INTERDEPENDENCE AMONG AGRICULTURAL COMMODITY MARKETS, MACROECONOMIC FACTORS, CRUDE OIL AND COMMODITY INDEX

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Abstract

This paper examines the degree of interdependence between three agricultural commodity prices, crude oil price returns, macroeconomic variables and the S&P GSCI commodity returns index. We apply Aielli (2013) cDCC model using monthly data from 1982 to 2012 to estimate the dynamic correlations of the returns series and endogenously detect any structural instability of the dynamic correlations. Our results indicate that crude oil price returns present statistically significant dynamic correlations with all the macroeconomic variables in addition to the GSCI index. Additionally, we detect structural changes in these dynamic correlations mainly associated with the financial crisis of 2008. On the other hand, our results show that there exists no degree of interdependence between maize, soybeans and sugar with crude oil price returns and most of the macroeconomic variables. The exceptions are between soybeans with the U.S. exchange rate and sugar with global economic activity. Nevertheless, only the GSCI index presents significant dynamic correlations with these commodity price returns.

Keywords: Volatility, crude oil, agricultural food commodities.

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1 Introduction

The aim of this study is to analyse the inter-relationship between commodity and energy markets, whilst incorporating the main macroeconomic determinants of these markets into the model. Understanding the nature of volatility spillovers between markets and how this interacts with the wider economy is increasingly important, particularly following the 2006/08 commodity price shock, which produced a period of extreme price movements and volatility, making it difficult to forecast agricultural prices and understand their behaviour. Recent studies have found a strong relationship between these markets (Fernández, 2014) and a corollary of these findings is that an increase in the causal relationship between energy and food prices can (in principle) be associated with stronger volatility spillover effects between them, which in turn may increase the farmers risk premium and reduce the effectiveness of stabilization policies (Serra, 2011). Thus, understanding volatility spillovers among these markets is also crucial for developing countries that are net importers of these agricultural and energy commodities and equally for those that rely on energy and commodity exports. Moreover, without an adequate understanding of commodity prices, it is very difficult to develop good policies to respond to commodity price fluctuations (Deaton, 1999). Therefore, it is critical for economists and policy makers to understand the degree to which energy prices stimulate food commodity price volatility and their broader social and economic repercussions.

Over the past fifteen years, the co-movement of commodity prices has received a substantial amount of attention in the literature. The price co-movements in commodity markets is thought to take place because macroeconomic and market fluctuations are common to all commodity prices. In the seminal paper by Pindyck and Rotemberg (1990), they showed that there existed unexplained price co-movement in seven raw commodities, which cannot be accounted for by market and macroeconomic fundamentals. In this case, the authors attributed these residual effects to herd behavior in the financial markets; thus, laying the foundations for the excess co-movement hypothesis. Nevertheless, the literature has questioned the initial findings from Pindyck and Rotemberg, firstly by Leybourne et al. (1994) and subsequently by Deb et al. (1996) among others. The former, points out the non-stationay nature of commodity price series and thus the methodological deciencies in Pindyck and Rotemberg analysis. Therefore, Leybourne et al. (1994) apply a pair-wise co-integration analysis to evaluate Pindyck and Rotemberg's hypothesis and conclude that only in two out fifteen pairs does such a phenomenon occur. Similarly, Ai et al. (2006) controlled for supply factors in addition to economic fundamentals and concluded that there is no excess co-movement within the agricultural commodity markets.

The period from 2006 to 2008 was one that attracted researchers particular attention due to a substantial increase in price levels and volatility in commodity markets. For example, Sumner (2009) points out that the percentage price increase in agricultural commodity markets for this period was the largest in the 140-year history for which U.S. data is available. Similarly,

Trujillo-Barrera et al. (2012) showed that historical maize volatility of daily percentage price changes were below 25% before 2006 and since then have increased to over 40% up to 2011. As a result, the literature has resumed its interest in the causal links between agricultural commodity and energy markets and economic fundamentals. This study contributes to this literature by analysing volatility linkages between these markets and the main macroeconomic fundamentals, using Aielli (2013) cDDC model.

Nevertheless, the channels through which volatility in agricultural markets operate are complex and arise from various sources in the economy (Prakash and Gilbert, 2011). These can vary from external factors such as climate change, globalization and new policies that link them with the energy sector. Additionally, there are intrinsic events affecting the volatility in agricultural markets arising from the global business cycle, monetary policy and exchange rate movements as well as uncertainties in price level variations and accelerating income growth in commodity dependent countries. Consequently, there exists an imperative need to understand the degree to which the volatility of agricultural commodities are vulnerable to shocks derived from these factors.

The effects of commodity price volatility can have severe repercussions throughout the economy. For instance, increasing agricultural commodity price volatility is translated into higher costs for managing risks in the form of increasing crop insurance premiums, which in turn translates into higher option premiums and hedging costs for farmers (Wu et al., 2011). Additionally, as a consequence of the financialization of commodity markets, volatility spillovers from the oil price to agricultural commodity prices can in turn diminish diversification efforts in the financial markets when agricultural and energy prices present any degree of price co-movement (Gardebroek and Hernandez, 2013). From a macroeconomic point of view, Byrne et al. (2013) explains that the design and effectiveness of stabilization policies are determined by both the volatility and persistence of commodity prices. Moreover, as a consequence of the recent increase in biofuel production, the increased price volatility in agricultural commodities used in biofuel production (e.g. maize, soybeans and sugar) can be transmitted to other agricultural markets. That is, as demand increases for biofuels (as a consequence of the mandates) and assuming that agricultural land is constrained, food production decreases and so increases food prices (Zilberman et al., 2013). Ultimately, all these effects are reflected in a decrease in welfare for the general population, particularly in the poorest countries, where a higher proportion of income is devoted to food consumption. Therefore, examining the extent to which the transmission of energy volatility to economic fundamentals stimulates food price volatility is vital for determining the severity of negative impacts on welfare, for both investment and risk management as well as the impact on economic growth and financial stability.

Despite these facts, the empirical literature is limited with respect to volatility interactions between energy, economic fundamentals and food agricultural commodities (Serra, 2011). Instead,

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the literature has placed a great deal of emphasis on price level transmission mechanisms using supply and demand frameworks, partial/general equilibrium models and vector error correction models, while price volatility interactions between food, energy commodities and fundamentals have received significantly less attention (Serra and Zilberman, 2013). Consequently, the aim of this study is to contribute to the literature by using a consistent dynamic conditional correlation (cDCC) model by Aielli (2013) in order to capture the degree of co-movement between world oil price returns, the U.S. exchange rate, short-term interest rates and a measurement of or global economic activity with three world traded agricultural commodities used in biofuels production, namely maize, soybean and sugar. Additionally, and in line with Turhan et al. (2014), we will evaluate the stability of the dynamic correlations during the sample period by endogenously detecting any significant shifts using a penalized contrast methodology by Lavielle (2005).

Economic theory using the standard demand and supply approach has developed several frameworks to explain commodity price dynamics. The main theories used to explain commodity price behavoir are: the storage model, the scarcity rent model, the cobweb model and the over-shooting model. With regard to this study, the most relevant of these models is the overshooting model proposed by Frankel (1986, 2008) as it emphasizes the importance of macroeconomic factors in explaining commodity price dynamics. In this model, an expansionary monetary policy causes investors to revise upward their future inflationary expectations, which in turn triggers their appetite for investments away from liquid assets towards other investments including commodities. Consequently, commodity prices suffer from upward pressures in their long-run equilibrium and increases proportionally more than the money supply and the general price level in the short-run. This is the so called overshooting and this trend will persist as long as commodities are overvalued by the market relative to all other goods Stigler (2011).

Recent literature on volatility spillovers between energy and commodity markets, whilst incorporating aspects of the wider economy includes Manera et al. (2013). They investigated whether macroeconomic factors are able to explain returns of energy and five world agricultural commodities (i.e. corn, oats, soybean oil, soybeans and wheat) using weekly data over the period 1986 to 2010 with pair-wise DCC-MGARCH models. The authors find that financial speculation is not correlated with returns for these energy and agricultural series. Nevertheless, Manera et al. present significant and positive conditional correlations among energy and agricultural commodities, which suffered dramatic strengthening during the 2006-08 period. Finally, Serra and Zilberman (2013) studied the volatility spillovers from energy prices, global economic conditions (3-Month U.S. Treasury bill) and U.S. corn price from January 1990 to December 2010 using a two-stage process. In the first stage, Serra and Gil use a conventional parametric two-dimensional GARCH and then apply the Long et al. (2011) nonparametric correction of the parametric conditional covariance estimators. Serra and Zilberman (2013) find that interest rate variability is associated with more volatile corn prices. As a consequence, the authors recommend expanding

the analyses of volatility spillovers among energy and agricultural markets by considering a wider range of explanatory variables (Serra and Gil, 2013).

Following the introduction, section 2 discussed the methodology used in this study and section 3 describes the dataset. Section 4. Discusses the interprets the results, whilst we end with a conclusion and policy implications.

2 Methodology

2.1 The General Multivariate GARCH (MGARCH) Model

Let us consider a column vector of excess returns $\{r_t\}$ of dimensions $N \times 1$ for $t = 1, \ldots, T$ such that $E(r_t|\mathcal{F}_{t-1}) = 0$ and $Var(r_t|\mathcal{F}_{t-1}) = H_t$. We denote $\mathcal{F}_{t-1}$ as the information set generated by the past observations of the series $\{r_t\}$ up to time $t-1$ (Mikosch et al., 2009). Multivariate GARCH models are assumed to be conditionally heteroskedastic given the information set $\mathcal{F}_{t-1}$ and can be represented as follows:

$$r_t = \mu_t(\theta) + \varepsilon_t \tag{1}$$

where θ is a finite vector of parameters, $\mu_t(\theta)$ is the vector of conditional expectations of r_t is conditionally heteroskedastic such that:

$$r_t - \mu_t(\theta) = \varepsilon_t = H_t^{1/2}(\theta)\eta_t \tag{2}$$

where $H_t^{1/2}(\theta)$ is any $N \times N$ positive define matrix of conditional variance of r_t such that $H_t^{1/2}$ is any square matrix such that $H_t = H_t^{1/2}(H_t^{1/2})'$ and where η_t is an unobservable random $N \times 1$ *iid* vector error process with zero mean $(E(\eta_t = 0))$ and identity matrix $(E(\eta_t\eta_t') = Var(\eta_t) = I_N)$. Thus, $\eta_t \sim N(0, I_N)$, where I_N is the identity matrix of order N. Therefore, the conditional variance matrix of r_t can be calculated as follows:

$$Var(r_t|\mathcal{F}_{t-1}) = Var_{t-1}(y_t) = Var_{t-1}(\varepsilon_t)$$
$$= H_t^{1/2}Var_{t-1}(\eta_t)(H_t^{1/2})'$$
$$= H_t$$

Consequently, $H_t^{1/2}$ is any symmetric, positive definite matrix of dimensions $N \times N$ such that H_t is the conditional variance matrix of r_t. $H_t^{1/2}$ can also be triangular, with positive diagonal elements (e.g. it can be obtained by the Cholesky factorization of H_t). It is the case that H_t and μ_t depend on the unknown parameter θ. In some cases μ_t functionally depends on H_t, in which case θ has to be jointly estimated (GARCH-in-mean models); however in most cases it is possible

to split θ into two disjointed parts, one corresponding for μ_t and another for H_t (Laurent et al., 2006).

2.2 Aielli (2013) cDCC model

Engle's DCC-GARCH model extends the CCC-GARCH model at the expense of extra parameters to estimate (Engle, 2002). For each correlation equation, the number of estimated parameters is $N(N-1)/2 + 2$. This is a strength, but also a weakness when considering large N since the correlation processes are restricted to have the same dynamic structure. Thus, it has been argued that in large systems DCC-GARCH estimators can be inconsistent (Aielli, 2013) .

Moreover, Aielli (2013) has shown that the estimation of D by Maximum Likelihood (ML) of R, which is given by

$$\widehat{R} = \frac{1}{T} \sum_{t=1}^{T} \widetilde{r}_t \widetilde{r}_t',$$

(3)

where $\widetilde{r}_t = R_t^{-1} r_t$, is inconsistent for large N since $E(\widetilde{r}_t \widetilde{r}_t') = E(E(\widetilde{r}_t \widetilde{r}_t' | \mathcal{F}_{t-1})) = E(r_t) \neq E(Q_t)$ (Bauwens et al., 2012). Thus, Aielli (2013) proposes a different specification for Q_t that in this case is consistent and thus the name (cDCC, consistent DCC). Therefore, the cDCC model can be substantially improved by reformulating the correlation driving process as

$$Q_t = (1 - \alpha - \beta)S + \alpha \left\{ Q_t^* \tilde{r}_{t-1} \tilde{r}_{t-1}' Q_t^* \right\} + \beta Q_{t-1},$$

(4)

where $Q_t^* \equiv diag(q_{11,t}^{1/2}, \ldots, q_{NN,t}^{1/2}) = (I_N \odot Q_t)^{1/2}$, thus Q is the unconditional variance covariance matrix of $Q_t^* \tilde{r}_t$. For example, in the bivariate case the correlation is defined as follows:

$$\rho_{ij,t} = \frac{\omega_{ij} + \alpha r_{i,t-1} r_{j,t-1} + \beta \rho_{ij,t-1}}{\sqrt{\left\{ \omega_i + \alpha r_{i,t-1}^2 + \beta \rho_{ii,t-1} \right\} \left\{ \omega_{jj} + \alpha r_{j,t-1}^2 + \beta \rho_{jj,t-1} \right\}}},$$

(5)

where $\omega_{ij,t} \equiv (1-\alpha-\beta)s_{ij}/\sqrt{q_{ii,t}q_{jj,t}}$. From Equation 5, is evident that "... the relevant innovations and past correlations are combined into a correlation-like ratio." The parameters α and β are the dynamic parameters of the correlation GARCH and the denominator of the time-varying parameters $\omega_{ij,t}$, $\omega_{ii,t}$ and $\omega_{jj,t}$ can be interpreted as ad hoc correction required for purposes of tractability (Aielli, 2013).

2.3 Endogenous detection of the shifts in dynamic correlations

The methodology developed by Lavielle (2005), which is based on a penalized contrast is applied in order to determine any shifts in both mean and variance (and the respective locations)

of the dynamic correlations along the entire sample period. Here we consider a sequence of random variables $Y_1, \ldots, Y_n$ that take values in $\mathbb{R}^p$. Lets denote the parameter $\theta \in \Theta$ some characteristics of Y_i that changes abruptly at some unknown interval and which remains constant between these two changes. Now, we define K to be some integer and let $\tau = (\tau_1, \tau_2, \ldots, \tau_{K-1})$ be a sequence of integers satisfying $0 < \tau_1 < \tau_2 < \cdots < \tau_{K-1} < n$. Thus, for any $1 \leqslant k \leqslant K$ let $U(Y_{\tau_{k-1}+1}, \ldots, Y_{\tau_k}; \theta)$ be a contrast function used for determining the unknown true value of the parameter of the segment k.

When the true number $K^\star$ of segments is known, the sequence $\hat{\tau}_n$ of change-point instants that minimizes the contrast function defined above follows the requirement that for any $1 \leqslant k \leqslant K^\star - 1$,

$$P\left(|\tau_{n_k} - \tau_k^\star| > \delta\right) \to 0$$
$$\text{as long as } \delta \to \infty \text{ and } n \to \infty$$

In particular, this result holds for weakly and strongly dependent processes. For example, lets consider the model with the following characteristics:

$$Y_i - \mu_i + \sigma_i \varepsilon_i, \quad 1 \leqslant i \leqslant n$$

where ε_i is a sequence of zero-mean random variables with unit variance. In case of changes in the mean, it is assumed that μ_i is a piecewise constant sequence and σ_i is a constant sequence. Therefore, there occur some instants $\tau_1^\star < \tau_2^\star < \cdots < \tau_{K^\star-1}^\star$ such that, for any $1 \leqslant k \leqslant K$, $\mu_{\tau_{k-1}^\star+1} = \mu_{\tau_{k-1}^\star+2} = \cdots = \mu_{\tau^\star}$. A key advantage of this methodology is that Gaussian log-likelihood can be used to define the contrast function, even if ε_i is not a Gaussian sequence.

On the other hand, when the number of shifts are unknown, these can be estimated by minimizing a penalized version $J(\tau, \mathbf{y})$ described above. That is, for any sequence of change point segments τ, let $pen(\tau)$ be an increasing function of $K(\tau)$. Then , let $\hat{\tau}_n$ be the sequence of change-point instants that minimizes

$$H(\tau) = J(\tau, \mathbf{y}) + \beta \cdot pen(\tau) \tag{6}$$

where β is a function of n that approaches to zero as n goes to infinite and the estimated number of segments $K_{\hat{\tau}_n}$ converges in probability to $K^\star$. The adequate penalization parameter β and the function $pen(\tau)$ are chosen according to Lavielle (2005).

3 Data Description

The objective of this analysis is to examine the volatility transmission between a number of macroeconomic variables (i.e. the real exchange rate, short-term interest rate and a measurement of global economic activity), world crude oil prices and three world traded agricultural commodities

used in the production of biofuels, namely maize, soybean and sugar. The data used in this analysis is monthly and runs from January 1982 until December 2012 (See Table 1). This sample period captures all major macroeconomic as well as commodity cycles over the past three decades as well as important institutional changes affecting both the energy and agricultural markets.

The real exchange rate (XR_t) is defined as the weighted average of the foreign exchange values of the U.S. dollar against the currencies of major U.S. trading partners converted to real terms and was obtained from and constructed by the Board of Governors of the Federal Reserve System. For the short-term interest rate (it) we have used the three-month Treasury bill secondary market rate as reported by the Federal Bank of St. Louis in the FRED database. Moreover, we have used Kilians index as a proxy for the real global economic activity as dened in Kilian (2009). We also included the world price of crude oil (O_t) measured as the trade weighted average price of crude oil in U.S. dollars per barrel, obtained from the IMF International Financial Statistics (IFS). On the other hand, the three agricultural commodities of interest are the price of maize (MZ_t), soybean (SB_t) and sugar (S_t), which were all obtained from the IFS database and are measured in U.S. dollars per metric tonne. All these agricultural price variables are world benchmark price series which are representative of the global market and are determined by the largest exporter of this specific commodity (Table 1). All price series have been deflated using the U.S. Producer Price Index (PPI) for all commodities (not seasonally adjusted) since the variables of interest are widely used as intermediate goods in industrial production. Furthermore, all the analysis is conducted un returns defined as $r_t = log(y_t/y_{t-1})$ where y_t corresponds to the series "y" at month t.

Figure 1 and 2 show the fluctuations of the series in the past thirty years in real terms. At first sight these series appear to be remarkably similar, particularly the commodity and crude oil price series at the end of the sample. There, is evidence of the increasing mean since 2000 in all series with a significant growth rate during the commodity and energy price boom leading up to 2007/08 and subsequent bust during the financial crisis at the end of 2008 and then the recovery after the instability period. During the 80s, the series experienced high levels of volatility due to the collapse in commodity prices and exogenous shocks (e.g. crude oil). During the 90s all series present a fair level of stability in terms of their volatility levels, but this is short-lived after the end of the millennium when the series begin to experience higher levels of fluctuations primarily up to the 2008 financial crisis also found by Gardebroek and Hernandez (2013) (See Figures 3-4) . Instead, the sources of higher volatility towards the end of the sample are present in the macroeconomic variables, particularly in the short-term interest rate, Kilian index and real exchange rate respectively. Thus, there exists some strong evidence indicating a co-movement in the volatility of these series that also coincides with the fluctuations in the macroeconomic fundamentals, particularly in the latter part of the sample.

Table 2 presents the monthly pair-wise returns correlation between all variables of interest

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along the entire sample period. The evidence presented in Table 2 further substantiates the interrelation between the unconditional volatility in the commodity markets themselves (e.g maize and soybeans). Specifically, it shows that the only statistically significant return correlation among commodities is between maize and soybean during the entire sample. This is not surprising, since it is expected that the factors driving these commodity markets are likely to be very similar. On the other hand, Table 2 does not show evidence of pair-wise correlation between crude oil and any of the commodities price returns. Crude oil returns, however, are strongly correlated with macroeconomic factors. For example, we find all commodity prices and crude oil returns to be negatively correlated with the indexed U.S. exchange rate and the real three month interest rate (except for sugar). Similarly, it appears that the global economic activity index is somewhat correlated with crude oil returns and less so with soybean but not statistically significant with regards to the remaining commodity return series However, at first glance it appears that there exists substantial evidence supporting the interdependence volatility transmission between commodity markets and economic fundamentals and less transmission between commodity markets themselves.

Table 3 provides descriptive summary statistics of all the return series across the sample period. At first glance the mean return for sugar is the highest among the commodity series followed by oil, maize and soybean individually. The mean return of oil is approximately 1.6 times higher than maize and 3.5 times than soybean, but about only half of the sugar returns. The return on each of these markets in the effective period has only been negative for sugar returns with approximately -0.240% while for maize, soybean and oil has been 0.083%, 0.037% and 0.139% respectively. Additionally, the series presents evidence of non-normality evidenced by the excess skewness and kurtosis that all the series suffer from and formally by the Jarque-Bera statistic which rejects the null hypothesis of a normal distribution for all the series or that the joint hypothesis of the skewness and excess kurtosis being zero. Particularly, all series present significant evidence of skewness and kurtosis (all well above 3). Consequently, in the estimation of the GARCH and cDCC models we use a $Student's-t$ density distribution for the residuals. Moreover, all the return series show stationary properties as shown in Table 4. The results from a battery of unit root tests (with both non-stationarity and stationarity as the null hypothesis) are presented and all the evidence suggests that all return series are stationary.

4 Empirical Analysis

In this section we present the results from the VAR-cDCC-MGARCH models and then determine whether these conditional correlations have suffered from any significant changes across the sample period.

4.1 Conditional Variance

Figures 5-7 contain the conditional variance between of all three agricultural commodities over time. Figure 5 show the conditional variance of maize and soybeans in the same figure along the entire period. Maize prices displayed relatively low levels of conditional variance for approximately fifteen years from the early 90s to just before the 2007/08 commodity price boom. Nevertheless, maize prices present several volatility clusters with peaks particularly visible during the 1998, 1997 and just after the financial crisis of 2008. Soybeans conditional variance also presents a similar stable period as maize, with peaks around 1983, 1988 and 2008. Overall, this pair of commodities appears to show several common periods of conditional variance; however, soybeans conditional variance is not as pronounced as it is in the case for maize during and after the 2007/08 period. One possible explanation for this might be the adoption of the biofuel mandates by the U.S. in late 2004 in conjunction with other market instability characterized during this period, which exasperated the uncertainty around maize prices. This is likely to have affected maize rather than soybeans markets since it is maize the main input into the production of ethanol and not soybeans, which instead is used for biodiesel production. On the other hand, Figures 6-7 show the conditional variance of maize and soybeans with sugar prices along the same period. In this case, sugar prices only exhibit periods of high conditional variance before 1988 and relatively low levels of price instability thereafter; although the conditional variance increased (relative to the previous period) after the year 2000, but then decreased shortly after. Contrary to the case of both maize and soybeans markets, the conditional variance in the sugar market was not present around the 2008 financial crises, but common peaks with the these commodities are observed during the 1988 period.

Figure 8 graphs the conditional variance between crude oil prices with each individual commodity along the same time period. From Figure 8, it is evident that crude oil price volatility reacts to energy market specific shocks with significant peaks around the years 1986, 1990 and after the 2008 financial crisis. It is only during the period during the financial crisis that we see crude oil price volatility coincide with movement in the maize and soybean markets, but crude oil exhibits a higher degree of price instability than any of the these commodities and the timing is not precisely the same. This graph along, raise doubts on the claim of volatility spillover from crude oil to these commodities, but this will be explored in more detailed when we present the results from the conditional correlation models.

Similarly, Figure 9 graphs the pair of conditional variance between the U.S. exchange rate and the agricultural commodity prices. In this case, the U.S. exchange rates conditional variance is stable, but persistent levels of relatively high conditional variance occurs during the decade of the 80s with respect to the more recent years. The conditional variance of this series reached its lowest level just before the 2008 financial crisis when then after a visible spike is present. Overall, it is evident that fluctuations in the conditional variance of the U.S. exchange rate are not related to movements of any of the commodities conditional variance. On the other hand, Figure 10 shows

similar graphs, but this time between the conditional variance of the short term interest rate and the commodity prices. Here however, there seems to appear some common peaks of the conditional variance of the interest rate and the commodities particularly between soybeans and sugar after the 2000s and less evident with sugar. This observation is significant since it sheds light on the argument of the financialization of commodities during this time period and the effect it had on the stability of commodity markets.

4.2 Results of VAR-cDCC-MGARCH

In order to estimate the VAR-cDCC-MGARCH we apply three separate models corresponding to each one of the commodities of interest (e.g. maize, soybeans and sugar) with crude oil price returns and the macroeconomic factors. There are two reasons why we have decided to estimate these in three different models. In the first case we experience the limitations of the cDCC models with large numbers of parameters being estimated simultaneously [1]. Secondly, we are not interested in the cross conditional correlation between the agricultural commodities, but in the interdependence between these and crude oil price returns and the macroeconomic factors.

The results from the estimations of the cDCC models are presented in Tables 8−10, which have been estimated in two steps. In the rst step we estimate the univariate part of the model and these are presented in Tables 5−7. The univariate estimations are dened by an $ARMA(p, q)$ process in order to capture the serial correlation in the residuals and a $GARCH(1, 1)$ specification with specific parametric forms for the conditional heteroskedasticity in order to capture the serial correlation in the residuals (See Table 12). In the second step, we estimate all the parameters simultaneously, by maximizing the log-likelihood function assuming a students-t distribution given that all variables suffer from excess kurtosis. This approach allows us to capture volatility clustering in commodity markets where we are more likely to observe high volatility at time t if it was also high at time $t − 1$.

The lag coefficients of the ARMA models for the univariate estimations are chosen by the AIC as well as the lagrange multiplier (LM) test for autocorrelation in the residual and square residuals (See Table 12) and the results for all three univariate models are presented in Tables 5−7. Table 5 presents the simultaneous estimation of the univariate parameters for maize, crude oil price returns and the macroeconomic factors (i.e. Model 1). In this model, both maize and crude oil show evidence of autoregressive and moving average behaviour in the returns series, which is consistent with the volatility clustering observed in commodity markets. On the other hand, the macroeconomic variables (i.e. exchange rate, interest rate and the Kilian Index) also show evidence of autoregressive and moving average behavior, but

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[1]As it is, the system has five variables and if including them all (e.g. the three commodities, oil and three macroeconomic factors) will be a system of seven variables and the likelihood function was not able to find a convergence solution.

to a lesser extent. Moreover, in neither of these cases does there exists evidence of drifting in the return series since the constant in the mean equation is not significant for any of these variables.

In order to simultaneously estimate all the parameters from Model 1, we must correctly specify the univariate GARCH process for each variable. From Table 5, we see that the best fitted model (based on the AIC) for maize is a GARCH(1, 1) and for crude oil it is an APARCH specification. For maize, α which captures the influence of new shocks on volatility, these are significant for the case of oil price returns. One explanation is that the rest of the variables are modelled using GJR-GARCH (e.g. Kilian Index and interest rates) and this type of model assumes that not all shocks have the same influence on the price return (i.e. leverage effect). On the other hand, the parameter β, which captures the persistence of volatility shocks or the impact of the own-variance on volatility development, is positive and statistically significant at the 1% level in all variables estimated. The value β for maize is about 0.94, which indicates that old shocks to the maize price returns are rather persistent and long lasting Crude oil has a low own variance,This combination of factors indicates that crude oil is more sensitive to external shocks during volatility phases than maize. Moreover, overall none of the sums between α and β are close to one (except perhaps for the exchange rate), which implies that compounded shocks to these series experience a decaying autocorrelation function. Furthermore, The asymmetry coefficient γ is positive and significant (at minimum to the 10% level) for all variables where GJR-GARCH was used (e.g. Kilian Index, interest rates and crude oil). For crude oil in particular, it indicates that shocks have an asymmetric effect on the volatility of crude oil prices. More precisely, it indicates (by the positive sign) that positive price shocks reduce volatility more than negative shocks3 (See Mensi et al. (2015) for similar conclusions). Generally, the literature assumes that negative shocks increase volatility more than positive shocks do. However, a positive price shock to the oil price increases the production costs of all other goods and in turn induces a higher risk premium for holding stocks. Finally, the power coefficient δ in the APARCH specification used to model crude oil is significant at the 1% level.

Table 6 presents the simultaneous univariate parameter estimation results for soybeans (i.e. Model 2). For soybeans the best fitted model according to the AIC is a GJR-GARCH(1, 1) and the same model specification used in Model 1 for the remaining variables. In this case, both α and β coefficients are significant for crude oil and soybeans. As before, the results indicate that soybeans (as it is the case for crude oil) is sensitive to external shocks relative to shocks to its own-variance. Additionally, the γ coefficient for the soybean GJR-GARCH model is statistically significant at the 1% level, suggesting an asymmetric effect on the volatility of soybean prices. Finally, Table 7 summarizes the results from the univariate parameter estimation results of using sugar (i.e. Model 3). Here, we found the best fitted model to be a GARCH (1, 1) for sugar and the same as in the previous cases. The α and β coefficients are significant for sugar and crude oil and they indicate that sugar is more sensitive to shocks to its own-variance on volatility development

than to external shocks (high β ralative to low α).

Tables 8−10 present the estimated parameters for the conditional correlations of the cDCC model. For Model 1, α and β are statistically significant at the 10% and 1% level respectively. In this case, the fact that the β coefficient is higher than α suggests that the conditional correlation between the residuals is persistent to a higher degree. This is the case for both maize and soybeans models; however, we observe the opposite for the model using sugar return prices. Finally, there does not appear to be any sign of misspecification given that we fail to reject the null hypothesis of no cross-correlations in the squared residuals (Hosking's Multivariate test) and find no evidence of ARCH effects (Li and McLeod's test) in all three models.

The results from Tables 8−10 suggest that maize does not show any sign of strong conditional correlation with crude oil or any of the macroeconomic factors included. That is, the volatility episodes that we have described are related to commodity specific and are not directly correlated with those in the crude oil market or by macroeconomic variables. However, this does not imply that crude oil prices can determine these commodity prices in the long-run. However, the interdependences between energy and these agricultural markets seems to be restricted to direct spillover effects particularly during and after the 2008 financial crisis.

Succinctly, soybeans appears to be the only agricultural commodity to show strong and significant correlation with the U.S. exchange rate and none of these with crude oil and the remaining macroeconomic factors. On the other hand, sugar appears to be correlated with the global economic index given a significance level of 10%, but the sign is negative. Crude oil prices, present a strong and negative correlation with the exchange rate and interest rate as well as a significant correlation at the 10% level with the global economic activity index. Finally, both the interest rate and exchange rate have a strong and positive correlation across all three models at the 5% significance level. Nevertheless, the results indicate that instability periods in these commodities are not associated with instability in macroeconomic fundamentals or crude oil market.

Since the 2007/08 commodity price shock there has been an extensive interest in the literature on the effects of the financialization of commodity markets had on this period. Consequently, economists and policy makers alike have tried to understand if there exists any causal relationship between financial and commodity markets particularly during and after the 2007/08 price shock. However, very few studies have attempted to understand the volatility links between the financialization of commodities and these markets.

As a consequence, we have decided to simultaneously estimate these variables and in addition include the S&P GSCI commodity excess return index obtained from Bloomberg in order to capture any links between commodity index investment had an impact on spot volatility in

commodity markets. The GSCI commodity index uses a weighted methodology based on 1/3 world production value and 2/3 market liquidity which contains 22 exchange-traded futures on physical commodities (e.g. crude oil, maize, soybean and sugar) and is rolled forward from the fifth to the ninth business day of each month. This commodity price index was valued at 100 in December 1990 and introduced to the market in January 1998[2].

In Table 11 we present the results from the simultaneous cDCC (1,1) model including the return on the GSCI commodity index using the dame data series and frequency from January 1991 to December 2012. The results from this model are remarkably similar to those presented in Tables 8-10. The only exception is the conditional correlation between soybeans and the exchange rate which magnitude is similar to that presented in Table 9, but the sign of the conditional correlation is the opposite. However, this can be explained by the instability (discussed in greater detail in the next section) between the return price to soybeans and the U.S. exchange rate from the mid 1990's until early 2000's where the conditional correlation was significantly lower (negative) during this period. Nevertheless, the important realization from this model is the strongly significant and positive correlation between the return to the GSCI commodity index with the return to all commodity prices (including oil) during this period. Thus, from this evidence it appears that, more than economic fundamentals, it is the commodity price index that is associated with periods of instability in the agricultural commodity markets. In addition to this, we are also able to determine that returns in the commodity markets are highly associate with the same fluctuations in the other commodity markets.

Although in this study we cannot claim causation, it is evident that activity in the futures market and the financialization of these commodities through the implementation of these commodity indexes is associated with the return price to these commodities. This conclusion is also supported by other authors in the literature such as Gilbert (2010) and more recently by Pen and Sevi (2013) and Creti et al. (2013).

4.3 Structural Changes in the cDCC Estimates

In order to estimate the structural changes in the dynamic correlations an endogenous approach developed by Lavielle (2005) has been used. In Figures 12-14 we present the results from applying the penalized contrast function to determine any shifts in both mean and variance of the dynamic correlations that had been found to be statistically significant during this time period.

In Figure 12 we show the results from the dynamic correlations between soybeans and the U.S. exchange rate (top) as well as that from sugar and the Kilian index (bottom). For the first

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[2]The only reason for using this commodity price index and not another is the availability of data and the length of the series. Other commodity indexes begin in the late 1990's.

conditional correlation, we observe that the dynamic correlation has become more negative since 1982 to 2012 with three regimes being detected. The first period is from January 1982 to October 1997, the second period from November 1997 to August 2008 and finally from September 2008 to the end of the sample in December 2012. All these shifts are associated with more negative correlations than the previous regime. The first shift in the dynamic correlation between soybeans and the U.S. exchange rate is detected during the Asian Financial Crisis of 1997, which also coincides with a period of high soybean prices. The second structural change in the dynamic correlation from these two variables is associated with the end of a period of historical commodity price increases and the financial crisis of 2008. This is a very interesting result since again the instability of the soybeans market is associated with major global macroeconomic events. The second graph (bottom) from Figure 12 corresponds to the dynamic correlations between sugar and the Kilian index. In this case, the relationship does not suffer from significant structural changes across the entire period and the conditional correlation remains negative along the sample.

Similarly, Figure 13 crude oil prices and all macroeconomic variables. The top figure shows the conditional correlation between crude oil price returns and the U.S. short term interest rate (3 Month T-Bill). In this case, and in this relationship we detect only one significant regime change at September 2007. The shift is associated with a more negative dynamic correlation than in the previous period. These results, to an extent, are remarkable since the full thrust of the financial crisis did not spread out through the economy until a year later and crude oil prices peaked by mid 2008 (about 10 months later). This date is associated with less than a month after the first decrease in the federal funds rate since mid 2003 by 50 basis points on August, 17 2007 and another 50 basis points by early September of the same year as well as a similar trends in the 3-Month Treasury Bill during this same period (FOC, 2007). Additionally, the end of this period ends coincides with the beginning of the steepest price shock period until the end of the 2007/08 commodity price boom. It is evident that the increasing troubles of market liquidity together with historical high oil prices significantly raised the uncertainty in the markets during this period.

The third graph (middle) from Figure 13 presents the shifts in the dynamic correlation between crude oil and the weighted U.S. dollar exchange rate. In this relationship we determine a similar instability in the means on July 2007. Overall, the conditional correlations are negative, but less so than with the interest rate. The bottom figure represents the dynamic conditional correlation associated with crude oil prices and the Kilian Index for global economic activity. Overall the correlation between this is positive as expected and two breaks are detected on July 2008 and March 2010. Since the breaks have been determined based on the means, the large swing during the financial crisis of 2008 is perhaps driving both the mean in the during the period of the financial crisis where the conditional correlation was the strongest. Therefore, although we claim the shifts as artifacts of the this particular event in 2008, the conditional correlation is still significant and positive as expected.

Finally, Figure14 present the dynamic conditional correlations between the U.S. exchange rate and the short-term interest rate. As expected the relationship is positive and significant along the entire period. Also, it presents a stable relation up to July 2007 where we find the mean of the conditional correlation to be significantly higher then after. The conditional correlations here presented show the links between monetary policy and the response to this in the U.S. dollar foreign exchange market.

5   Conclusion and Policy Implications

Our results indicate that although the long-run relationship between global crude oil and agricultural commodity price levels is overwhelmingly strong as shown in Fernández (2014), the volatility interdependence between these cannot be explained by the crude oil price returns and macroeconomic factors. For instance, we are not able to establish any interdependence between maize price returns with crude oil prices and macroeconomic factors. Moreover, although soybeans price return presents a negative and statistically significant relationship with the U.S. exchange rate return, it is a weak relationship. Additionally, these results indicate that this relationship is not constant over time and there is evidence of asymmetry during these periods of macroeconomic instability. Similarly, sugar price returns do not present any evidence of being linked with crude oil price returns and any of the macroeconomic factors except the Kilian index of global economic activity. Thus, we can safely conclude that the observed price instability leading to the commodity price shock of 2006-08 is not associated with volatility in the energy or demand-side factors. Thus, our results indicate that in these global agricultural markets the volatility appears to be associated with the financialization of commodities. Our results are in disagreement with those found by Manera et al. (2013) but in line with a number of studies already in the literature such as Gilbert (2010) and Gilbert (2015). Consequently, from a policy perspective, our results indicate that in order to reduce future agricultural market volatility it is important to create and foment efficient market monitoring mechanisms.

On the other hand, the results from the cDCC model show that crude oil price returns are closely linked with fluctuations in monetary and global macroeconomic policy. Specifically, we determined that crude oil price returns are associated with the U.S. exchange rate and the Kilian index to a lesser extent and present strong volatility correlation with the rate of U.S. three month treasury bills. These results also confirm the findings of a number of recent studies. For example, Schryder and Peersman (2013) show that changes in the U.S. dollar exchange rate are an important determinant of the volatility of the global price of crude oil given its influence on oil demand. Similarly, our results also show the importance of monetary policy (interest rates) in determining fluctuations in the global oil market, which also coincides with the findings of Frankel (2008). More precisely, as interest rates increase, crude oil becomes less attractive as an asset

for investors in addition to the fact that contractionary monetary policy has as a main aim to decrease overall demand and that of crude oil. Similarly, positive shocks in the global oil market force central banks to increase interests rate in order to counteract inflationary pressures and thus contribute to a decline in economic activity.

Although the volatility in global agricultural commodity prices has been argued to be linked to a strengthening relationship with energy markets, our results do not support this argument. Moreover, it does not support the view that global macroeconomic factors can explain this phenomena. Consequently, we conclude that there appears to be an excessive volatility in these agricultural commodity markets that cannot be explained by the traditional channels, which makes decisions from a producing and investment aspect very difficult in the near future. On the other hand, fluctuations in the global crude oil prices are fundamentally explained by global macroeconomic factors and in line with recent developments in the literature. Moreover, we show that the there exists a strong and significant relation between the returns to the futures commodity price index and all the commodites analyzed including crude oil. These results, support the view that a substantial source of the volatility in agricultural commodities, not captured by our model, might be due to the financialization of these commodities. In fact we show that there is strong and significant conditional correlation between the return on commodity index investment and the commodity markets here analyzed. However, as far as to claim that there exists a causal link is beyond the scope our methodology and ultimately an empirical question to address. Therefore, given the results we have presented, a natural extension of our work is to determine the extent to which the financialization of these agricultural commodities is responsible for the observed volatility in these markets.

Appendix A - Tables

Table 1: Data Definition and Source

Variable	Frequency	Range	Units	Source	Code
Maize (MZ_t)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IFS	PZPIMAIZ
Soybean $(SOYB_t)$	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IFS	PZPISOYB
Sugar (S_t)	Monthly	Jan 1982 Dec 2012	U.S. Dollars per Metric Ton	IFS	PZPISUG
Crude Oil (O_t)	Monthly	Jan 1982- Dec 2012	U.S. Dollars per Barrel	IFS	PZPIOIL
PPI (P_t)	Monthly	Jan 1982- Dec 2012	Index (1982=100)	FRED	PPIACO
Three-Month T-Bill (I_t)	Monthly	Jan 1982- Dec 2012	Percentage	FRED	TB3MS
Trade Weighted USD Index (XR_t)	Monthly	Jan 1982- Dec 2012	Real Index (1997=100)	FRED	TWEXBMTH
Indx. Global Econ. Activity (Y_t)	Monthly	Jan 1982- Dec 2012	Index	Lutz Kilian	-

Table 2: Pearson's Correlation Matrix of Monthly Returns (1982:01 - 2012:12)

	Maize	Sugar	Soybean	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Maize	1						
Sugar	0.027	1					
Soybean	0.594***	0.003	1				
Oil	-0.065	-0.022	0.021	1			
Exchg.Rate	-0.054	-0.104**	-0.178***	-0.155***	1		
Int.Rate	-0.158***	0.019	-0.172***	-0.356***	0.200***	1	
Glob.Econ.Actv.	0.015	-0.037	0.024***	0.201*	-0.102	-0.0421	1
No. Observ	370	370	370	370	370	370	

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 3: Summary Statistics and Unit Root Tests of Monthly Returns (1982:01 - 2012:12)

	Maize	Sugar	Soybean	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Mean	0.083	-0.240	0.037	0.139	-0.052	-0.002	-0.084
Median	0.007	0.266	-0.046	0.405	-0.011	-0.002	0.256
Maximum	28.005	37.569	24.593	43.936	5.535	5.748	36.476
Minimum	-25.098	-32.001	-25.341	-29.523	-3.795	-3.561	-41.063
Std. Dev.	0.057	0.100	0.056	0.079	0.013	0.011	0.067
Skewness	-0.049	0.101	0.130	0.037	0.202	1.143	-0.849
Kurtosis	6.579	3.958	6.019	6.769	4.069	9.402	12.185
Jarque-Bera	197.623***	14.774***	141.539***	219.106***	20.135***	712.411***	1345.078***
Sum Sq. Dev.	1.202	3.684	1.150	2.283	0.061	0.042	1.659
Observations	370	370	370	370	370	370	370

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 4: Unit Root Tests of Monthly Returns (1982:01 - 2012:12)

	Maize	Sugar	Soybean	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Test for Stationarity							
ADF (M1 - MAIC)	-14.611***	-14.196***	-14.506***	-14.316***	-13.460***	-28.549***	-13.744***
ADF (M2 - MAIC)	-14.520***	-14.170***	-14.750***	-14.300***	-13.460***	-28.510***	-13.720***
DF-GLS (ERS-MAIC)	-9.457***	-6.974***	-12.463***	-2.358**	-1.887*	-9.689***	-3.746***
KPSS (Bartlett Kernel)	0.126	0.078	0.072	0.215	0.125	0.016	0.131

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 5: Univariate Estimation Results for Maize of the MGARCH - Model 1

	AR(1)	AR(2)	AR(3)	MA(1)	MA(2)	ω	α	β	γ	δ
Glob.Econ.Actv.[1]										
Coeff.	1.278***	-0.451***	0.115**	-0.958***		1.243	0.010	0.859***	0.189*	
S.E.	0.057	0.090	0.055	0.023		0.983	0.016	0.082	0.105	
Int. Rate[1]										
Coeff.	0.388***	-0.043	0.054	-0.969***		0.012**	0.033	0.836***	0.243***	
S.E.	0.056	0.057	0.049	0.013		0.006	0.033	0.048	0.062	
Exchg. Rate[2]										
Coeff.	-0.392***	0.094	-0.021	0.735***		0.006	0.007	0.988***		
S.E.	0.118	0.074	0.069	0.108		0.016	0.012	0.019		
Oil[3]										
Coeff.	-0.39**			0.512***	-0.050	0.004	0.183***	0.750***	0.264*	1.188***
S.E.	0.201			0.194	0.060	0.004	0.050	0.060	0.151	0.310
Maize[2]										
Coeff.	-0.64***	0.177***		0.889***		1.503	0.007	0.937***		
S.E.	0.081	0.050		0.082		1.075	0.013	0.038		

No. Observations : 370
Log Likelihood : 4189.299

Notes: Significance at the the 1%, 5% and 10% level are denoted by $(***)$, $(**)$ and $(*)$ respectively.

[1] GJR-GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \gamma\epsilon_{t-1}^2 I_{\{\epsilon_{t-1}\geq 0\}}$;

[2] GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$;

[3] APARCH(1,1): $h_t^\delta = \omega + \alpha\left[|\epsilon_{t-1}| - \gamma_1\epsilon_{t-1}\right]^\delta + \beta h_{t-1}^\delta + \gamma\epsilon_{t-1}^2$

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Table 6: Univariate Estimation Results for Soybean of the MGARCH - Model 2

	AR(1)	AR(2)	AR(3)	MA(1)	MA(2)	ω	α	β	γ	δ
Glob.Econ.Actv.[1]										
Coeff.	1.255***	-0.42***	0.108*	-0.95***		1.263	0.009	0.857***	0.200*	
S.E.	0.061	0.096	0.058	0.028		1.006	0.016	0.082	0.112	
Int. Rate[1]										
Coeff.	0.386***	-0.040	0.062	-0.97***		0.011**	0.033	0.838***	0.231***	
S.E.	0.056	0.058	0.050	0.013		0.006	0.035	0.048	0.059	
Exchg. Rate[2]										
Coeff.	-0.38***	0.088	-0.020	0.723***		0.005	0.009	0.986***		
S.E.	0.114	0.071	0.066	0.104		0.013	0.009	0.013		
Oil[3]										
Coeff.	-0.380			0.508**	-0.040	0.004	0.188***	0.739***	0.245*	1.188***
S.E.	0.253			0.241	0.066	0.004	0.052	0.063	0.149	0.305
Soybeans[1]										
Coeff.	0.590**	-0.150		-0.300		2.390**	0.145**	0.843***	-0.159***	
S.E.	0.241	0.095		0.237		0.987	0.067	0.049	0.078	
No. Observations :	370									
Log Likelihood :	4189.299									

Notes: Significance at the the 1%, 5% and 10% level are denoted by $(***)$, $(**)$ and $(*)$ respectively.

[1] GJR-GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \gamma\epsilon_{t-1}^2 I_{\{\epsilon_{t-1}\geq 0\}}$;

[2] GARCH(1,1): $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$;

[3] APARCH(1,1): $h_t^\delta = \omega + \alpha\left[|\epsilon_{t-1}| - \gamma_1\epsilon_{t-1}\right]^\delta + \beta h_{t-1}^\delta + \gamma\epsilon_{t-1}^2$

Table 7: Univariate Estimation Results for Sugar of the MGARCH - Model 3

	AR(1)	AR(2)	AR(3)	MA(1)	MA(2)	ω	α	β	γ	δ
Glob.Econ.Actv.[1]										
Coeff.	1.268***	-0.43***	0.108*	-0.96***		1.526	0.008	0.834***	0.218	
S.E.	0.058	0.093	0.058	0.024		1.299	0.017	0.105	0.136	
Int. Rate[1]										
Coeff.	0.375***	-0.030	0.054	-0.96***		0.011**	0.042	0.834***	0.222***	
S.E.	0.059	0.059	0.050	0.015		0.006	0.037	0.048	0.059	
Exchg. Rate[2]										
Coeff.	-0.41**	0.103	-0.030	0.746***		0.008	0.005	0.987***		
S.E.	0.159	0.084	0.074	0.147		0.019	0.014	0.025		
Oil[3]										
Coeff.	-0.37*			0.498**	-0.040	0.006	0.202***	0.730***	0.212	1.053***
S.E.	0.222			0.213	0.060	0.006	0.051	0.062	0.144	0.285
Sugar[2]										
Coeff.	0.822**	-0.600		-0.23*		0.000***	0.074**	0.910***		
S.E.	0.349	0.385		0.136		0.000	0.033	0.026		

No. Observations : 370
Log Likelihood : 3992.379

Notes: Significance at the the 1%, 5% and 10% level are denoted by $(***)$, $(**)$ and $(*)$ respectively.

[1] GJR-GARCH$(1,1)$: $h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1} + \gamma \epsilon_{t-1}^2 I_{\{\epsilon_{t-1} \geq 0\}}$;

[2] GARCH$(1,1)$: $h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1}$;

[3] APARCH$(1,1)$: $h_t^\delta = \omega + \alpha \left[|\epsilon_{t-1}| - \gamma_1 \epsilon_{t-1}\right]^\delta + \beta h_{t-1}^\delta + \gamma \epsilon_{t-1}^2$

Table 8: Dynamic Correlation cDCC (1,1) for Maize

	Maize	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Maize	**1**				
Oil	-0.070	**1**			
Exchg.Rate	0.000	-0.120*	**1**		
Int.Rate	-0.050	-0.490***	0.151**	**1**	
Glob.Econ.Actv.	-0.060	0.097	-0.030	-0.080	**1**
α	0.013*				
β	0.937***				
Hosking's	Hosking (5)	101.967			
	Hosking (10)	220.702			
Li and McLeod's	Li-McLeod (5)	102.262			
	Li-McLeod (10)	221.176			

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 9: Dynamic Correlation cDCC (1,1) for Soybeans

	Soybeans	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Soybean	**1**				
Oil	-0.030	**1**			
Exchg.Rate	0.130**	-0.120*	**1**		
Int.Rate	-0.080	-0.480***	0.158**	**1**	
Glob.Econ.Actv.	-0.020	0.096	-0.040	-0.080	**1**
α	0.012*				
β	0.940***				
Hosking's	Hosking (5)	99.189			
	Hosking (10)	233.881			
Li and McLeod's	Li-McLeod (5)	99.507			
	Li-McLeod (10)	233.975			

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 10: Dynamic Correlation cDCC (1,1) for Sugar

	Sugar	Oil	Exchg.Rate	Int.Rate	Glob.Econ.Actv.
Sugar	**1**				
Oil	-0.020	**1**			
Exchg.Rate	-0.080	-0.120**	**1**		
Int.Rate	0.034	-0.490***	0.166**	**1**	
Glob.Econ.Actv.	-0.100*	0.110*	-0.050	-0.090	**1**
α	0.013*				
β	0.899***				
Hosking's	Hosking (5)	115.518			
	Hosking (10)	223.876			
Li and McLeod's	Li-McLeod (5)	115.653			
	Li-McLeod (10)	224.385			

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 11: Dynamic Correlation cDCC (1,1) for all variables

	GSCI	Glob.Econ.Actv	Int.Rate	Exchg.Rate	Oil	Maize	Soybean	Sugar
GSCI	1							
Glob.Econ.Actv	0.109	1						
Int.Rate	-0.377	-0.053	1					
Exchg.Rate	-0.262***	-0.006	0.203***	1				
Oil	0.535***	0.141$^{(**)}$	-0.575***	-0.180**	1			
Maize	0.227***	-0.119	-0.080	-0.080	-0.074	1		
Soybean	0.289***	-0.075	-0.103	-0.191**	-0.026	0.576***	1	
Sugar	0.095***	-0.100	0.043	-0.068	-0.058	0.123*	0.145**	1
α	0.008							
β	0.910***							
Hosking's	Hosking (5)	311.364						
	Hosking (10)	622.187						
Li and McLeod's	Li-McLeod (5)	311.953						
	Li-McLeod (10)	623.120						

Notes: Significance at the the 1%, 5% and 10% level are denoted by $^{(***)}$, $^{(**)}$ and $^{(*)}$ respectively.

Table 12: Univariate ARMA (p,q) Selection

		ARMA(1,0)	ARMA(2,0)	ARMA(3,0)	ARMA(0,1)	ARMA(0,2)	ARMA(0,3)	ARMA(1,1)	ARMA(1,2)	ARMA(1,3)	ARMA(2,1)	ARMA(3,1)	ARMA(2,2)	Min. Inf.Crit.
Maize (2,1)	Akaike info Criterion	-2.954	-2.947	-2.939	-2.954	-2.951	-2.948	-2.949	-2.944	-2.940	**-2.966**	-2.960	-2.962	-2.966
	Schwarz Criterion	**-2.933**	-2.915	-2.896	-2.933	-2.919	-2.906	-2.917	-2.901	-2.887	-2.923	-2.907	-2.909	-2.933
	Hannan-Quinn Criterion	-2.946	-2.934	-2.922	-2.946	-2.938	-2.931	-2.936	-2.927	-2.919	**-2.949**	-2.939	-2.941	-2.949
Soyb (2,1)	Akaike info Criterion	-3.015	-3.013	-3.011	-3.019	-3.018	-3.019	-3.014	-3.016	-3.013	**-3.024**	-3.007	-3.012	-3.024
	Schwarz Criterion	-2.994	-2.981	-2.969	**-2.998**	-2.986	-2.977	-2.982	-2.974	-2.960	-2.981	-2.954	-2.959	-2.998
	Hannan-Quinn Criterion	-3.007	-3.000	-2.994	**-3.010**	-3.005	-3.002	-3.001	-2.999	-2.992	-3.007	-2.986	-2.991	-3.010
Sug (1,2)	Akaike info Criterion	-1.837	-1.849	-1.846	-1.845	-1.840	-1.835	-1.840	**-1.857**	-1.852	-1.846	-1.855	-1.854	-1.857
	Schwarz Criterion	-1.816	-1.818	-1.804	**-1.824**	-1.808	-1.793	-1.808	-1.815	-1.800	-1.804	-1.802	-1.801	-1.824
	Hannan-Quinn Criterion	-1.829	-1.837	-1.829	-1.837	-1.827	-1.818	-1.827	**-1.840**	-1.831	-1.829	-1.834	-1.833	-1.840
Oil (1,2)	Akaike info Criterion	-2.327	-2.323	-2.318	-2.329	-2.323	-2.322	-2.325	**-2.321**	-2.319	-2.323	-2.318	-2.241	-2.329
	Schwarz Criterion	-2.306	-2.291	-2.276	**-2.307**	-2.291	-2.279	-2.293	-2.278	-2.266	-2.281	-2.265	-2.209	-2.307
	Hannan-Quinn Criterion	-2.318	-2.310	-2.301	**-2.320**	-2.311	-2.305	-2.313	-2.304	-2.298	-2.306	-2.297	-2.228	-2.320
MTB3 (3,1)	Akaike info Criterion	-6.397	-6.441	-6.470	-6.500	-6.599	-6.618	-6.629	-6.625	-6.611	-6.627	**-6.653**	-6.620	-6.653
	Schwarz Criterion	-6.375	-6.410	-6.427	-6.479	-6.567	-6.576	-6.597	-6.583	-6.558	-6.585	**-6.599**	-6.567	-6.599
	Hannan-Quinn Criterion	-6.388	-6.429	-6.453	-6.491	-6.586	-6.601	-6.616	-6.608	-6.590	-6.610	**-6.632**	-6.599	-6.632
LXR (3,1)	Akaike info Criterion	-5.998	-6.002	-6.000	-6.004	-5.999	-5.997	-6.004	-6.011	-6.006	-6.014	**-6.019**	-6.016	-6.019
	Schwarz Criterion	-5.977	-5.971	-5.957	**-5.983**	-5.967	-5.954	-5.973	-5.969	-5.953	-5.971	-5.966	-5.963	-5.983
	Hannan-Quinn Criterion	-5.990	-5.990	-5.983	-5.996	-5.986	-5.980	-5.992	-5.994	-5.985	-5.997	**-5.998**	-5.995	-5.998
Y (3,1)	Akaike info Criterion	-2.666	-2.734	-2.727	-2.721	-2.720	-2.729	-2.719	-2.733	-2.738	-2.730	**-2.739**	-2.593	-2.739
	Schwarz Criterion	-2.644	**-2.702**	-2.684	-2.700	-2.688	-2.686	-2.687	-2.680	-2.696	-2.687	-2.686	-2.562	-2.702
	Hannan-Quinn Criterion	-2.657	**-2.722**	-2.710	-2.713	-2.707	-2.712	-2.706	-2.712	-2.721	-2.713	-2.718	-2.581	-2.722

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Appendix B - Figures

Figure 1: Logarithm of Prices and Macroeconomic Factors Adjusted for PPI (1982-84=100)
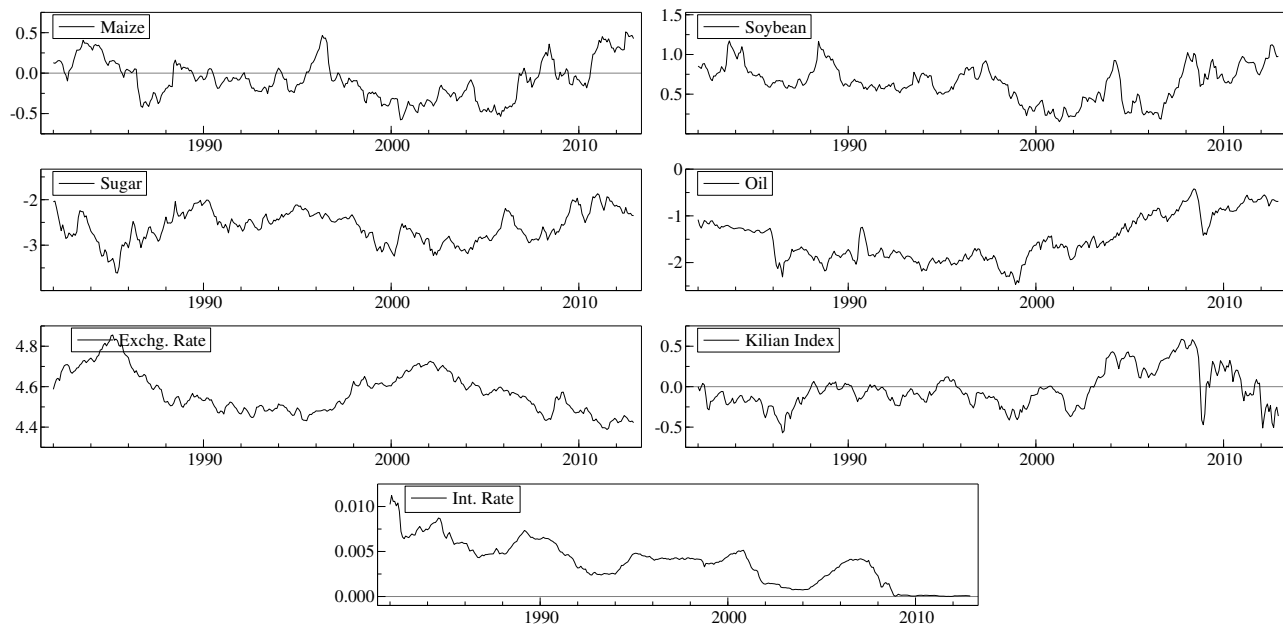

Figure 2: Logarithm of Prices and Macroeconomic Factors Returns (1982-2012)
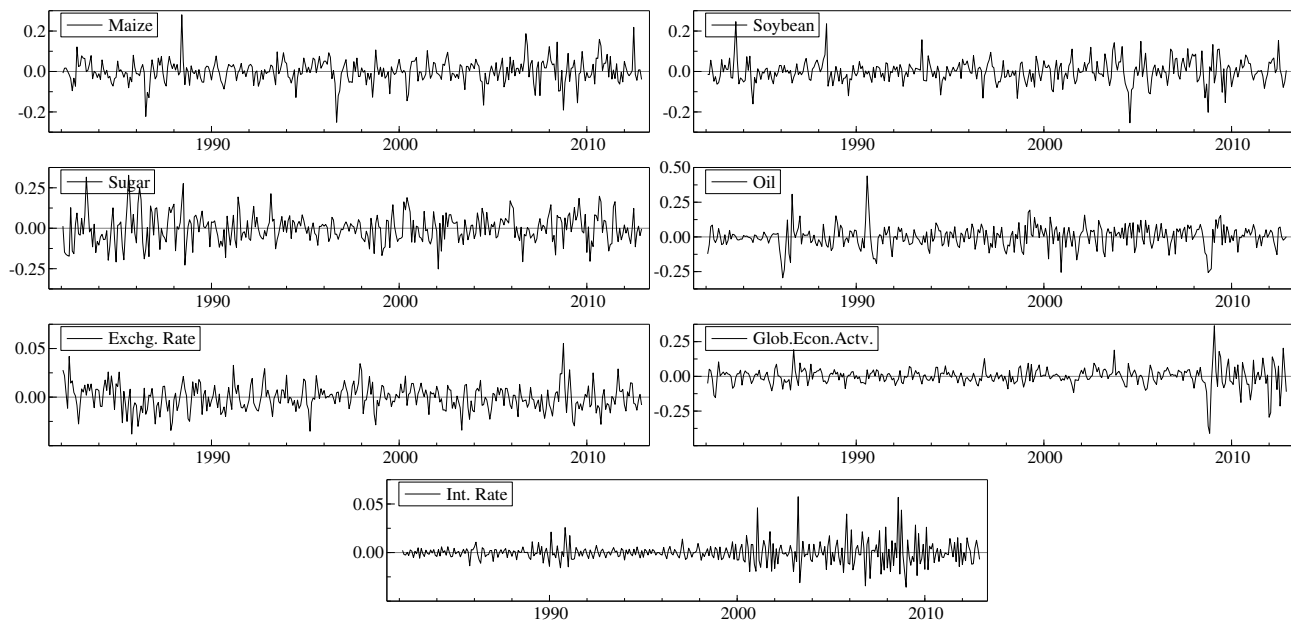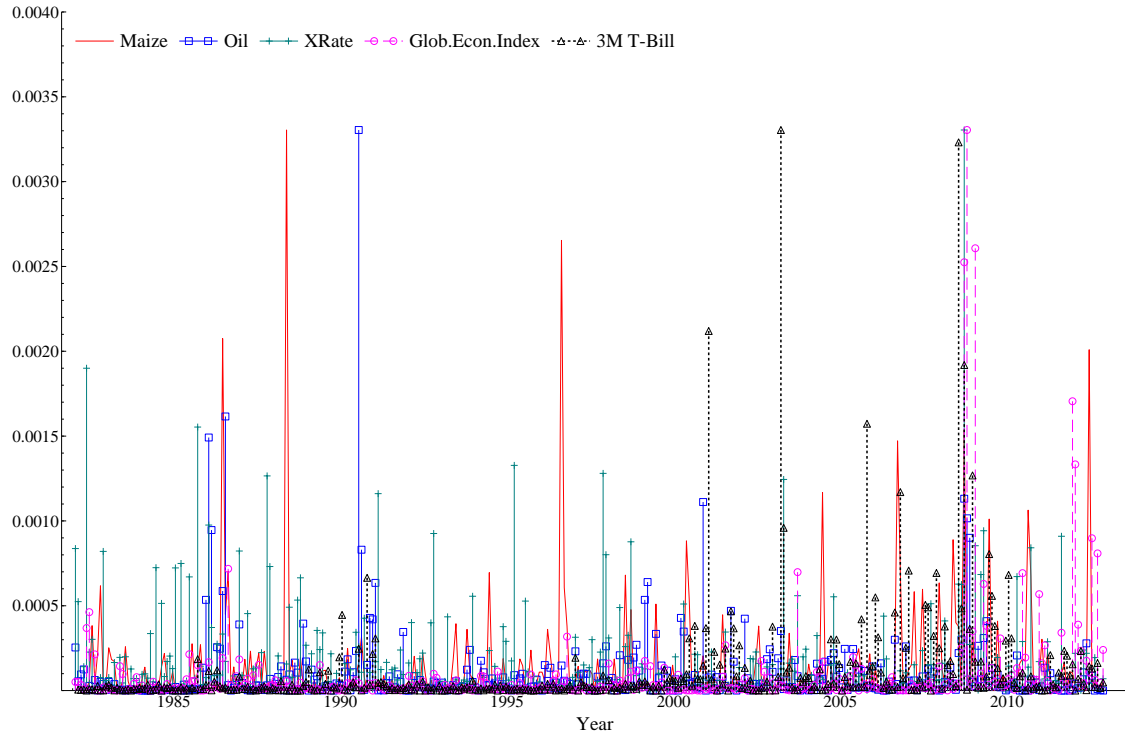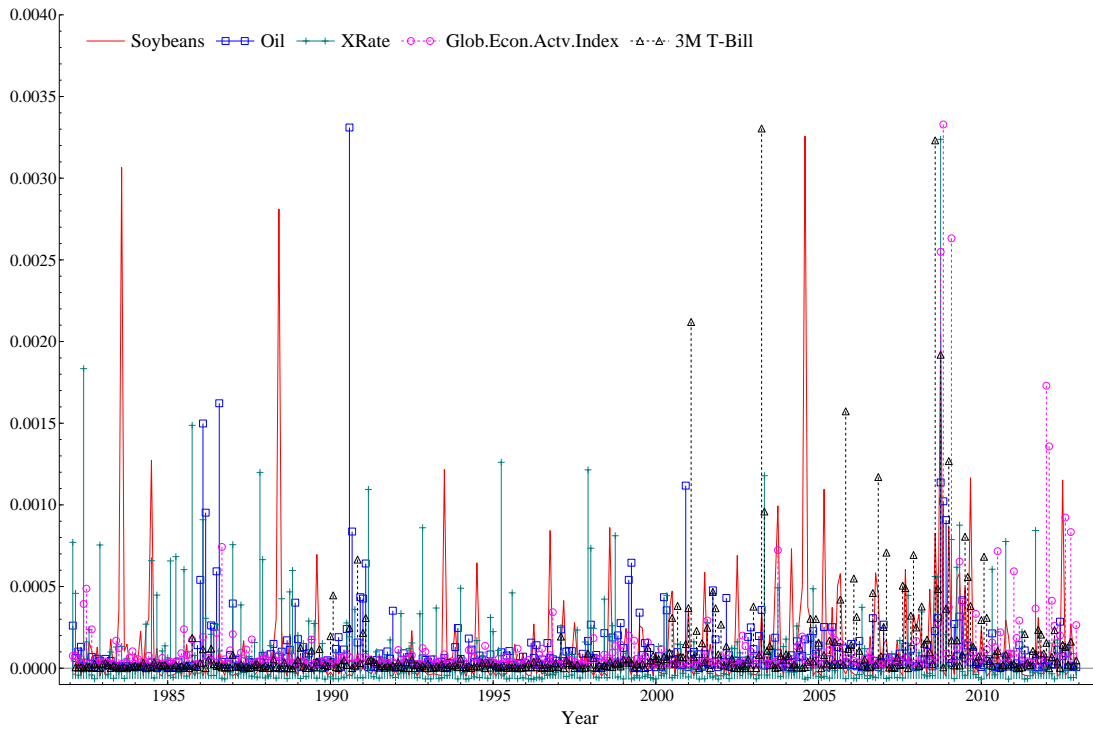
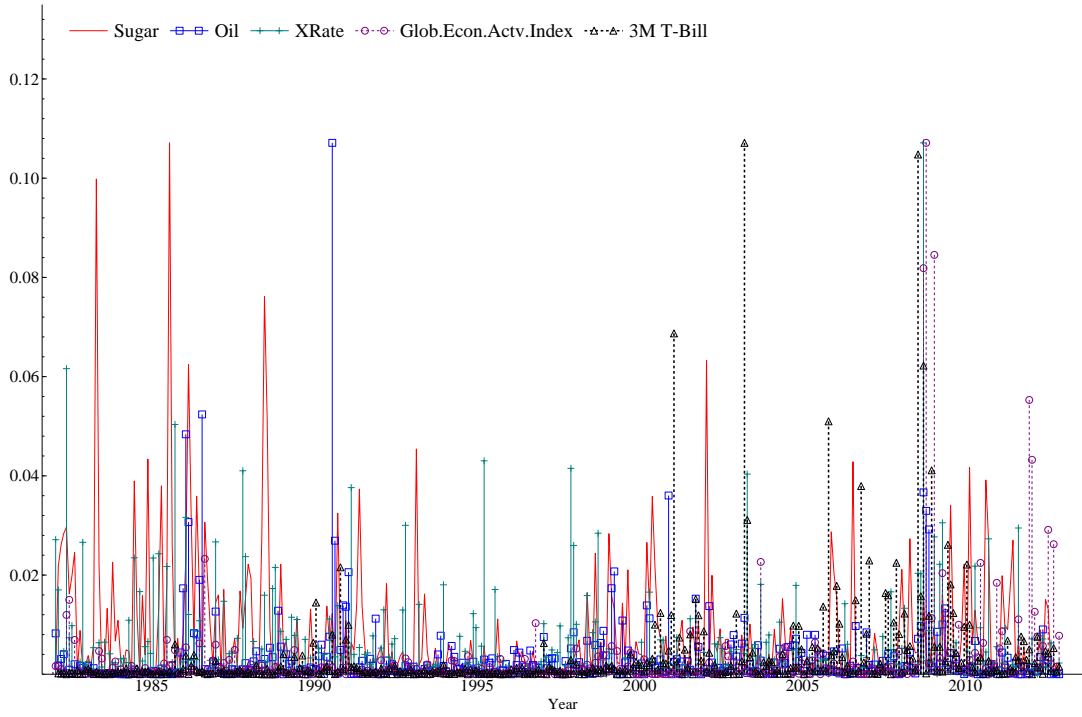Figure 3: Monthly Price Returns and Macroeconomic Factors (1982:01-2012:12)
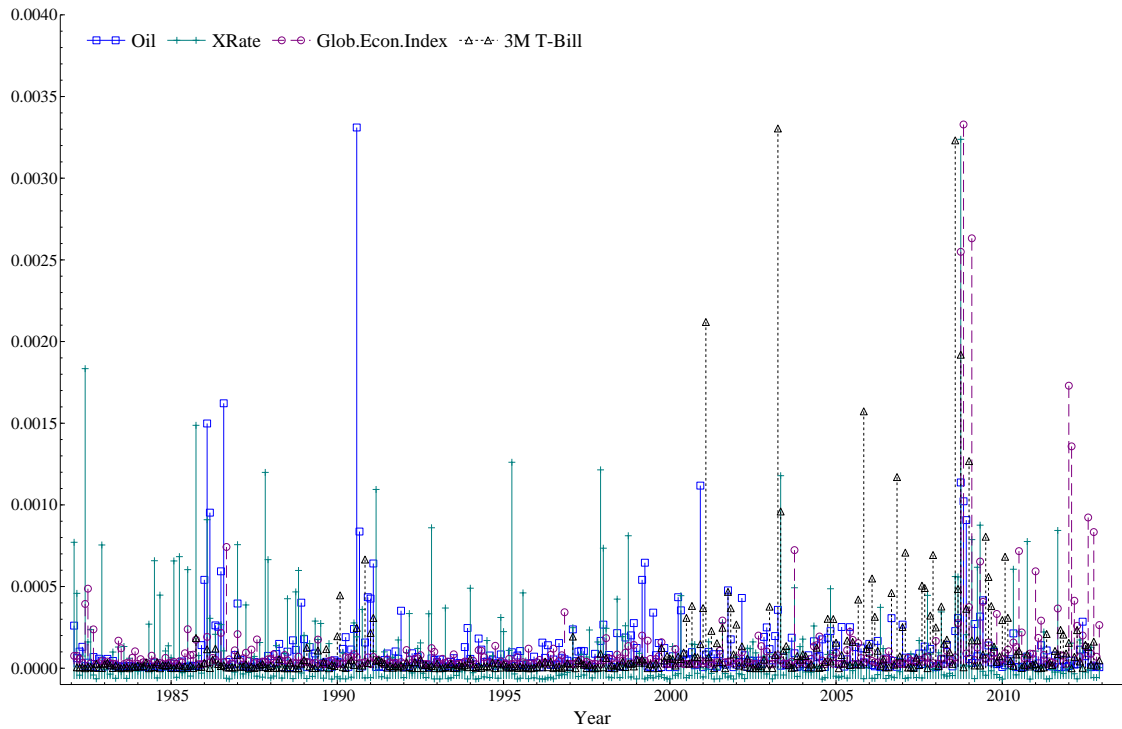

(a) Maize with Macroeconomic Factors

(b) Soybeans with Macroeconomic Factors

Figure 4: Monthly Price Returns and Macroeconomic Factors (1982:01-2012:12)

(a) Sugar with Macroeconomic Factors

(b) Oil with Macroeconomic Factors

Figure 5: Conditional variance of Maize and Soybeans price returns (1982:01-2012:012). The figure on the bottom side presents the same series duing the peak of the 2007/08 commodity price boom. All figures have been scaled using Oxmetrics**tm**.
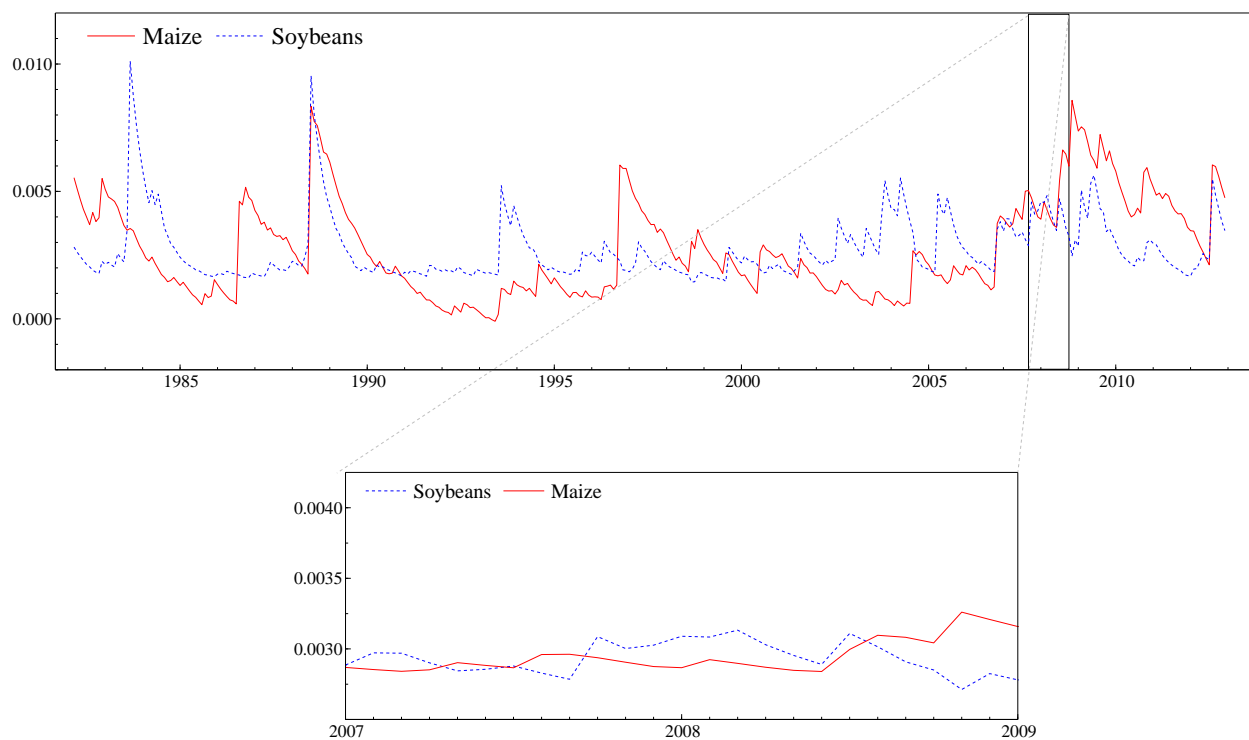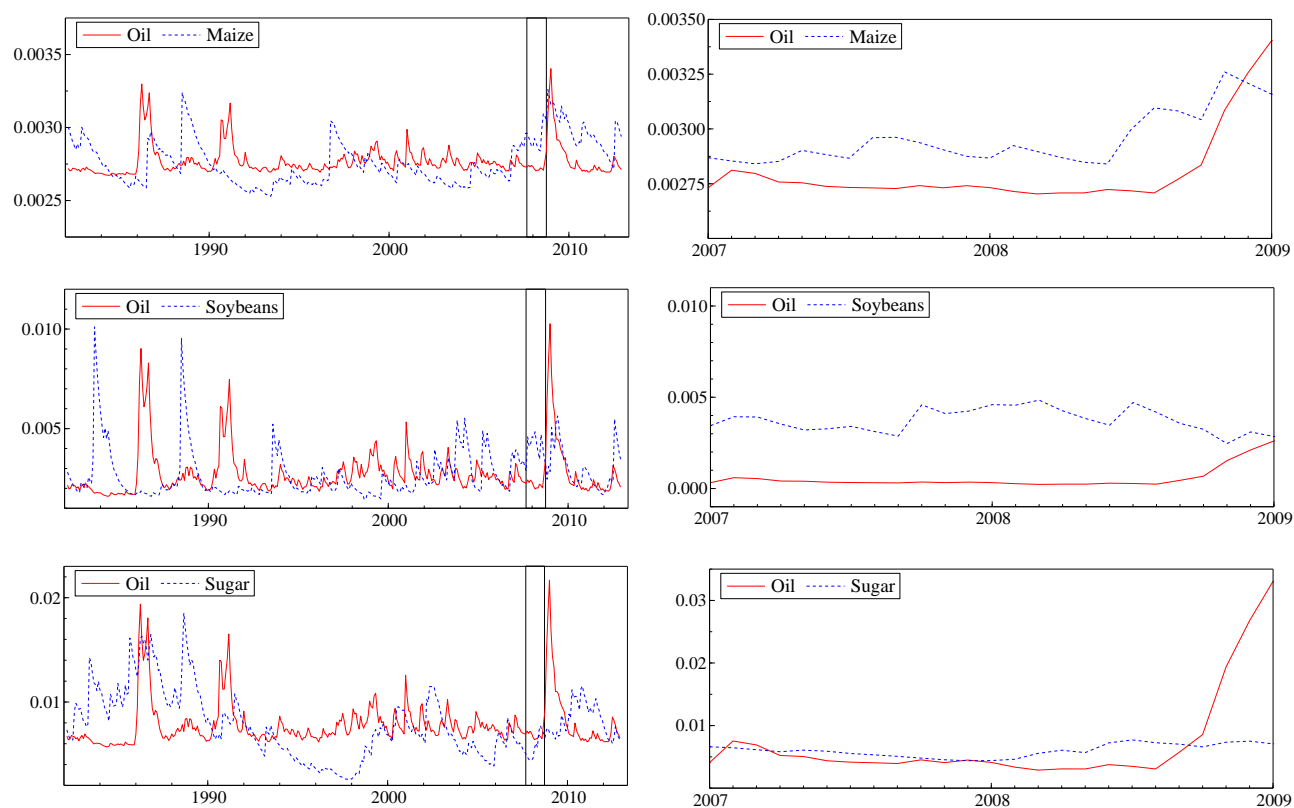
Figure 6: Conditional variance of Maize and Sugar price returns (1982:01-2012:012). The figure on the bottom presents the same series duing the peak of the 2007/08 commodity price boom. All figures have been scaled using Oxmetrics**tm**.
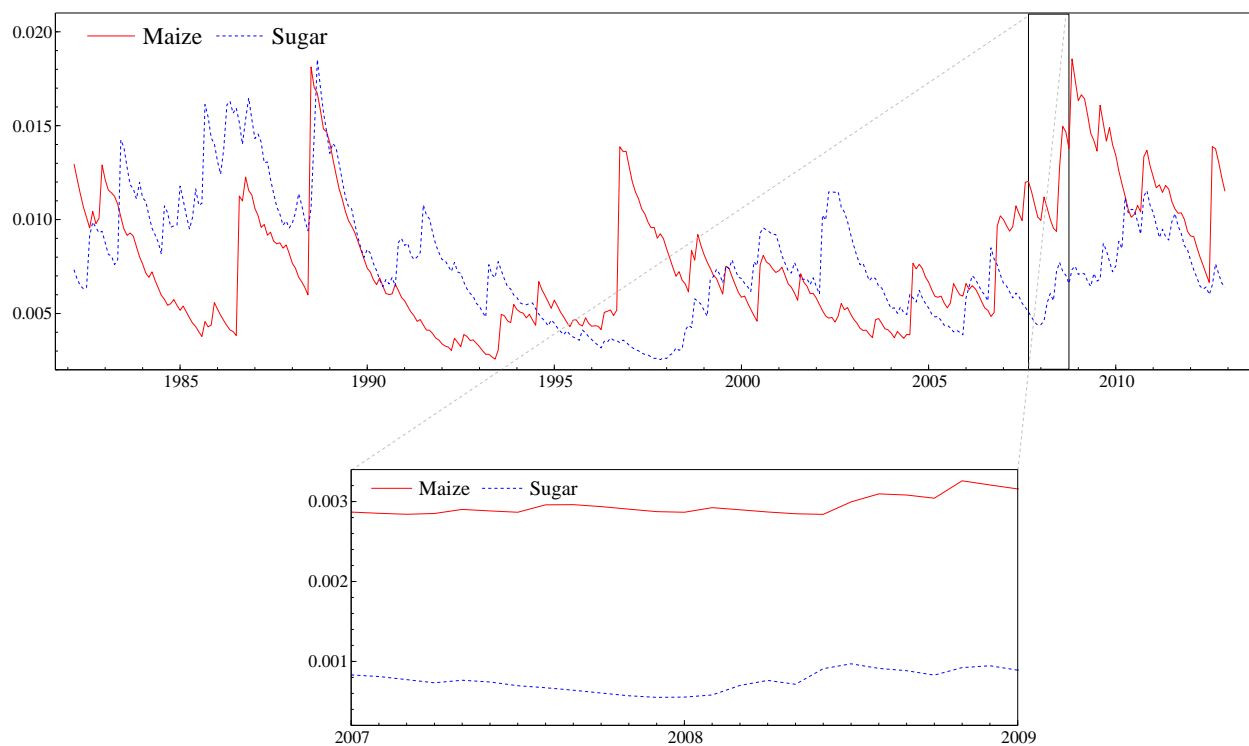
Figure 7: Conditional variance of Soybeans and Sugar price returns (1982:01-2012:012). The figure on the bottom presents the same series duing the peak of the 2007/08 commodity price boom. All figures have been scaled using Oxmetrics**tm**.
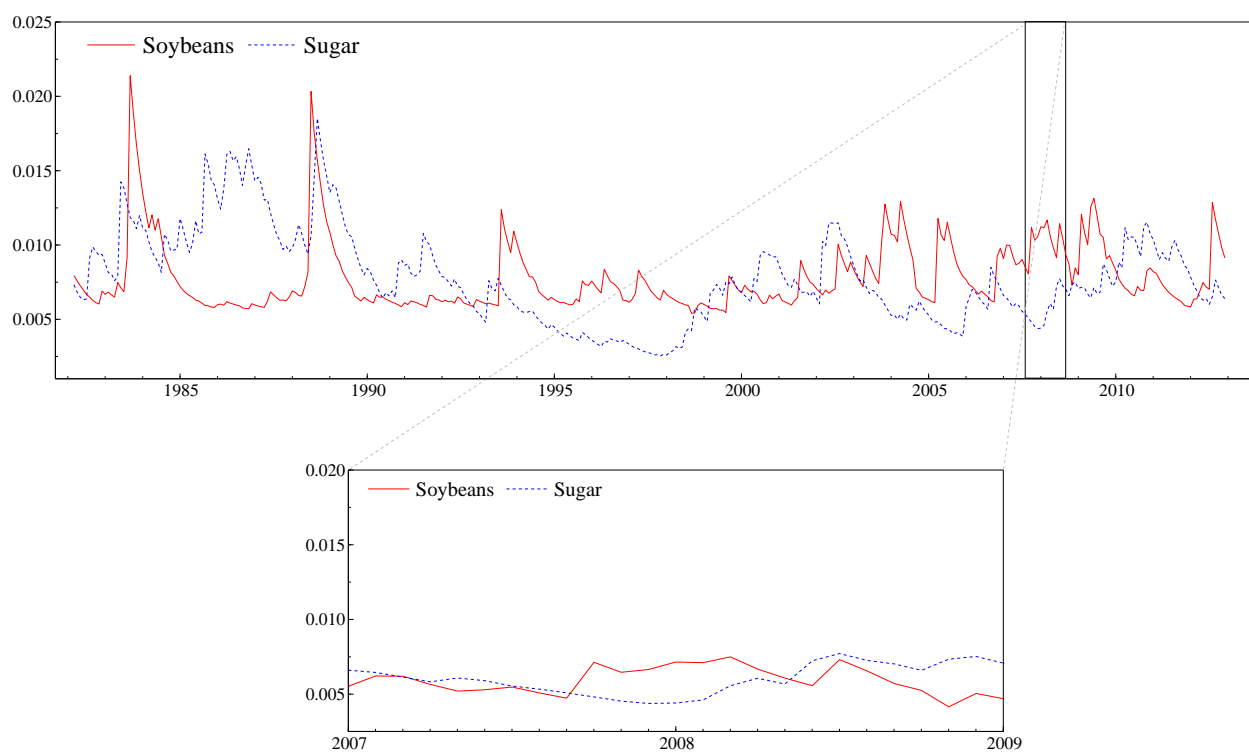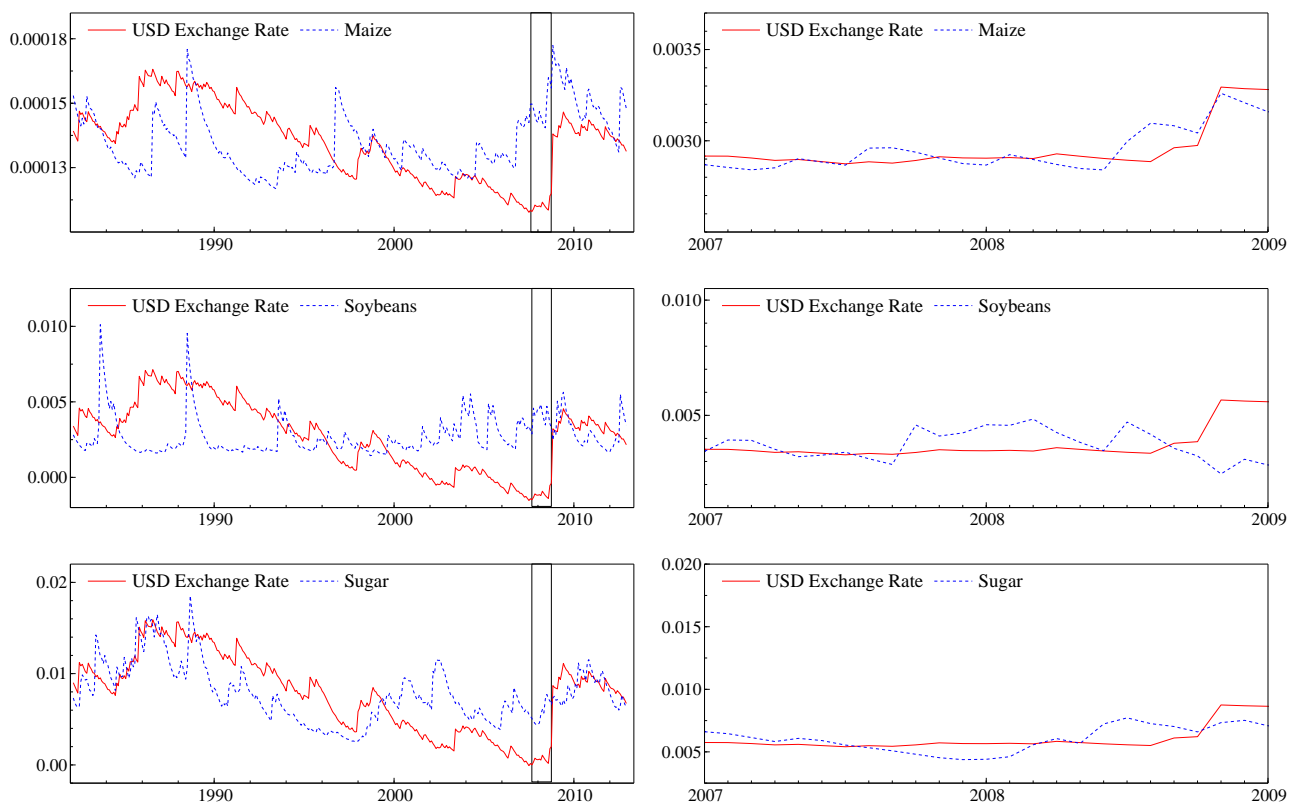
Figure 8: Conditional variance of Crude Oil with the commodity price returns (1982:01-2012:012). The figures on the right-hand side present the same series duing the peak of the 2007/08 commodity price boom. All figures have been scaled using Oxmetrics$^{\mathbf{tm}}$.
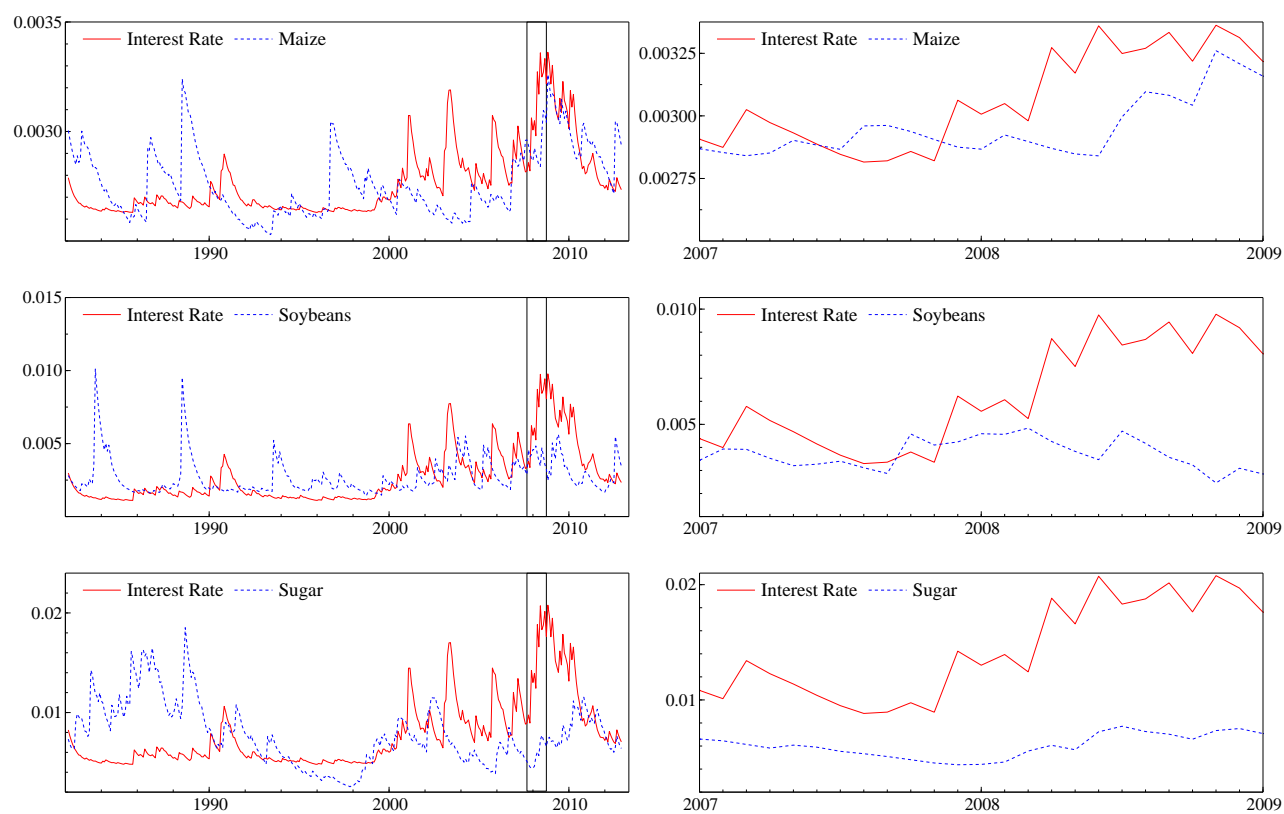
Figure 9: Conditional variance of USD exchange rate with the commodity price returns (1982:01-2012:012). The figures on the right-hand side present the same series duing the peak of the 2007/08 commodity price boom. All figures have been scaled using Oxmetrics$^{\mathbf{tm}}$.

Figure 10: Conditional variance of Interest Rate with the commodity price returns (1982:01-2012:012). The figures on the right-hand side present the same series duing the peak of the 2007/08 commodity price boom. All figures have been scaled using Oxmetrics$^{\mathbf{tm}}$.

Figure 11: Conditional variance of Crude Oil price returns with Macroeconomic variables (1982:01-2012:012). All figures have been scaled using Oxmetrics$^{\mathbf{tm}}$.
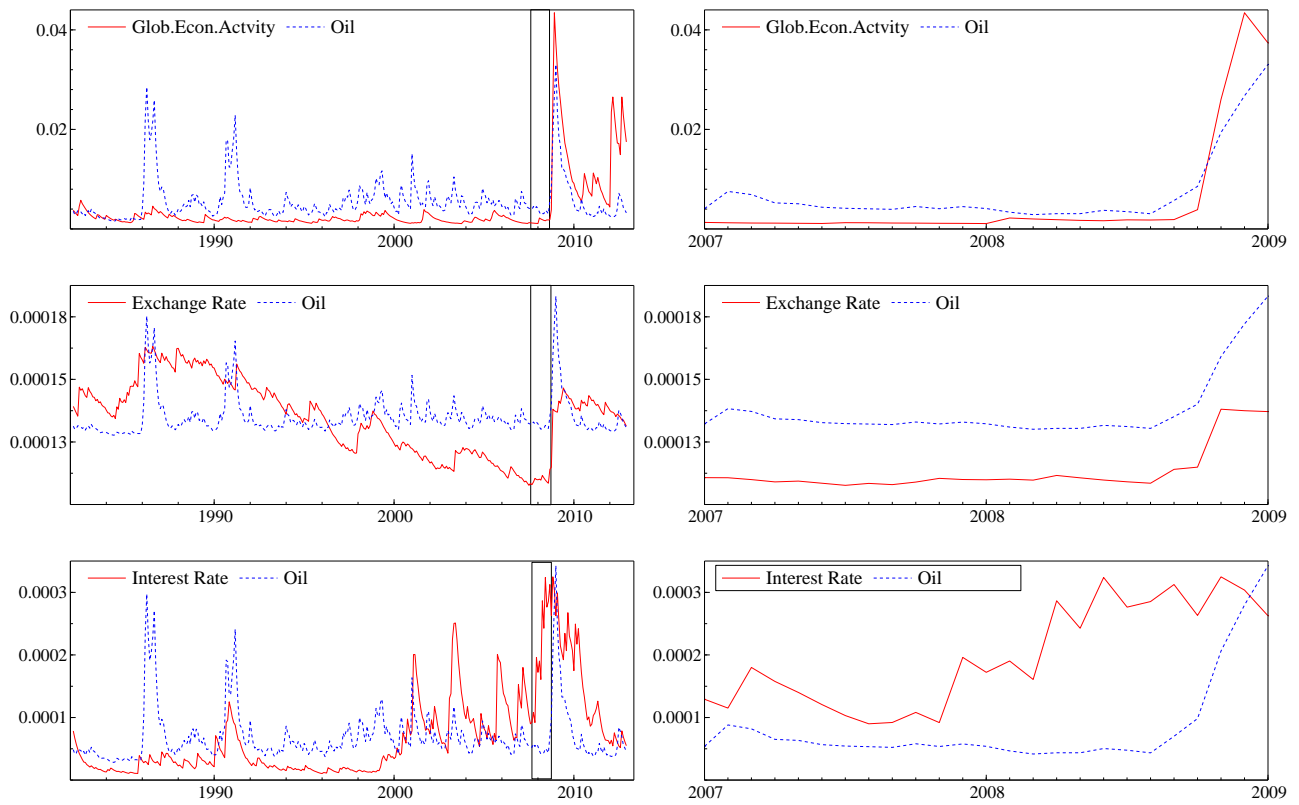
Figure 12: Structural Changes of cDCC for Soybean and Sugar (1982:01-2012:012).
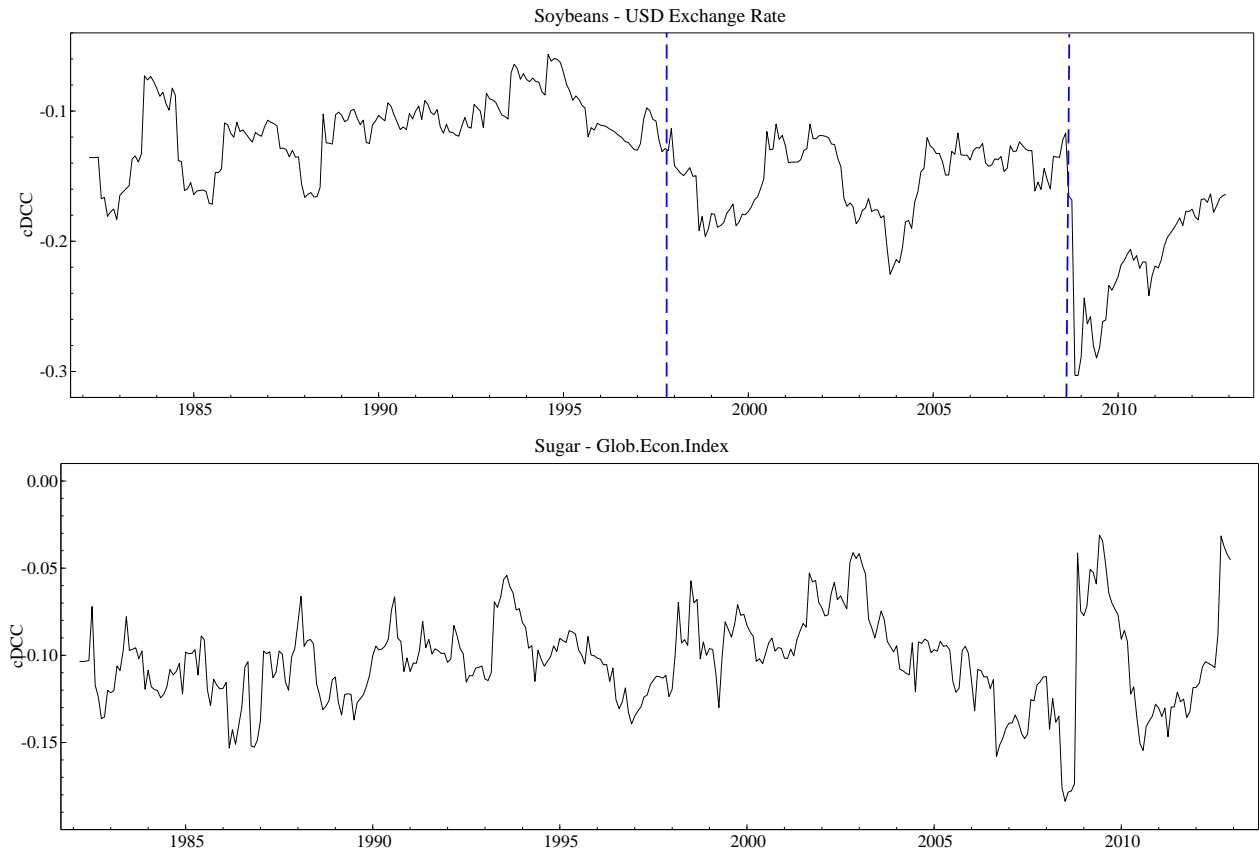

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Figure 13: Structural Changes of cDCC for Crude Oil with Macroeconomic variables (1982:01-2012:012).
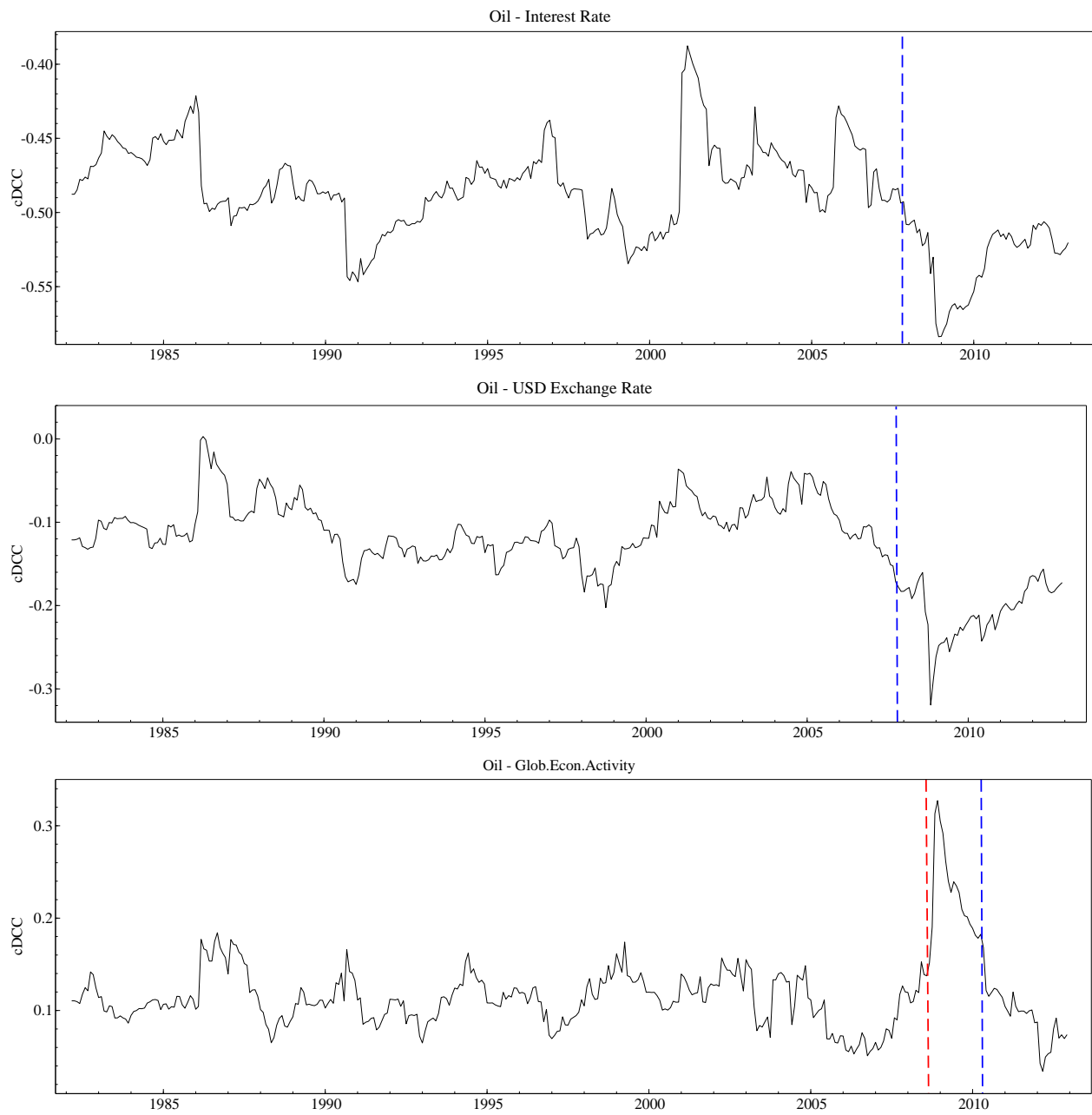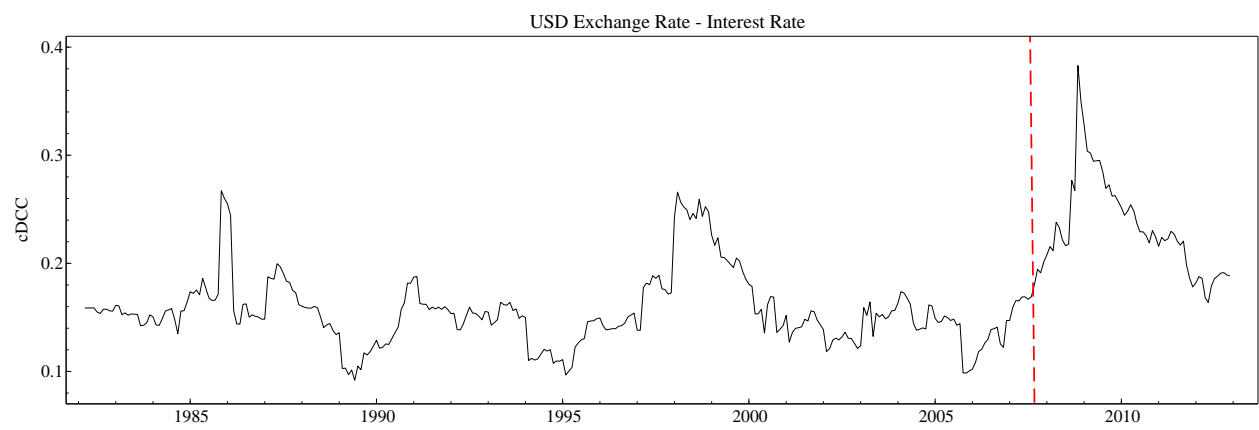
Figure 14: Structural Changes of cDCC for USD Exchange Rate and Interest Rate (1982:01-2012:012).

USD Exchange Rate - Interest Rate

References

AI, C., A. CHATRATH AND F. SONG, "On the Comovement of Commodity Prices," *American Journal of Agricultural Economics* 88 (2006), 574–588.

AIELLI, G. P., "Dynamic Conditional Correlation: On Properties and Estimation," *Journal of Business & Economic Statistics* 31 (2013), 282–299.

BAUWENS, L., C. HAFNER AND S. LAURENT, eds., *Volatility Models, in Handbook of Volatility Models and Their Applications* (Hoboken, NJ, USA: John Wiley & Sons, Inc., 2012).

BYRNE, J. P., G. FAZIO AND N. FIESS, "Primary commodity prices: Co-movements, common factors and fundamentals," *Journal of Development Economics* 101 (2013), 16 – 26.

CRETI, A., M. JOETS AND V. MIGNON, "On the links between stock and commodity markets' volatility," *Energy Economics* 37 (May 2013), 16–28.

DEATON, A., "Commodity Prices and Growth in Africa," *Journal of Economic Perspectives* 13 (Summer 1999), 23–40.

DEB, P., P. K. TRIVEDI AND P. VARANGIS, "The Excess Co-movement of Commodity Prices Reconsidered," *Journal of Applied Econometrics* 11 (May-June 1996), 275–91.

ENGLE, R., "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models," *Journal of Business & Economic Statistics* 20 (July 2002), 339–50.

FERNÁNDEZ, J. M., "Long Run Dynamics of World Food, Crude Oil Prices and Macroeconomic Variables: A Cointegration VAR Analysis," Bristol Economics Discussion Papers 14/646, Department of Economics, University of Bristol, UK, Nov 2014.

FOC, "Federal Open Market Committee," Online (August 17 2007).

FRANKEL, J. A., "Expectations and Commodity Price Dynamics: The Overshooting Model," *American Journal of Agricultural Economics* 68 (1986), pp. 344–348.

———, "The Effect of Monetary Policy on Real Commodity Prices," in *Asset Prices and Monetary Policy*NBER Chapters (National Bureau of Economic Research, Inc, 2008), 291–333.

GARDEBROEK, C. AND M. A. HERNANDEZ, "Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets," *Energy Economics* 40 (2013), 119–129.

GILBERT, C. L., "How to Understand High Food Prices," *Journal of Agricultural Economics* 61 (2010), 398–425.

———, "Food price, food price volatility and the financialization of agricultural futures markets," Technical Report, SAIS Bologna Center, Johns Hopkins University, 2015.

KILIAN, L., "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review* 99 (June 2009), 1053–69.

LAURENT, S., L. BAUWENS AND J. V. K. ROMBOUTS, "Multivariate GARCH models: a survey," *Journal of Applied Econometrics* 21 (2006), 79–109.

LAVIELLE, M., "Using penalized contrasts for the change-point problem," *Signal Processing* 85 (2005), 1501–1510.

LEYBOURNE, S. Y., T. A. LLOYD AND G. V. REED, "The excess comovement of commodity prices revisited," *World Development* 22 (November 1994), 1747–1758.

MANERA, M., M. NICOLINI AND I. VIGNATI, "Financial Speculation in Energy and Agriculture Futures Markets: A Multivariate GARCH Approach," *The Energy Journal* 34 (2013), –.

MENSI, W., S. HAMMOUDEH AND S.-M. YOON, "Structural breaks, dynamic correlations, asymmetric volatility transmission, and hedging strategies for petroleum prices and USD exchange rate," *Energy Economics* 48 (2015), 46–60.

MIKOSCH, T., J.-P. KREIB, R. A. DAVIS AND T. G. ANDERSEN, eds., *Handbook of Financial Time Series* (Springer Berlin Heidelberg, 2009).

PEN, Y. L. AND B. SEVI, "Futures Trading and the Excess Comovement of Commodity Prices," Working Paper 1301, Aix-Marseille School of Economics, Marseille, France, Jan 2013.

PINDYCK, R. S. AND J. J. ROTEMBERG, "The Excess Co-movement of Commodity Prices," *Economic Journal* 100 (December 1990), 1173–89.

PRAKASH, A. AND C. L. GILBERT, *Rising vulnerability in the global food system: Beyond market fundamentals*, chapter Safeguarding food security in volatile global markets (Rome: FAO, 2011), 45–66.

SCHRYDER, S. D. AND G. PEERSMAN, "The U.S. Dollar Exchange Rate and the Demand for Oil," CESifo Working Paper Series 4126, CESifo Group Munich, 2013.

SERRA, T., "Volatility spillovers between food and energy markets: A semiparametric approach," *Energy Economics* 33 (2011), 1155–1164.

SERRA, T. AND D. ZILBERMAN, "Biofuel-related price transmission literature: A review," *Energy Economics* 37 (2013), 141–151.

STIGLER, M., *Rising vulnerability in the global food system: Beyond market fundamentals*, chapter Commodity prices: theoretical and empirical properties (Rome: FAO, 2011), 27–43.

SUMNER, D. A., "Recent Commodity Price Movements in Historical Perspective," *American Journal of Agricultural Economics* 91 (2009), 1250–1256.

TRUJILLO-BARRERA, A., M. L. MALLORY AND P. GARCIA, "Volatility Spillovers in U.S. Crude Oil, Ethanol, and Corn Futures Markets," *Journal of Agricultural and Resource Economics* 37 (August 2012), 247–262.

TURHAN, M. I., A. SENSOY AND E. HACIHASANOGLU, "A comparative analysis of the dynamic relationship between oil prices and exchange rates," *Journal of International Financial Markets, Institutions and Money* 32 (2014), 397–414.

WU, F., Z. GUAN AND R. J. MYERS, "Volatility spillover effects and cross hedging in corn and crude oil futures," *Journal of Futures Markets* 31 (2011), 1052–1075.

ZILBERMAN, D., G. HOCHMAN, D. RAJAGOPAL, S. SEXTON AND G. TIMILSINA, "The Impact of Biofuels on Commodity Food Prices: Assessment of Findings," *American Journal of Agricultural Economics* 95 (2013), 275–281.