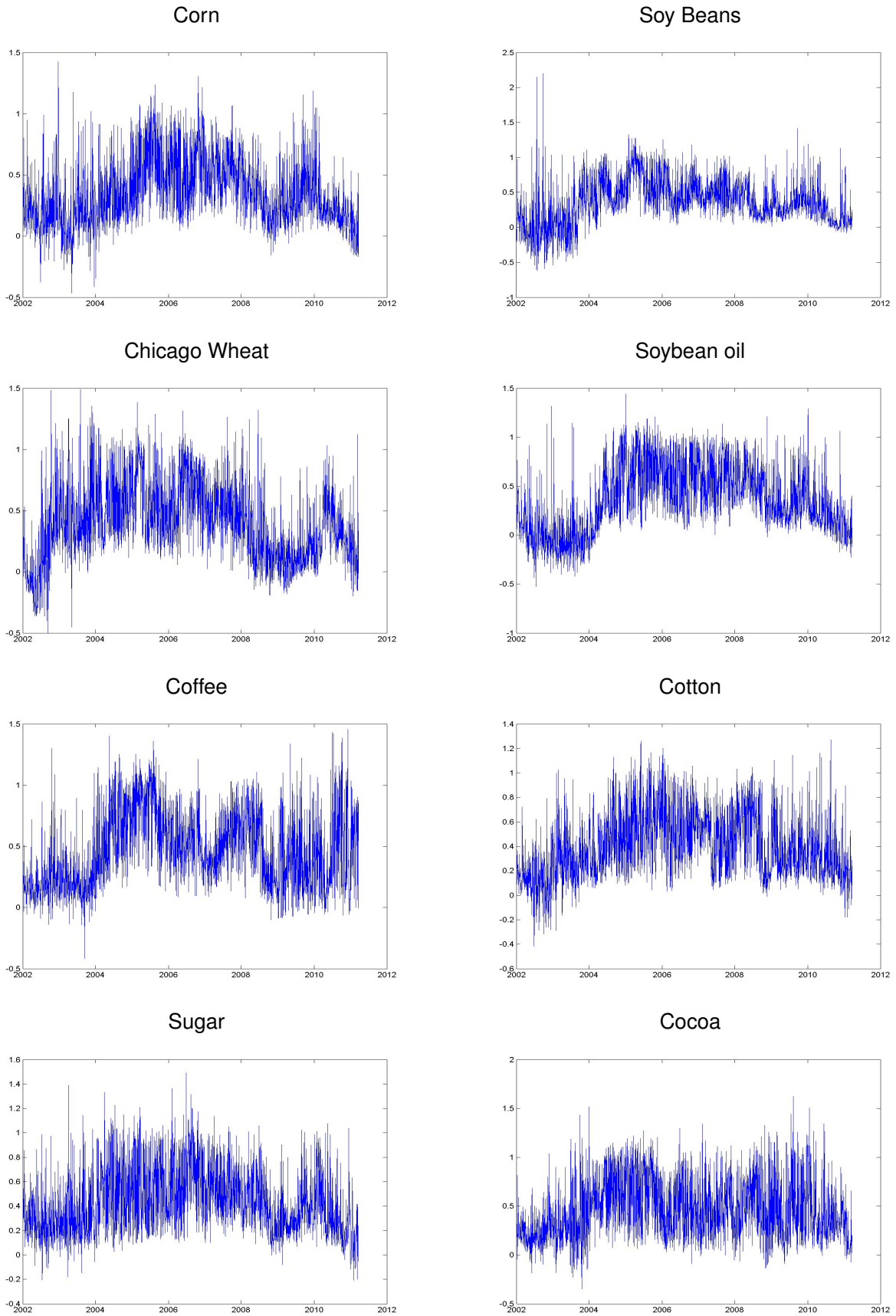
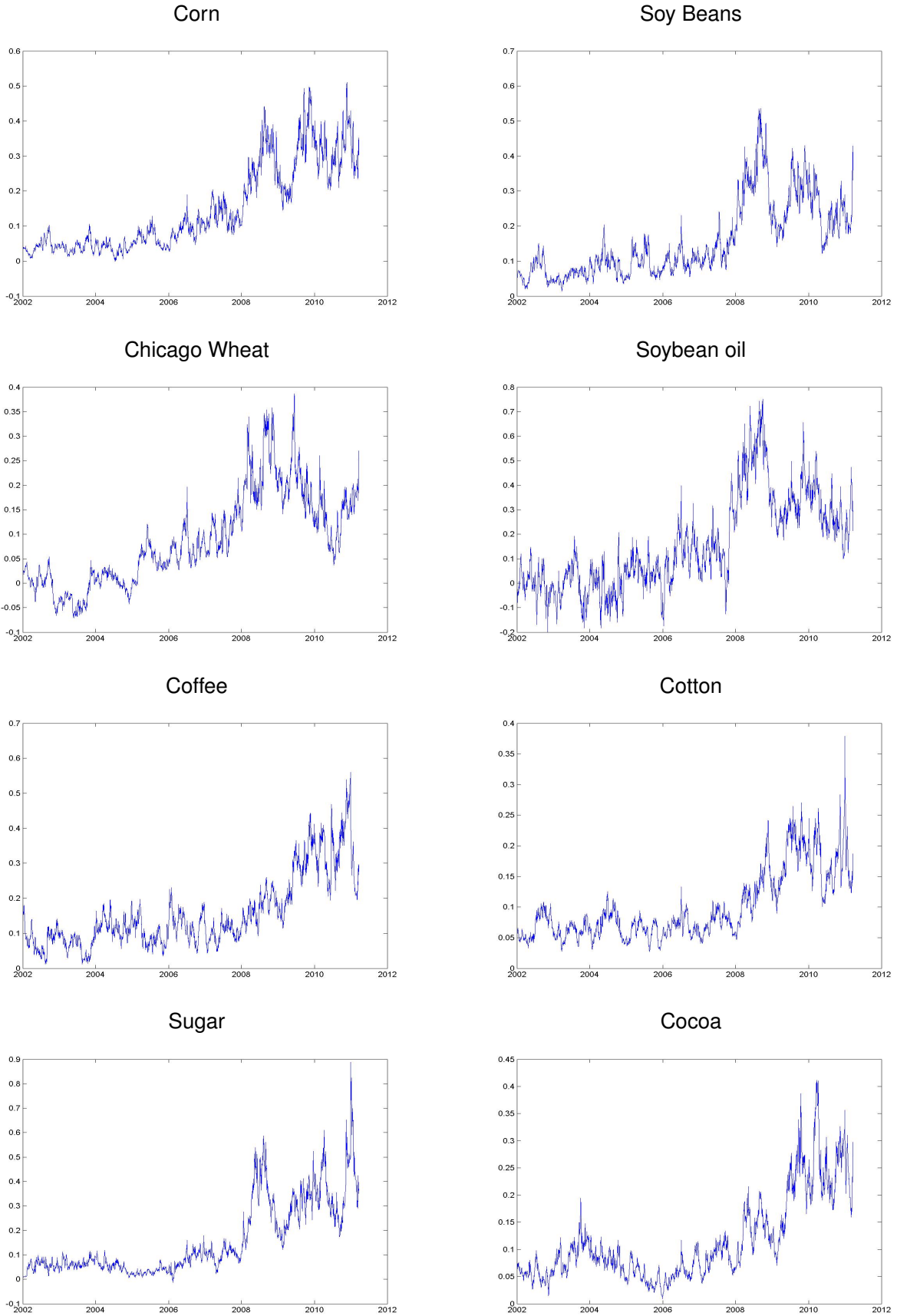**Figure 4:** Spillover effects between oil and Grains and Softs commodities.

Figure 5: Model realized betas between oil and Grains and Softs commodities.

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model, we can easily obtain the optimal hedge ratio between oil (the market commodity) and all other individual commodities.

The concept of realized betas is not new. It was first introduced by Bollerslev and Zhang (2003). They carried out a large-scale estimation of the Fama-French three-factor model using 5-minute data on 6,400 stocks over a period of 7 years. They show that using high-frequency data can improve the pricing accuracy of asset pricing models. In a related paper Andersen et al. (2006) investigate the time variation in realized variances, covariances and betas using daily returns to construct quarterly realized measures. They found evidence of strong persistence in the variance and covariance process, but less persistency in the beta process. This indicates that realized volatility and realized covariance are fractionally cointegrated. Other related studies include Barndorff-Nielsen and Shephard (2004), who derived asymptotic results for realized beta and Dovonon et al. (2013), who established a theory for bootstrapping inference. MSE-optima estimation of realized betas was analyzed in Bandi and Russel (2005). Patton and Verado (2012) studied the impact of news on betas. Corradi et al. (2011) use realized betas in order to extract the conditional 'alphas'. Morana (2009) employ realized betas to explain variation in expected returns.

Model realized betas are plotted in Figure 5. For all agricultural commodities, the optimal hedge ratios show in increasing pattern. In particular, starting from around 2005, the beta between each individual commodity and oil has not only become larger but also much more volatile. This findings have important implication in terms of portfolio hedging strategies: the low betas observed prior to 2005 suggest that agricultural investment risk could be hedged by taking a short position in oil futures. After this date, more and more oil futures are needed in order to minimize the risk of holding a position in agricultural commodities and thus resulting in higher hedging costs.

These results, together with the increased realized correlation between oil and other agricultural commodities again signal that the joint dynamics of agricultural and energy futures have changed in the last 10 years. In particular, an increase in comovement can be observed.

5 Concluding remarks

Over the last decade, commodity futures have become a popular asset class for portfolio investors, as investors increasingly sought out commodities for portfolio diversification after the equity market crash in 2000. This process is sometimes referred to as the financialization of commodity markets. The increase in commodity investment (particularly in the form of investment in commodity indices) coincided with increasing correlations between the returns of different commodity classes.

In this paper we employed a dataset of intra-day commodity futures prices and a recently introduced econometric methodology with the goal of providing further evidences that the joint dynamics of agricultural and energy commodities have profoundly changed.

From the methodological side, we rely on the recently introduced realized beta GARCH model of Hansen et al. (2014). The realized beta GARCH is a multivariate volatility model which incorporates both generalized autoregressive conditional heteroskedasticity (GARCH) and realized measures of variances and covariances. Realized measures are important as they extract information about the current levels of volatilities and correlations from high-frequency data. The model provides a very flexible tool to asses the dynamics of the correlations, spillovers effects and optimal hedge ratios between to individual assets belonging to the same class. We use two major commodities, corn and sugar, as representative of the market commodity for the Grains and Softs sector, respectively, and oil as commodity market index.

Using high-frequency price data for oil and 8 major US-traded agricultural commodities (corn, soybeans, wheat and soybean oil for Grains; coffee, cotton, sugar and cocoa for Softs) and estimating the realized beta GARCH model of Hansen et al. (2014), we have first shown that starting from

2006 correlation within Grains and Softs commodities have increased. Correlations between oil and agricultural commodities have also significantly increased. Similarly, spillover effects between oil and agricultural commodities has risen in size. This same conclusion holds for the optimal hedging ratio of a portfolio consisting of a position in an agricultural commodities hedged with a short position on oil.

Our results are important for investor exposed to the commodity market as they show that while diversification benefits in investing in this market have decreased, volatility transmission risk has increased. As a consequence, higher hedging costs need to be born.

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