# Financialization of food - The determinants of the time-varying relation between agricultural prices and stock market dynamics

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## The determinants of the time-varying relation between agricultural prices and stock market dynamics

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**Abstract** This paper studies the correlation of agricultural prices with stock market dynamics. We discuss the possible role of financial, macroeconomic and monetary factors in driving this time-varying relation, with the aim of understanding what has caused positive correlation between agricultural commodities and stocks in recent years. While previous works on commodity-equity correlation have focused on broad commodity indices, we study 16 main agricultural prices, in order to be able to assess patterns that are specific to agricultural commodities (but also differences across agricultural markets). We show that an explanation based on a combination of financialization and financial crisis is consistent with the empirical evidence, while global demand factors and monetary forces don't appear to play a significant role. In particular, we find that the correlation between agricultural price changes and stock market returns tends to get higher as the so-called TED spread (our proxy for financial turmoil) increases. Moreover, the impact of financial turmoil on the correlation gets stronger as the share of financial investors in agricultural derivatives markets (our proxy for financialization) rises. Our findings suggest that the influence of financial shocks on agricultural prices is likely to decrease as global financial tensions settle down but also that, as long as agricultural derivatives markets are populated mainly by financial investors, it can be expected to rise again when it is less needed, i.e. in the presence of new financial turmoil.

# 1 Introduction

Until recent years, commodity price dynamics had usually been regarded as largely independent of short-run fluctuations in financial markets [13]. It was indeed this belief, together with forecasts of rising prices and the liberalization of commodity derivatives markets, which encouraged financial institutions in search of alternative investments to increase substantially their engagement in commodities since the early 2000s [2].

However, since the burst of the global financial crisis, commodity and equity indices have become positively and significantly correlated. This is a concern not only for financial investors at risk of losing diversification opportunities, but also for societies and governments coping with commodity price fluctuations, since the transmission of financial shocks could significantly add to the volatility of commodity prices in periods of financial turmoil.

Some recent empirical and theoretical studies are concerned with the correlation of commodities with stocks. They find that the correlation is present also at very high frequencies [3], that financial shocks appear to be important predictors of correlation dynamics [24] and that the correlation between the broad commodity index S&P-GSCI and the stock market index S&P500 tends to increase amid greater participation of speculators, and in particular hedge funds that are active also in the stock market, in commodity derivatives market [5]. Basak and Pavlova [1] develop a theoretical dynamic general equilibrium model of commodity futures markets populated by index traders alongside traditional speculators, in which an increase in index-based investment determines an increase in equity-commodity correlations, as well as in the price and volatility of all commodities (including the ones which are not part of the index).

This paper focuses on agricultural commodities. We study the time-varying correlation of 16 agricultural prices with stock market returns. We assess the time-path of this relation in the last five decades, employing a Dynamic Conditional Correlation (DCC) approach [8] that avoids biases due to volatility clustering, in order to identify common patterns and specificities among markets (Section 2). We then try to assess what drives changes in the time-varying relation between agricultural prices and stock market dynamics, in order to understand what has caused the positive relation that we have been observing in recent years. In particular, we focus on the role of macroeconomic fundamentals, monetary expansion, financial turmoil and the financialization of agricultural derivatives markets. After having discussed the possible role of these factors (Section 3), we test empirically their influence in an ARDL model (Section 4), employing the estimated DCCs between agricultural commodities and equities as the dependent variable.

# 2 The time-varying correlation between agricultural prices and stock market returns

As a first step, let us assess how the correlation between agricultural prices and stock market returns has evolved in last decades[1]. Popular ways of estimating the pattern of a time-varying correlation coefficient are moving-window analysis and Kalman filters [20]. However, both rolling correlations[2] and Kalman filtering can be seriously biased in the presence of volatility clustering[3] [19]. For this reason, since it is well-known that both stock market returns and agricultural prices display heteroskedasticity [23, 25], we employ a Dynamic Conditional Correlation (DCC) approach.

The DCC [8] is estimated in two steps. First, the mean and the variance of each variable are modelled as Garch [6, 4] processes. Standardized residuals from the first step are then used in order to estimate a time-varying correlation matrix. This procedure yields a consistent estimation of the likelihood function [7]. Basically, we are estimating the contemporaneous correlation between the two variables at each point in time as a function of past realizations of both the volatility of the variables and the correlation between them, i.e. as a weighted average of past correlations.

The time path of the daily correlation between returns on agricultural commodities[4] and on the S&P500 index is depicted in Fig.1, which presents averages of the DCCs computed for grains, softs and livestocks, while DCCs for each single commodity are shown in Fig.2.

Before the recent financial crisis the correlation of agricultural price changes with stock market returns appears to have fluctuated mildly, oscillating mainly in the range between zero and 0.1, with the only exception of the early Eighties.

[1] Information about the data employed is provided in Appendix A

[2] A rolling (or moving) correlation is a linear correlation coefficient calculated over an initial subset of the series, usually the first year of the sample, and then rolled forward over the entire sample.

[3] In particular, since these methods don't take into account heteroskedasticity, they can estimate spurious correlations in periods of higher volatility (a nice practical example is provided in [19])

[4] For an investor trading agricultural commodity derivatives, returns are simply price changes (since commodity derivatives obviously pay no dividend). So we use here the terms 'price changes' and 'returns' interchangeably, when referring to agricultural commodities.

Strikingly, the DCC displays a sudden upward shift in late 2008, immediately after the bankruptcy of Lehman Brothers, which marked the beginning of the most severe phase of the financial crisis. The correlation has then stayed positive, with peaks in early 2009 and mid-2011, and a declining trend starting in late 2011 (Fig. 1).

While in the early Eighties positive correlation with equities was much stronger for grains than for softs and livestock, the recent surge appears to concern the three categories to the same degree (Fig. 1). The only commodities in our sample that seem to behave in a different way are lean hogs and lumber. The correlation of lean hogs price with stock prices fluctuates much more wildly in the whole sample, and several periods of positive correlation are displayed. The price of lumber, instead, seems to have been slightly positively related with financial market dynamics during the whole period, and the after-2008 increase is not as dramatic as in all other agricultural markets[5].

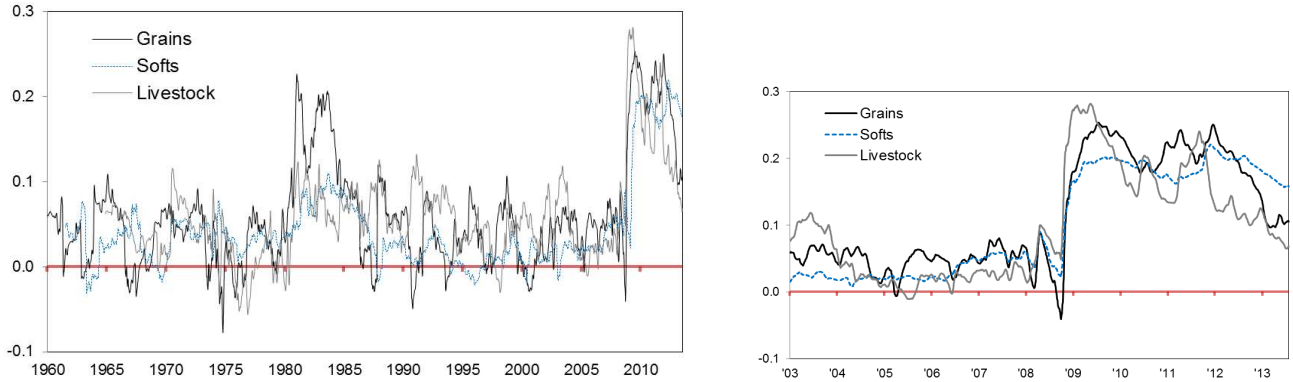


Figure 1: Time path of the Dynamic Conditional Correlation (DCC) between agricultural prices and S&P500 (20-days moving averages - Left panel: Jan.1960-Jul.2013; Right panel: Jan.2003-Jul.2013)

*Note: Here lean hogs is excluded from livestocks, because its DCC follows a very different pattern from that of other commodities in this group*

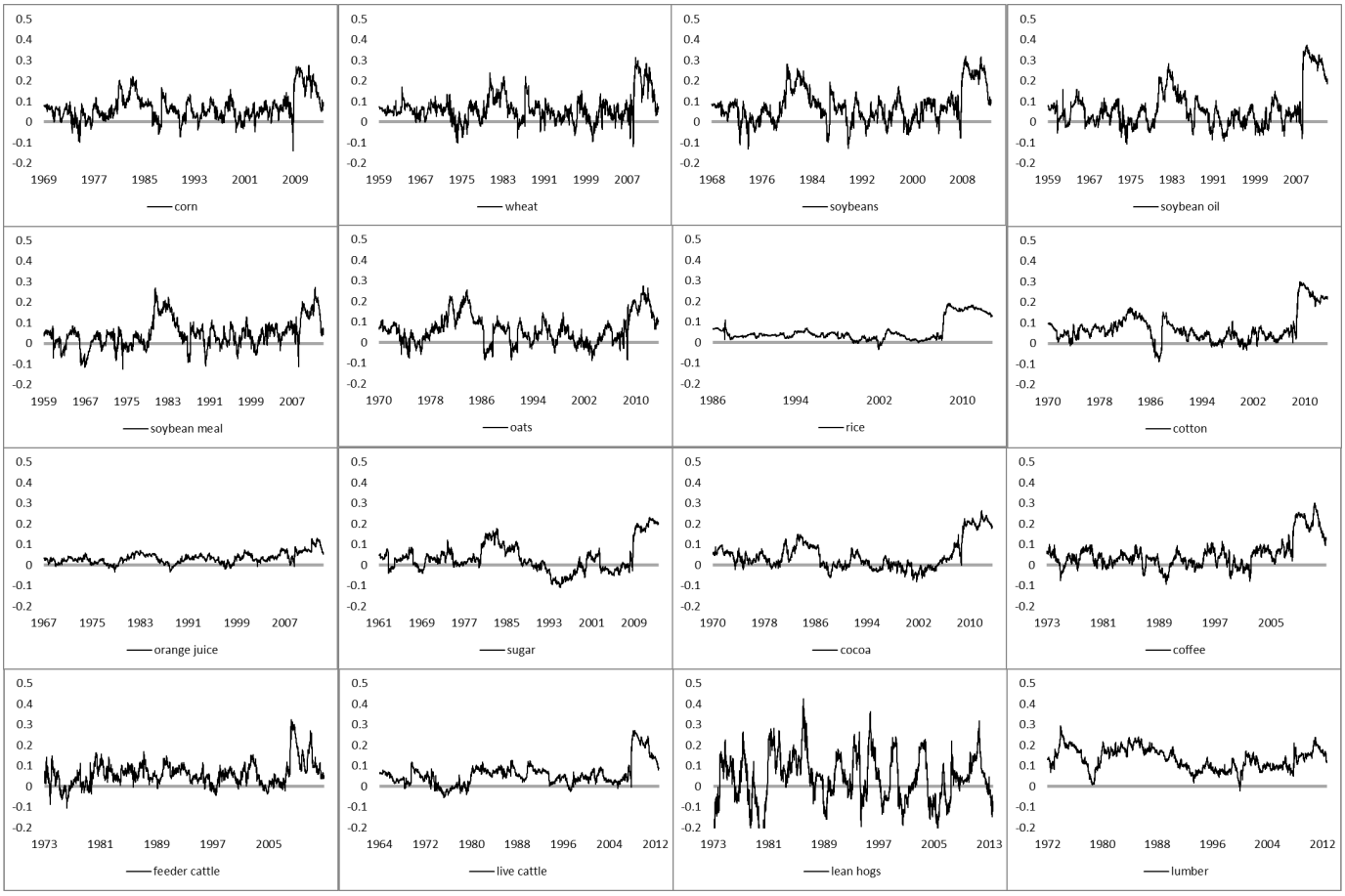


Figure 2: Time path of the Dynamical Conditional Correlation with S&P500(daily data)

[5]This pattern could perhaps be explained by the employment of lumber in the construction sector. This makes the price of lumber positively related to investment in housing, which in turn has a positive correlation with financial market trends.

In order to complete the picture, we need to assess whether we are only dealing with a contemporaneous correlation or one of the two variables tends to lead the other. To do so, we perform a battery of univariate Granger causality tests[6] by estimating the following OLS regressions for the sub-period September 2008-July 2013:

$$r_{i,t} = \beta_{0,i} + \beta_{1,i} * r_{i,t-1} + \beta_{2,i} * SP500_{t-1} + \epsilon_i$$

$$SP500_t = \gamma_{0,i} + \gamma_{1,i} * SP500_{t-1} + \gamma_{2,i} * r_{i,t-1} + u_i$$

where $r_{i,t}$ is the daily price change of the i-th agricultural commodity in our sample at time $t$ and $SP500$ is the return on the S&P-500 index. Results, reported in Tables 6 to 8, indicate that stock market returns tend to lead agricultural prices in 11 markets out of 16, while the reverse is not true in any market, as we infer from the fact that $\beta_2$ is statistically significant at the 5% significance level for 11 agricultural commodities out of 16, while $\gamma_2$ is never significant at any conventional level[7]. The sign of $\beta_2$ is positive in all cases, implying that there are spillovers of positive sign: if stock market values increase in a given day, agricultural price changes tend to be higher on the following trading day. Of course, Granger-causality does not necessarily imply true causality but only a lead-and-lag relationship. Moreover, the $R^2$ of the regressions is rather low, as expected since we are modelling asset price changes on the basis of lagged returns, so the relation doesn't carry relevant predictive power. However, that stock market returns tend to lead agricultural price changes is a fact to be taken into account when interpreting the observed correlation.

# 3 Causes of positive correlation between agricultural commodities and stocks: financial factors or global demand?

What has caused positive correlation between agricultural commodities and stocks in recent years? In what follows we discuss the possible role of financial, macroeconomic and monetary factors, before trying to quantify their impact empirically.

**Financial turmoil** The timing of the recent upward shift in the DCC series (Fig. 1) strongly suggests that financial turmoil may have played a role. The sudden increase in commodity-equity correlation clearly coincided with the burst of the global financial crisis in September 2008. Moreover, the most severe phase of the Euro crisis (in mid 2011) seems to have coincided with a new increase in commodity-equity correlations. It has been shown empirically [5] that in recent years[8] the correlation between the broad commodity index S&P-GSCI (which is however dominated by energy commodities) and the S&P500 index has tended to be higher in the presence of systemic financial distress.

Descriptive evidence regarding previous periods appears less clear-cut but still suggestive of a relation between financial turbulence and commodity-equity correlation. As better explained in section 4, the TED spread is commonly employed as a measure of financial turmoil. Unfortunately it is not possible to calculate it for the period 1960-1985, since its main component, the LIBOR, started being published in 1986. We are thus unable to check whether the generalized and sustained increase in the DCC series in the early Eighties (more precisely in the period 1980-1986 - see Fig.1) coincided with a rise in the TED spread. However, the first half of the Eighties was characterized by the burst of the Savings and Loan crisis in the US and by a major international debt crisis due to the insolvency of several developing countries (the most severe phase of which started in August 1982, when Mexico declared its inability to entirely repay its debt) [9, 15]. It thus seems fairly plausible that the 1980-1986 increase in the DCC series came against a backdrop of high financial turmoil, even though it is not possible to employ the TED spread to quantify it. We can be more precise about the subsequent period.

Figure 3 compares fluctuations in the TED spread (expressed as a % of LIBOR as in [5]) and in the average correlation between agricultural commodities and equities in 1986-2013. Before 2008 there were three main peaks in the TED spread, and they coincided with three peaks in the correlation between agricultural commodities and equities: the abrupt increase in the TED spread triggered by the financial panic of October 19th 1987 ('Black Monday") is indeed matched by a strikingly similar increase in the average DCC; also during the 1997-1998 "Asian" financial crisis and the 2002-2003

[6] Granger causality test is useful in identifying lead-and-lag relationships between time-series. The variable X causes the variable Y, in the sense of Granger, if past values of X contain useful information to predict the present value of Y. Formally, X Granger-causes Y if $E(y_t|y_{t-1}, y_{t-2} \ldots x_{t-1}, x_{t-2}, \ldots) \neq E(y_t|y_{t-1}, y_{t-2} \ldots)$.

[7] For brevity, we report in the tables only results showing that stock market returns Granger-cause agricultural price changes, and not the ones showing that agricultural price changes don't Granger-cause stock market returns, but the latter are available upon request.

[8] In particular, the analysis of Büyükşahin and Robe [5] concerns the period 2000-2008

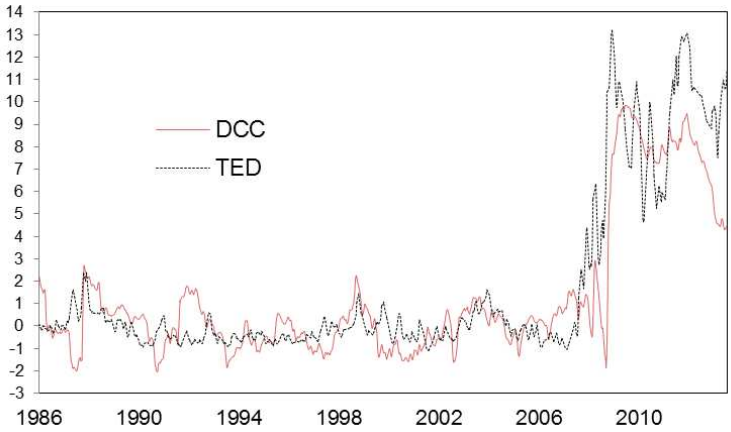


Figure 3: Average correlation between agricultural commodities and equities (DCC) vs. financial turmoil (TED) (standard deviations from the mean; 20-days moving averages; Jan.1986 - Jul. 2013)

Notes: DCC is averaged across our sample of agr.commodities (excluding lumber because of its peculiar pattern); TED spread is expressed as a % of LIBOR;

downturn, the rise in the TED spread was accompanied by a peak in equity-commodity correlation. The rise in the average DCC in late 1991, instead, doesn't appear to have coincided with a major rise in the TED spread (the latter rose relevantly only later, in late 1992, probably because of the European currency crisis[9]).

We then need to explain how financial turmoil would result in positive correlation between agricultural and stock prices. Commodity derivatives trading by financial institutions represents a possible channel through which financial turbulence could be transmitted to agricultural markets.

**Financialization of agricultural derivatives markets** Commodity derivatives markets experienced a remarkable growth during the second half of the last decade, which involved both centralized exchanges and over-the-counter (OTC) transactions. Rocketing transaction volumes and open interest resulted from a huge inflow of financial investments, coming from investment banks, pension funds, hedge funds and other institutional investors. Those investors are active at the same time in equity and commodity markets, so it is plausible that their strategies in the different markets in which they operate are not independent from one another. As suggested by Tang and Xiong [26], when stock market value increases diversification incentives may induce investors to move some money into commodities, producing a positive correlation between commodity prices and stock market dynamics. Empirical evidence [27] points out that commodity index funds[10] caused increasing correlation between oil and non-energy commodities. Even more importantly from our point of view, Büyükşahin and Robe [5] showed that the DCC between S&P-GSCI and S&P500 tends to increase amid greater participation of hedge funds in commodity derivatives markets.

The financialization of agricultural commodity markets has started in the early 2000s and was already overwhelming in 2006-2007 [28], while equity-commodity correlation increased only in late 2008. Clearly, financialization alone didn't imply an increase in equity-commodity correlation. What could be argued, instead, is that it was a combination of financialization and financial stress that determined the positive correlation. During periods of financial turmoil, with stock prices decreasing, investors may be pushed into selling commodity derivatives in order to get liquidity and cover losses, causing a decrease in prices. During 'normal' periods, instead, the link between stock market dynamics and financial investment in commodities is less clear. Diversification incentives like the ones suggested by Tang and Xiong [26] may be at work, but it is also possible that some investors turn to commodities when facing a negative trend in the stock market (so they would buy commodities while selling stocks). Moreover, some investors may simply attempt to anticipate future commodity price changes, with no relation to what happens in the stock market. An explanation based on a combination of financial crisis and increasing presence of financial institutions in commodity markets would also be consistent with the fact that the relation between financial turmoil and our estimated DCCs appears to have been less tight before financialization (Fig. 3).

[9] On September 16th 1992 the British sterling was forced out of the European Exchange Rate Mechanism

[10] Financial instruments which passively track a commodity index, which is a weighted average of different commodity prices

**Global demand** Turning to the possible role of market fundamentals, a trend that is common to a well-diversified basket of commodities is highly unlikely to be due to market-specific supply shocks, as shown formally by Gilbert [12]. However, common global demand factors may in principle have played a role. Changes in the pace of global economic growth may have caused both stock and commodity price fluctuations. Previously mentioned empirical work aimed at explaining increasing correlation between the indices S&P-GSCI and S&P500 [5] has indeed considered necessary to control for global macroeconomic conditions.

The problem with this "real" explanation is that global macroeconomic factors were at work also before 2008, when commodities and stocks were uncorrelated. Sustained global economic growth in early 2000s, for example, didn't result in positive correlation between agricultural commodities and equities. Perhaps what can be argued is that exceptionally strong negative macroeconomic shocks (like the global recession of 2008-2009) may cause demand for different real and financial assets, which are usually unrelated, to go down together during a deep recession. This interpretation seems more plausible, but it appears to clash with the fact that the correlation remained relevant in 2010-2012.

**Inflation** Inflation is another possible determinant of the correlation. Higher inflation expectations could increase demand for both stocks and commodities, because of decreasing willingness to hold cash. However, visual inspection of Figs.1 and 9 doesn't support this idea. Periods of high inflation in OECD countries (as the mid-Seventies) are not associated with particularly high correlation between equities and commodities in our sample, while inflation was decreasing during the Early Eighties and low in recent years.

**Monetary Expansion** Monetary expansion is also mentioned in the literature on recent agricultural price trends. The idea that increases in the quantity of money automatically trigger increases in goods' prices (as argued by monetarist scholars drawing on the so-called Fisher equation [10, 11]) is based on the assumption of full-employment. In our sample advanced economies were not constantly near to full employment (not to mention emerging economies). Yet, sensitivity of agricultural prices to monetary expansion can be justified on different grounds, namely on the basis of supply-side bottlenecks. Since the supply of agricultural goods is extremely rigid in the short run, while their prices are rather flexible, an increase in demand due to monetary expansion is likely to result in a significant increase in prices. Furthermore, monetary expansion could influence agricultural prices through greater speculation. Gilbert [12] presents empirical evidence suggesting that monetary growth (measured by the M3 aggregate) has influenced agricultural price dynamics in the last four decades and that in the second half of the 2000s the channel through which this influence was exerted was financial investment in commodity futures. Hence one could argue that monetary expansion may have, at least in part, driven demand for both stocks and agricultural goods, resulting in positive correlation between their prices.

In any case, it is important to note that the problem of whether the quantity of money should be considered endogenous or exogenous is relevant in interpreting empirical results pointing to a positive relation between monetary expansion and agricultural prices. Of course if one admits that money is endogenous[11], then there is an element of reverse causality: higher (cost-driven) inflation due to rising commodity prices causes an increase in demand for money which, given the interest rate set by the Central Bank, determines the quantity of money in the system [18].

**Exchange rates** Both commodities and US-listed stocks are priced in US Dollars. Their prices can therefore be influenced by fluctuations in the value of the 'greenback' . If, ceteris paribus, real values are to remain unchanged, depreciations (appreciations) in the measuring rod should be compensated by increases (declines) in nominal prices. If this was the case, exchange rate fluctuations could result in positively correlated movements of commodity and stock prices. Of course, things are not that simple. While in the case of commodity prices both theory and empirical evidence largely point to a negative relation with the US Dollar exchange rate (as explained for example by Gilbert [12]), in the case of US equities both theoretical links and empirical evidence are far more ambiguous. For example, an upward trend in the US dollar exchange rate could induce investors to buy US stocks if they expect the trend to continue. Furthermore, exchange rate changes can affect in a different way the expected profits of different firms, thus affecting the market valuation of their shares. Moreover, reverse causality is likely to play a role. What matters for our analysis is that if US stock prices are, at least in some periods, negatively related to the value of the US Dollar, then rising volatility in its exchange rate is a possible cause for higher correlation between commodities and equities.

[11] Apart from theoretical issues, there is a compelling practical reason to consider money as endogenous in our period of interest. All main central banks have generally been following, explicitly or implicitly, some kind of inflation-targeting rule. They set the interest rate according to the desired inflation rate (possibly taking into account also considerations related to output and unemployment) and then accommodate the resulting demand for money. It appears really difficult, within this policy framework, to consider the quantity of money as exogenous.

As shown in Figure 11, the period of positive equity-commodity correlation in the Early Eighties coincided with a strong appreciation of the US Dollar, which resulted in high exchange rate volatility. It thus seems reasonable to speculate that exchange rate fluctuations played a part in connecting agricultural prices to stock market dynamics in the first half of the Eighties. Volatility of the US Dollar exchange rate increased dramatically also in late 2008, because of a steep appreciation due to financial panic, suggesting that also the new increase in equity-commodity correlation could be somehow related to currency movements. However, two rather compelling objections can be made. The first is that exchange-rate volatility declined in 2010-2012, while commodity-equity correlation remained rather high. The second is that during the late-2008 financial crash falls in stock prices were certainly not driven by exchange rate movements. To the contrary, it was financial market dynamics that determined exchange rate movements immediately after the Lehman bankruptcy.

# 4 Empirical test

In what follows, we aim to test empirically the impact of the factors discussed above on the time-varying correlation between agricultural commodities and equities. We do so by using the DCC calculated in Section 2 as the dependent variable in an Autoregressive Distributed Lag (ARDL) model.

**Data** Our proxy for financial turmoil is the so-called 'TED spread' , which is the difference between the interest rate on interbank loans (as measured by the LIBOR) and on short-term US government debt (measured by yields on 3-month Treasury bills). Given that the short term T-Bill rate is universally considered as the best approximation to the riskless interest rate, the TED spread represents the risk-premium on interbank lending. That is why it is widely considered a good measure of perceived systemic risk in financial markets.

As an indicator of the degree of financialization, we employ the share of reportable positions taken by financial institutions in agricultural derivatives exchanges[12] (as opposed to commercial operators using derivatives to hedge their transactions on the physical market). Among financial investors, we distinguish between commodity index traders (CIT) and other financial actors (which we term "money managers").

As a proxy for global demand for commodities, we employ the index of global real economic activity in industrial commodity markets, proposed and calculated by Kilian[13] [17] on the basis of dry cargo ocean freight rates.

Core inflation in OECD countries (since we are using data on Western commodity exchanges) is measured by percentage changes in the Consumer Price Index excluding food and energy. As a proxy for monetary expansion, we employ changes in the quantity of broad money in OECD countries, as measured by the M3 aggregate.

US Dollar exchange rate fluctuations can be measured through trade-weighted indices. Here we employ the 'Trade Weighted US Dollar Index' against Major Currencies (TWEXM) calculated by the Federal Reserve, which is available at a weekly frequency since January 1973. We measure its volatility by taking 12-weeks standard deviations.

A more detailed description of the dataset and a list of all sources is provided in Appendix A. Some of these variables are available only at weekly or monthly frequencies. We take weekly observations of all variables, after interpolating monthly series (the Kilian Index, M3 and core inflation) by assuming linear growth between weeks of the same month[14]. At this stage, we limit our empirical analysis to the period 1986-2013, for which all our variables of interest are available.

[12] Some recent studies (for example [5] and [16]) employ the so called 'Working's speculative T-index' [29] as a measure of financialization of commodity markets. The Working's T-Index is meant to be a measure of excess speculation in commodity markets, and it is measured as $T = 1 + SS/(HL + HS)$ if $(HS \geq HL)$, or $T = 1 + SL/(HL + HS)$ if $(HL > HS)$ (SS = short positions of non-commercial traders, SL = long positions of non-commercial traders, HL = long positions of commercial hedgers, HS = short positions of commercial hedgers).

The logic behind the T-Index is that it would quantify the measure by which financial investors' positions are in excess of the level that would be required to fill any gap between long and short positions of commercial hedgers. The problem with this idea, in my view, is that the implicit assumption is made that the quantities of short and long positions demanded by commercial traders are not affected by the presence of other traders. But if the other traders affect the price, because their individual demand and supply functions (obviously) add to, and modify, the aggregate demand and supply functions, then in order for the T-index to measure "excess speculation", the demand and supply of commercial hedgers should be perfectly inelastic to price, which is of course a very heroic assumption. When speculation affects the market, it does so precisely by inducing commercial operators to keep hedging an increasing part of their stocks (at higher prices) in the futures market, instead of selling it immediately in the spot market. This means that speculation can affect both the numerator and the denominator of the T-index. This is why we don't make use of the T-index here. Instead, we simply employ the number of reportable positions of financial investors, normalized by the total size of the market.

[13] As Kilian writes, his index is "a measure of the component of worldwide real economic activity that drives demand for industrial commodities in global markets." [17].

[14] In the case of the DCCs, we calculate them again on weekly returns on agricultural prices and on S&P500

Table 1: P-value for the null hypothesis of non-stationarity of the DCC series (Jul.1986 - Jul.2013)
(computed through and Augmented Dickey Fuller (ADF) unit-root test)

| Corn | Wheat | Soybeans | Soy. Oil | Soy. Meal | Oats | Rice | Cotton |
|---|---|---|---|---|---|---|---|
| 0.48 | $1.0 \cdot 10^{-3}$ | 0.24 | 0.73 | 0.14 | 0.30 | 0.72 | 0.66 |
| Cocoa | Coffee | Orange Juice | Sugar | Live Cattle | Lean Hogs | Feeder Cattle | Lumber |
| 0.38 | 0.65 | 0.77 | $1.1 \cdot 10^{-15}$ | 0.04 | 0.06 | 0.02 | $2.1 \cdot 10^{-30}$ |

Table 2: P-value for the null hypothesis of non-stationarity of the DCC series after controlling for the late-2008 structural break (Jul.1986 - Jul.2013)
(ADF unit-root test applied on the residuals of a regression of the DCC series on the post-Lehman dummy)

| Corn | Wheat | Soybeans | Soy. Oil | Soy. Meal | Oats | Rice | Cotton |
|---|---|---|---|---|---|---|---|
| 0.07 | $3.1 \cdot 10^{-6}$ | $8.0 \cdot 10^{-3}$ | $3.1 \cdot 10^{-3}$ | $2.8 \cdot 10^{-3}$ | 0.05 | 0.10 | 0.01 |
| Cocoa | Coffee | Orange Juice | Sugar | Live Cattle | Lean Hogs | Feeder Cattle | Lumber |
| 0.01 | 0.04 | 0.03 | $2.9 \cdot 10^{-17}$ | $1.3 \cdot 10^{-4}$ | 0.06 | 0.01 | $2.1 \cdot 10^{-30}$ |

**Stationarity and structural breaks** As suggested by visual inspection of Figs.1 and 2, almost all the DCCs present a structural break in late 2008. ADF unit-root tests [22] reveal that we cannot reject at any conventional level the null of non-stationarity for 10 agricultural commodities out of 16 (Table 1). However, after accounting for the upward shift in late 2008, the series become stationary. Indeed if we regress the DCCs on a dummy which is equal to 0 before the bankruptcy of Lehman Brothers and 1 afterwards, we obtain stationary residuals (Table 2). We will use these stationary residuals as the dependent variable in our analysis, which is of course equivalent to including the "Post-Lehman dummy" in our regressions[15].

**Estimation and results** We estimate the following ARDL model:

$$DCC_{i,t} = \beta_{0,i} + \beta_{1,i} \cdot DCC_{i,t-1} + \beta_{2,i} \cdot SHIP_t + \beta_{3,i} \cdot SHIP_{t-1} + \beta_{4,i} \cdot TED_t + \beta_{5,i} \cdot TED_{t-1} +$$

$$+ \beta_{6,i} \cdot M3_t + \beta_{7,i} \cdot M3_{t-1} + \beta_{8,i} \cdot CPI_t + \beta_{9,i} \cdot CPI_{t-1} + \beta_{10,i} \cdot USD\_V_t + \beta_{11,i} \cdot USD\_V_{t-1} + \beta_{12,i} \cdot Lehman_t + \epsilon_{i,t} \quad (1)$$

Where $DCC_{i,t}$ is the DCC between agricultural commodity $i$ and the S&P500 index at week $t$; $SHIP$ is the Kilian index of global real economic activity in commodity markets; $TED$ is the TED spread; $M3$ is the increase in the monetary aggregate M3 in OECD countries; $CPI$ is the change in the Consumer Price Index excluding food and energy for OECD countries; $USD\_V$ is the 12-weeks standard deviation in the US dollar trade-weighted exchange rate index; $Lehman$ is a dummy which is equal to 0 before September 15, 2008 and 1 afterwards; $\epsilon$ is a random disturbance. In this first stage we have excluded financialization of commodity derivatives markets from the analysis, since comprehensive data on the composition of trading in derivatives markets are available only for the period after 2006 (see Appendix A). They will be introduced in the next paragraph. Usual selection criteria (Schwartz and Akaike) pointed to the introduction of just one lag of each variable. Results are summarized in Tables 9, 10 and 11.

For most agricultural commodities in our sample, the correlation with the S&P500 index is increasing in the current level of financial turmoil. Indeed, the contemporaneous effect of $TED$ on the DCC is positive and significant at the 99% confidence level for all grains (with the exception of oats, for which it is significant at the 95% level), cotton and sugar and at the 90% level for coffee, orange juice and feeder cattle. However, financial turmoil doesn't seem to affect the correlation of cocoa, live cattle, lean hogs and lumber with stock market dynamics.

For those cases in which the contemporaneous effect of $TED$ is positive and significant (12 commodities out of 16), the coefficient of the lagged value of $TED$ is negative and significant, and lower in absolute value than the contemporaneous one. An adjustment process seems to be at work: a surge in the correlation, due to contemporaneous financial turmoil,

[15] Another way to deal with non-stationarity, without having to include the Post-Lehman dummy, would have been to follow the approach proposed by Pesaran and Shin [21], which show that in the presence of a single cointegrating relationship, ARDL models can be used to obtain consistent estimates even if some variables are integrated of order 1. (This approach is followed by Büyükşahin and Robe [5].) However, we don't find significant evidence of cointegration between our variables of interest, so it would not be legitimate, in our case, to follow this approach.

Table 3: Long-run multiplier for the effect of TED spread on the time-varying correlation with S&P500
(expressed in standard deviations from the mean - sample period: Jul.1986-Jul.2013)

| Corn | Wheat | Soybeans | Soy. Oil | Soy. Meal | Oats | Rice |
|---|---|---|---|---|---|---|
| 0.66 | 0.45 | 0.45 | 0.19 | 0.31 | 0.47 | 0.14 |
| Cotton | Cocoa | Coffee | Orange Juice | Sugar | Feeder Cattle | Average |
| 0.81 | −0.07 | 0.28 | 0.28 | 0.31 | 1.29 | 0.43 |

Note: The long-run multiplier is $\frac{\beta_4+\beta_5}{1-\beta_1}$ (see eq.1)

tends to be partially corrected by a subsequent decrease. Long-run coefficients for the $TED$ variable are reported in Table 3. On average for all commodities for which the effect of $TED$ is significant, the long-run multiplier is 0.43, which means that an increase of one standard deviation in the TED spread tends to be associated with a cumulated increase of 0.43 standard deviations in the weekly DCC.

Global macroeconomic conditions appear to be less important in determining our DCCs. The coefficient of the Kilian index of global demand for industrial commodities is negative (as expected) and significant at the 95% confidence level only for soybeans, soybean meal and lean hogs and at the 90% level for soybean oil, while it is positive and significant at the 90% level for coffee and not significant at any conventional level for the remaining 11 commodities.

Exchange rates, inflation and monetary expansion don't appear to exert any effect on our DCCs (the coefficients of $CPI$ and $M3$ are significant only for live cattle, and with a "wrong" negative sign which doesn't seem to make much sense and probably arose our of randomness).

The dummy accounting for the post-Lehman period is positive and highly significant for all commodities except lean hogs, feeder cattle and lumber, suggesting that, even after accounting for financial turmoil, there is still an upward shift in the DCCs in late 2008.

The high (but below-unity) autoregressive coefficient that we find in the DCCs of all commodities is likely to be partly due to the way in which the DCC is calculated (as said in section 2, it can be seen as a weighted average of current and past correlations) but also to the persistency of the phenomenon. This is revealed by differences among commodities: while most AR(1) coefficients are above 0.9, the ones for the DCCs of sugar and lumber are respectively 0.8 and 0.5. These differences cannot be explained by the way the DCC is calculated, which is obviously the same for all commodities.

**Interaction with financialized commodity markets** As previously pointed out, while financialization of agricultural derivatives markets alone didn't imply increasing correlation between equities and commodities, the combination of financialization and financial crisis may explain the recent increase in correlation. In other words, financial turmoil may be more powerfully transmitted to agricultural prices when most trades in agricultural exchanges are made by financial investors. We test whether the effect of financial turmoil on the DCCs of agricultural prices with stock market returns is increasing in financialization, by including in our ARDL model an interaction term. We do so for the commodities for which data on the composition of derivatives markets are available and for which the impact of the variable $TED$ on the DCC proved to be significant. We are forced to restrict our analysis to the 2006-2013 period because of data availability (see Appendix A). We exclude changes in M3, exchange rates and inflation from the analysis, since they were shown to have no effect on the DCC. Thus, we estimate the following model

$$DCC_{i,t} = \beta_{0,i} + \beta_{1,i} \cdot DCC_{i,t-1} + \beta_{2,i} \cdot SHIP_t + \beta_{3,i} \cdot SHIP_{t-1} + (\beta_{4,1} + \beta_{5,i} \cdot Financial_{i,t}) \cdot TED_t +$$
$$+ (\beta_{6,i} + \beta_{7,i} \cdot Financial_{i,t-1}) \cdot TED_{t-1} + \beta_{8,i} \cdot Lehman_t + \epsilon_{i,t}$$

(2)

in which $Financial_{i,t}$ is the share of financial investors in total reportable positions in week $t$ in the US agricultural exchange where commodity $i$ is traded. If the interaction term $\beta_{5,i}$ ($\beta_{7,i}$) is positive and significant, it means than the effect of current (lagged) financial turmoil on the correlation between commodity i and S&P500 is increasing in the share of financial investors in the futures market.

Results are reported in Tables 12 and 13. The contemporaneous interaction term $\beta_{5,i}$ is positive and significant at the 95% confidence level for corn, wheat, soybean oil, cotton, cocoa, and feeder cattle and at the 90% confidence level

Table 4: Long-run multiplier for the effect of TED spread on the time-varying correlation with S&P500 (expressed in standard deviations from the mean - sample period: Jan.2006-Jul.2013)

| when change in $Financial = 0$ | | | | |
|---|---|---|---|---|
| Corn | Wheat | Soybeans | Soy. Oil | Cotton |
| 0.47 | 0.24 | 1.10 | 0.22 | 0.24 |
| Cocoa | Coffee | Sugar | Feeder Cattle | Average |
| 0.67 | 0.18 | 0.45 | 1.15 | 0.53 |
| when $Financial$ increases by one standard deviation | | | | |
| Corn | Wheat | Soybeans | Soy. Oil | Cotton |
| 0.88 | 1.29 | 2.04 | 0.29 | 0.18 |
| Cocoa | Coffee | Sugar | Feeder Cattle | Average |
| 1.51 | 0.37 | 0.79 | 1.65 | 1.00 |

Note: The long-run multiplier is $\frac{(\beta_4+\beta_6)+(\beta_5+\beta_7)\cdot\Delta Financial}{1-\beta_1}$ (see eq.2)

for soybeans, while it is not significant for coffee and sugar and negative for feeder cattle. For example, an increase of one standard deviation in the TED spread is associated, ceteris paribus, with an increase of 0.1 standard deviations in the DCC between wheat price and S&P500 in the same week, while in the presence of a one-standard deviation increase in financialization, the same increase in $TED$ determines an increase of 0.2 standard deviations in the DCC. Also in this case there tends to be a partial correction in the subsequent week (since the coefficient for the lagged value is negative and significant).

On average across commodities, the long-run coefficient of $TED$ is 0.5 and it tends to increase by 0.5 for each standard deviation increase in the variable $Financial$ (Table 4)

**Commodity index traders and money managers** Financial investors operating in commodity derivatives markets can be divided into (at least) two categories, commodity index traders and money managers.

Commodity index traders follow a passive strategy, aimed at gaining a broad exposure to commodities as an asset class. They do so by tracking a commodity index, which is a weighted average of different commodity prices, with fixed weights (mainly) dependent on world production and updated once a year. The most tracked commodity indices are the Standard & Poors-Goldman Sachs Commodity Index (S&P-GSCI) and the Deutsche Bank Liquid Commodity Index (DBLCI). To invest in these indices, investors buy financial instruments whose value is proportional to the value of the chosen index. These instruments - swap agreements, ETFs and ETNs - are typically offered by large financial institutions. These institutions buy commodity futures contracts in order to hedge their commitment with their clients. By contrast, we term money managers financial investors who dont track a commodity index, but instead actively buy and sell futures contracts in an attempt to anticipate price changes and/or to diversify their portfolio.

Public data about the composition of agricultural derivatives markets (see Appendix A) allow us to isolate, among positions of financial investors, the ones attributable to commodity index traders. As already mentioned, Büyükşahin and Robe [5] found that the correlation between the broad commodity index S&P-GSCI and the S&P500 index rises amid greater partecipation by money managers (and in particular hedge funds) in commodity derivatives markets, while index traders seem to exert no such effect. In order to assess the relative importance of money managers and index traders in the agricultural markets in our sample, we estimate the following ARDL model

$$DCC_{i,t} = \beta_{0,i} + \beta_{1,i} \cdot DCC_{i,t-1} + \beta_{2,i} \cdot SHIP_t + \beta_{3,i} \cdot SHIP_{t-1} + (\beta_{4,i} + \beta_{5,i} \cdot MM_{i,t} + \beta_{6,i} \cdot CIT_{i,t}) \cdot TED_t +$$

$$+(\beta_{7,i} + \beta_{8,i} \cdot MM_{i,t-1} + \beta_{9,i} \cdot CIT_{i,t-1}) \cdot TED_{t-1} + \beta_{10,i} \cdot Lehman_t + \epsilon_{i,t}$$

(3)

in which $MM$ is the share of reportable positions attributed to money managers and $CIT$ is the share of commodity index traders. Of course the interpretation of the interaction terms ($\beta_5$, $\beta_6$, $\beta_8$ and $\beta_9$) is totally analogous to the one that we put forward in discussing eq.2.

Results, summarized in Tables 14 and 15, seem to suggest that money managers play a more important role than index traders in linking agricultural prices to stock market dynamics. The contemporaneous interaction term $\beta_5$ (related

Table 5: Long-run multiplier for the effect of TED spread on the time-varying correlation with S&P500 (expressed in standard deviations from the mean - sample period: Jan.2006-Jul.2013)

| | | | | |
|---|---|---|---|---|
| when change in both $MM$ and $CIT = 0$ | | | | |
| Corn | Wheat | Soybeans | Soy. Oil | Cotton |
| 0.41 | 0.23 | 0.98 | 0.26 | 0.23 |
| Cocoa | Coffee | Sugar | Feeder Cattle | Average |
| 0.49 | 0.20 | 1.82 | 0.03 | 0.52 (0.52*) |
| when $MM$ increases by one standard deviation | | | | |
| Corn | Wheat | Soybeans | Soy. Oil | Cotton |
| 0.77 | 1.26 | 1.99 | 0.26 | 0.16 |
| Cocoa | Coffee | Sugar | Feeder Cattle | Average |
| 0.40 | 0.45 | 1.90 | 0.04 | 0.81 (0.85*) |
| when $CIT$ increases by one standard deviation | | | | |
| Corn | Wheat | Soybeans | Soy. Oil | Cotton |
| 0.59 | 0.48 | 1.09 | 0.45 | 0.17 |
| Cocoa | Coffee | Sugar | Feeder Cattle | Average |
| 3.05 | 0.34 | 1.97 | 0.05 | 0.88 (0.64*) |

Note: The long-run multiplier is $\frac{(\beta_4+\beta_7)+(\beta_5+\beta_8)\cdot\Delta MM+(\beta_6+\beta_9)\cdot\Delta CIT}{1-\beta_1}$ (see eq.3)
* Excluding cocoa

to money managers) is positive and significant at the 95% confidence level in all markets but two (coffee and feeder cattle - for which in the preceding stage of the analysis we didn't find evidence of an impact of financialization on the $TED$ coefficient) and its average value (excluding these two cases) is 0.08. $\beta_6$ (the contemporaneous interaction term related to CIT), instead, is positive and significant at the 95% confidence level only in two cases (cocoa and sugar) and at only the 90% confidence level in other two cases (wheat and coffee). Its average in these four cases is 0.10 (but if we exclude sugar it falls to 0.06). The lagged interaction term $\beta_8$ (relative to money managers) is negative and significant at the 95% level in four cases (suggesting, as already discussed, a partial correction process), positive and significant at the 95% level in two cases and not significant at any conventional level in three cases. Its average value across all markets is $-0.03$. The lagged interaction term related to CIT, $\beta_9$, is positive and significant in three cases (two of which at the 95% level), negative and significant in two cases and not significant at any conventional level in four cases.

On average across all commodities in the sample, the long-run coefficient for the effect of financial turmoil on the DCC tends to increase by 0.29 (a 57% increase) for each standard deviation increase in the market share of money managers and by 0.36 (+71%) for each standard deviation increase in the market share of commodity index traders. However, if we exclude the cocoa market, in which the impact of index traders seems to be particularly strong, these averages become 0.34 (+65%) for money managers and 0.12 (+24%) for index traders.

Summing up, in the short run money managers appear to be more important than commodity index traders in transmitting financial shocks to agricultural markets. The interaction term relative to money managers was found to be significant in more markets and with an higher marginal effect. However, for those market in which it is positive and significant - 6 out of 9 (wheat, soybeans, soybean oil, cocoa, coffee and sugar) if we consider both the contemporaneous and the lagged interaction term and a 90% confidence level - the effect of commodity index trading seems to be greater in the long- than in the short-run.

## 4.1 Sensitivity analysis

Results don't appear to be sensitive to the methodology employed in aggregating futures prices. In particular, if instead of averaging in the way described in Appendix A, we use the price of the nearest-to-expiration contract until the month of maturity is reached (at which point we switch to the second-nearby contract), with returns always calculated on the same contract in order to avoid biases (as done by Irwin and Sanders, 2011 and Power and Turvey, 2011), results are basically unchanged. We also tried employing a weighted average of all traded contracts, with weights equal to volumes exchanged, and got the same results.

Also including squared and higher-power terms of the independent variables in estimating equation 1 doesn't change any result (coefficients of squared independent variables are all insignificant while other coefficients are basically unaf-

fected).

## Concluding Remarks

We have studied the time-varying correlation of 16 agricultural prices with stock market dynamics by means of a Dynamic Conditional Correlation (DCC) approach [8]. On average across commodities, the correlation has fluctuated mildly in the last five decades, oscillating mainly in the range between zero and 0.1, with the only exception of the Early Eighties, before rising dramatically in late 2008. While this trend is rather general in our sample, two commodities, namely lean hogs and lumber, appear to have behaved differently, with positive (although fluctuating) correlation also before the crisis, and no dramatic increase in recent years.

We have then discussed the possible role of financial, macroeconomic and monetary factors in driving this time-varying relation. We have argued that an explanation based on a combination of financialization and financial turmoil seems most convincing and consistent with the empirical evidence, while we have highlighted some theoretical and practical problems with claims that macroeconomic and monetary factors were the most important.

We tested empirically the influence of the discussed factors. The DCC of each agricultural commodity with the stock index S&P500 was employed as the dependent variable in an ARDL model. For most agricultural commodities in our sample (12 out of 16), the correlation with the S&P500 index is increasing in the current level of financial turmoil (measured by the TED spread). The effect of financial turmoil seems to be stronger in grain markets, weaker in softs and livestocks and absent in the market of lumber. Deteriorating macroeconomic fundamentals appear to be significantly related to the DCCs only in few markets (3 out of 16 at the 95% confidence level), while monetary factors (inflation and monetary expansion) don't appear to exert any influence.

We also found that the impact of financial shocks on the correlation between agricultural commodities and equities is increasing in the market share of financial investors in agricultural derivatives markets (which is our proxy for financialization). In other words, financial turmoil appears to be more powerfully transmitted to agricultural prices when most trades in agricultural exchanges are made by financial investors. Distinguishing between different types of financial investors, we found that in the short run money managers appear to be more important than commodity index traders in transmitting financial shocks to agricultural markets. However, the effect of index investment appears to be more apparent in the long than in the short run, suggesting that an analysis of longer time-horizon correlations may be more appropriate in order to assess the importance of commodity index funds. In any case, we find that the relative influence of different types of traders seems to vary across markets. For example the influence of commodity index traders seems to be particularly strong in the cocoa markets, and relatively weaker in corn and wheat markets.

The evidence provided appears to suggest that increasing correlation between agricultural prices and stock market dynamics depends on a combination of financialization and financial crisis. This means that the influence of financial shocks on agricultural prices is likely to decrease as global financial tensions settle down (consistently with the decrease in the DCCs that we observe since late 2011 - Fig.1). But also that, as long as agricultural derivatives markets are populated mainly by financial investors, it can be expected to rise again when it is less needed, i.e. in the presence of new financial turmoil.

Table 6: Granger causality tests - Grains (subsample Oct.2008-Jul.2013)

| | (1) Corn | (2) Wheat | (3) Soybeans | (4) Soyb. Oil | (5) Soyb. Meal | (6) Oats | (7) Rice |
|---|---|---|---|---|---|---|---|
| AR(1) | 0.0138 | -0.0692** | -0.0170 | -0.0658** | -0.0124 | 0.123*** | 0.0930*** |
| | (0.641) | (0.020) | (0.572) | (0.034) | (0.671) | (0.000) | (0.002) |
| $SP500_{t-1}$ | 0.0706* | 0.102*** | 0.0785** | 0.134*** | 0.0425 | 0.0965*** | 0.0208 |
| | (0.067) | (0.009) | (0.011) | (0.000) | (0.202) | (0.010) | (0.448) |
| Const. | 0.0119 | 0.0139 | 0.0228 | 0.00433 | 0.0421 | 0.0102 | -0.00228 |
| | (0.839) | (0.816) | (0.620) | (0.923) | (0.412) | (0.860) | (0.957) |
| Obs. | 1213 | 1213 | 1213 | 1213 | 1213 | 1213 | 1213 |
| F | 2.135 | 4.870 | 3.293 | 9.538 | 0.832 | 15.31 | 6.168 |
| $R^2$ | 0.00352 | 0.00799 | 0.00541 | 0.0155 | 0.00137 | 0.0247 | 0.0101 |
| adj. $R^2$ | 0.00187 | 0.00635 | 0.00377 | 0.0139 | -0.000277 | 0.0231 | 0.00846 |

$p$-values in parentheses

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

All variables taken in daily percent changes

Table 7: Granger causality tests - Softs (subsample Oct.2008-Jul.2013)

| | (1) Cotton | (2) Cocoa | (3) Coffee | (4) Orange Juice | (5) Sugar_F1 |
|---|---|---|---|---|---|
| AR(1) | 0.0549* | -0.0301 | -0.0578* | 0.116*** | -0.0671** |
| | (0.065) | (0.308) | (0.052) | (0.000) | (0.023) |
| $SP500_{t-1}$ | 0.0883** | 0.134*** | 0.0983*** | 0.0836** | 0.0826** |
| | (0.013) | (0.000) | (0.004) | (0.020) | (0.028) |
| Const. | 0.0366 | 0.00509 | 0.00711 | 0.0447 | 0.0327 |
| | (0.497) | (0.924) | (0.891) | (0.424) | (0.568) |
| Obs. | 1213 | 1213 | 1213 | 1213 | 1213 |
| F | 6.542 | 7.444 | 4.855 | 12.24 | 4.059 |
| $R^2$ | 0.0107 | 0.0122 | 0.00796 | 0.0198 | 0.00666 |
| $adj.R^2$ | 0.00906 | 0.0105 | 0.00632 | 0.0182 | 0.00502 |

$p$-values in parentheses

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

All variables taken in daily percentage changes

Table 8: Granger causality tests - Livestock and lumber (subsample Oct.2008-Jul.2013)

| | (1) Live Cattle | (2) Lean Hogs | (3) Feeder Cattle | (4) Lumber |
|---|---|---|---|---|
| AR(1) | -0.0246 | -0.110*** | 0.109*** | 0.0792*** |
| | (0.409) | (0.000) | (0.000) | (0.006) |
| $SP500_{t-1}$ | 0.0351** | 0.0479** | 0.0214 | 0.00242 |
| | (0.020) | (0.041) | (0.164) | (0.945) |
| Const. | 0.0226 | 0.0245 | 0.0324 | 0.0466 |
| | (0.322) | (0.506) | (0.168) | (0.390) |
| Obs. | 1213 | 1213 | 1213 | 1213 |
| F | 2.715 | 8.961 | 9.614 | 3.859 |
| $R^2$ | 0.00447 | 0.0146 | 0.0156 | 0.00634 |
| $adj.R^2$ | 0.00282 | 0.0130 | 0.0140 | 0.00470 |

$p$-values in parentheses

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

all variables taken in daily percentage changes

Table 9: Determinants of the Dynamic Conditional Correlations with SP-500 - Grains

| | (1) DCC_corn | (2) DCC_wheat | (3) DCC_soy | (4) DCC_soyoil | (5) DCC_soymeal | (6) DCC_oats | (7) DCC_rice |
|---|---|---|---|---|---|---|---|
| AR(1) | 0.972*** | 0.933*** | 0.968*** | 0.956*** | 0.973*** | 0.973*** | 0.982*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\text{SHIP}_t$ | -0.0382 | -0.0717 | -0.0752** | -0.0382* | -0.0817** | -0.0489 | -0.0288 |
| | (0.139) | (0.251) | (0.013) | (0.087) | (0.021) | (0.125) | (0.147) |
| $\text{SHIP}_{t-1}$ | 0.0426 | 0.0898 | 0.0759** | 0.0332 | 0.0851** | 0.0614* | 0.0246 |
| | (0.100) | (0.152) | (0.012) | (0.138) | (0.017) | (0.055) | (0.216) |
| $\text{TED}_t$ | 0.0529*** | 0.0905*** | 0.0560*** | 0.0452*** | 0.0565*** | 0.0334** | 0.0242*** |
| | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.015) | (0.005) |
| $\text{TED}_{t-1}$ | -0.0333*** | -0.0575** | -0.0417*** | -0.0385*** | -0.0486*** | -0.0190 | -0.0223*** |
| | (0.003) | (0.034) | (0.001) | (0.000) | (0.002) | (0.168) | (0.009) |
| $\text{M3}_t$ | -0.00709 | -0.0319 | -0.00752 | 0.00637 | -0.0139 | -0.0191* | 0.00337 |
| | (0.442) | (0.153) | (0.486) | (0.425) | (0.272) | (0.094) | (0.633) |
| $\text{M3}_{t-1}$ | 0.00242 | 0.0277 | 0.00799 | -0.00376 | 0.0172 | 0.0134 | 0.00358 |
| | (0.793) | (0.215) | (0.459) | (0.637) | (0.175) | (0.240) | (0.611) |
| $\text{CPI}_t$ | 0.0428 | -0.312 | -0.0304 | 0.110 | -0.0702 | 0.0777 | -0.00696 |
| | (0.793) | (0.429) | (0.874) | (0.436) | (0.754) | (0.700) | (0.956) |
| $\text{CPI}_{t-1}$ | -0.0466 | 0.336 | 0.0273 | -0.102 | 0.0678 | -0.0713 | 0.0110 |
| | (0.776) | (0.395) | (0.887) | (0.470) | (0.763) | (0.724) | (0.931) |
| $\text{USD\_V}_t$ | -0.00347 | 0.00148 | -0.00173 | -0.00965 | 0.00587 | 0.00325 | 0.000714 |
| | (0.793) | (0.963) | (0.911) | (0.399) | (0.747) | (0.842) | (0.946) |
| $\text{L.USD\_V}_{t-1}$ | 0.000303 | -0.00903 | 0.00218 | 0.0141 | -0.00437 | -0.00835 | 0.00205 |
| | (0.982) | (0.778) | (0.888) | (0.218) | (0.810) | (0.609) | (0.844) |
| Lehman | 0.0965*** | 0.185*** | 0.0886*** | 0.145*** | 0.0728*** | 0.0871*** | 0.0471*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Const- | -0.0160*** | -0.0108 | -0.0158*** | -0.0146*** | -0.0135* | -0.0106* | -0.00645 |
| | (0.002) | (0.361) | (0.009) | (0.001) | (0.065) | (0.087) | (0.110) |
| Obs. | 1437 | 1437 | 1437 | 1437 | 1437 | 1437 | 1404 |
| F | 11513.2 | 1929.7 | 6973.0 | 15027.7 | 5933.1 | 7295.7 | 14048.5 |
| $R^2$ | 0.990 | 0.942 | 0.983 | 0.992 | 0.980 | 0.984 | 0.992 |
| adj. $R^2$ | 0.990 | 0.942 | 0.983 | 0.992 | 0.980 | 0.984 | 0.992 |

$p$-values in parentheses

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

All variables were standardized (except the dummy accounting for the post-Lehman period)

Table 10: Determinants of the Dynamic Conditional Correlations with SP-500 - Softs

| | (1) DCC_cotton | (2) DCC_cocoa | (3) DCC_coffee | (4) DCC_oj | (5) DCC_sugar |
|---|---|---|---|---|---|
| AR(1) | 0.978*** | 0.972*** | 0.962*** | 0.983*** | 0.803*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\text{SHIP}_t$ | 0.0152 | 0.00228 | 0.0328* | -0.00104 | -0.00356 |
| | (0.587) | (0.936) | (0.074) | (0.953) | (0.976) |
| $\text{SHIP}_{t-1}$ | -0.0244 | -0.000525 | -0.0297 | 0.000292 | -0.0258 |
| | (0.383) | (0.985) | (0.106) | (0.987) | (0.826) |
| $\text{TED}_t$ | 0.0419*** | 0.0195 | 0.0130* | 0.0147* | 0.169*** |
| | (0.001) | (0.115) | (0.100) | (0.051) | (0.001) |
| $\text{TED}_{t-1}$ | -0.0232* | -0.0241* | -0.00319 | -0.00890 | -0.113** |
| | (0.054) | (0.052) | (0.687) | (0.240) | (0.026) |
| $\text{M3}_t$ | -0.000450 | 0.00814 | -0.00594 | -0.00203 | 0.00329 |
| | (0.964) | (0.426) | (0.365) | (0.746) | (0.937) |
| $\text{M3}_{t-1}$ | 0.00172 | -0.000709 | 0.00841 | 0.00197 | 0.0171 |
| | (0.863) | (0.945) | (0.199) | (0.752) | (0.683) |
| $\text{CPI}_t$ | -0.0324 | 0.166 | 0.0949 | 0.0915 | -0.921 |
| | (0.854) | (0.358) | (0.413) | (0.408) | (0.213) |
| $\text{CPI}_{t-1}$ | 0.0262 | -0.168 | -0.113 | -0.0922 | 0.915 |
| | (0.882) | (0.353) | (0.330) | (0.405) | (0.217) |
| $\text{USD\_V}_t$ | 0.0105 | 0.00168 | 0.00549 | -0.0105 | 0.0648 |
| | (0.461) | (0.909) | (0.559) | (0.243) | (0.281) |
| $\text{L.USD\_V}_{t-1}$ | -0.0127 | 0.00710 | -0.00333 | 0.00558 | -0.0533 |
| | (0.375) | (0.628) | (0.723) | (0.534) | (0.374) |
| Lehman | 0.0685*** | 0.0700*** | 0.0913*** | 0.0423*** | 0.172*** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| Const. | -0.0121** | -0.0120** | -0.0148*** | 0.00382 | -0.0445** |
| | (0.022) | (0.042) | (0.000) | (0.312) | (0.047) |
| Obs. | 1437 | 1437 | 1437 | 1437 | 1437 |
| F | 9642.1 | 8839.4 | 18825.9 | 14072.4 | 290.8 |
| $R^2$ | 0.988 | 0.987 | 0.994 | 0.992 | 0.710 |
| adj. $R^2$ | 0.988 | 0.987 | 0.994 | 0.992 | 0.708 |

$p$-values in parentheses

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

All variables were standardized (except the dummy accounting for the post-Lehman period)

Table 11: Determinants of the Dynamic Conditional Correlations with SP-500 - Livestock and Lumber

| | (1)<br>DCC_lc | (2)<br>DCC_lh | (3)<br>DCC_fc | (4)<br>DCC_lumber |
|---|---|---|---|---|
| AR(1) | 0.953*** | 0.985*** | 0.963*** | 0.505*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $\text{SHIP}_t$ | -0.0495 | -0.0945** | -0.0495 | 0.0748 |
| | (0.182) | (0.033) | (0.248) | (0.686) |
| $\text{SHIP}_{t-1}$ | 0.0607 | 0.0887** | 0.0300 | -0.0388 |
| | (0.103) | (0.046) | (0.484) | (0.834) |
| $\text{TED}_t$ | 0.0111 | 0.0147 | 0.0326* | -0.00577 |
| | (0.489) | (0.443) | (0.077) | (0.942) |
| $\text{TED}_{t-1}$ | -0.0111 | -0.00347 | 0.0135 | 0.0310 |
| | (0.491) | (0.856) | (0.468) | (0.699) |
| $\text{M3}_t$ | -0.0386*** | 0.0207 | -0.0192 | -0.0162 |
| | (0.004) | (0.192) | (0.208) | (0.807) |
| $\text{M3}_{t-1}$ | 0.0204 | -0.0232 | 0.0165 | 0.0779 |
| | (0.126) | (0.144) | (0.279) | (0.239) |
| $\text{CPI}_t$ | -0.545** | 0.136 | -0.119 | -0.511 |
| | (0.021) | (0.627) | (0.659) | (0.662) |
| $\text{CPI}_{t-1}$ | 0.561** | -0.150 | 0.0797 | 0.585 |
| | (0.018) | (0.594) | (0.767) | (0.617) |
| $\text{USD\_V}_t$ | -0.0268 | 0.0371 | 0.000928 | -0.0346 |
| | (0.159) | (0.104) | (0.966) | (0.716) |
| $\text{L.USD\_V}_{t-1}$ | 0.0171 | -0.0474** | 0.000844 | 0.00655 |
| | (0.370) | (0.037) | (0.969) | (0.945) |
| Lehman | 0.109*** | -0.00604 | 0.0254 | 0.0726 |
| | (0.000) | (0.730) | (0.184) | (0.319) |
| Const. | -0.0000810 | -0.00628 | -0.0244*** | -0.0231 |
| | (0.991) | (0.462) | (0.003) | (0.511) |
| Obs. | 1437 | 1437 | 1437 | 1437 |
| F | 3486.1 | 3084.2 | 2741.0 | 43.71 |
| $R^2$ | 0.967 | 0.963 | 0.959 | 0.269 |
| adj. $R^2$ | 0.967 | 0.963 | 0.958 | 0.263 |

$p$-values in parentheses

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

All variables were standardized (except the dummy accounting for the post-Lehman period)

Table 12: Determinants of the Dynamic Conditional Correlations with S&P500 - Grains

| | (1)<br>DCC_corn | (2)<br>DCC_wheat | (3)<br>DCC_soy | (4)<br>DCC_soyoil |
|---|---|---|---|---|
| AR(1) | 0.887*** | 0.907*** | 0.966*** | 0.918*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $\text{SHIP}_t$ | 0.00979 | 0.0739 | -0.0415 | -0.0456 |
| | (0.810) | (0.412) | (0.340) | (0.159) |
| $\text{SHIP}_{t-1}$ | 0.0297 | -0.00752 | 0.0475 | 0.0388 |
| | (0.465) | (0.933) | (0.276) | (0.231) |
| $\text{TED}_t$ | 0.137*** | 0.104* | 0.0996*** | 0.126*** |
| | (0.000) | (0.088) | (0.000) | (0.000) |
| $\text{TED}_{t-1}$ | -0.0836*** | -0.0820 | -0.0623** | -0.108*** |
| | (0.002) | (0.176) | (0.012) | (0.000) |
| $\text{TED}_t \cdot Financial_{i,t}$ | 0.0551** | 0.166*** | 0.0272* | 0.0463** |
| | (0.016) | (0.007) | (0.076) | (0.040) |
| $\text{TED}_{t-1} \cdot Financial_{i,t-1}$ | -0.00945 | -0.0680 | 0.00499 | -0.0403* |
| | (0.676) | (0.275) | (0.740) | (0.077) |
| $\text{Lehman}_t$ | 0.424*** | 0.387*** | 0.139*** | 0.276*** |
| | (0.000) | (0.000) | (0.001) | (0.000) |
| $\text{Constant}_i$ | -0.132*** | -0.183*** | -0.0461** | -0.0562*** |
| | (0.000) | (0.000) | (0.028) | (0.001) |
| Observations | 394 | 394 | 394 | 394 |
| F | 3651.7 | 1020.7 | 2642.5 | 8064.4 |
| $R^2$ | 0.987 | 0.955 | 0.982 | 0.994 |
| adj.$R^2$ | 0.987 | 0.954 | 0.982 | 0.994 |

$p$-values in parentheses

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

All variables were standardized (except the dummy accounting for the post-Lehman period)

Table 13: Determinants of the Dynamic Conditional Correlations with S&P500 - Other agricultural commodities

| | (1) DCC_cotton | (2) DCC_cocoa | (3) DCC_coffee | (4) DCC_sugar | (5) DCC_fc |
|---|---|---|---|---|---|
| AR(1) | 0.908*** | 0.982*** | 0.891*** | 0.802*** | 0.948*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\text{SHIP}_t$ | 0.0516 | 0.00962 | 0.0457** | 0.132 | 0.000959 |
| | (0.155) | (0.798) | (0.029) | (0.416) | (0.988) |
| $\text{SHIP}_{t-1}$ | -0.0623* | -0.0136 | -0.0282 | -0.141 | -0.0142 |
| | (0.087) | (0.719) | (0.183) | (0.385) | (0.816) |
| $\text{TED}_t$ | 0.111*** | 0.0756*** | 0.0500*** | 0.275*** | 0.213*** |
| | (0.000) | (0.000) | (0.000) | (0.005) | (0.000) |
| $\text{TED}_{t-1}$ | -0.0887*** | -0.0636*** | -0.0301** | -0.185* | -0.153*** |
| | (0.000) | (0.002) | (0.011) | (0.057) | (0.000) |
| $\text{TED}_t \cdot Financial_{i,t}$ | 0.0475** | 0.0623*** | -0.00868 | 0.0605 | -0.163*** |
| | (0.023) | (0.000) | (0.364) | (0.465) | (0.000) |
| $\text{TED}_{t-1} \cdot Financial_{i,t-1}$ | -0.0537** | -0.0472*** | 0.0288*** | 0.00684 | 0.189*** |
| | (0.012) | (0.001) | (0.002) | (0.934) | (0.000) |
| $\text{Lehman}_t$ | 0.288*** | 0.0730** | 0.282*** | 0.303*** | 0.127*** |
| | (0.000) | (0.012) | (0.000) | (0.002) | (0.005) |
| $\text{Constant}_i$ | -0.0662*** | -0.0155 | -0.00427 | -0.116 | -0.0502 |
| | (0.004) | (0.433) | (0.684) | (0.136) | (0.118) |
| Observations | 394 | 394 | 394 | 394 | 394 |
| F | 5182.9 | 2285.8 | 8380.5 | 148.6 | 1848.6 |
| $R^2$ | 0.991 | 0.979 | 0.994 | 0.755 | 0.975 |
| adj.$R^2$ | 0.991 | 0.979 | 0.994 | 0.750 | 0.974 |

$p$-values in parentheses

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

All variables were standardized (except the dummy accounting for the post-Lehman period)

Table 14: Determinants of the Dynamic Conditional Correlations with SP-500 - Grains

| | (1)<br>DCC_corn | (2)<br>DCC_wheat | (3)<br>DCC_soy | (4)<br>DCC_soyoil |
|---|---|---|---|---|
| AR(1) | 0.890*** | 0.909*** | 0.958*** | 0.918*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $\text{SHIP}_t$ | 0.0154 | 0.0776 | -0.0416 | -0.0458 |
| | (0.706) | (0.388) | (0.344) | (0.147) |
| $\text{SHIP}_{t-1}$ | 0.0198 | -0.0320 | 0.0310 | 0.0431 |
| | (0.628) | (0.723) | (0.475) | (0.172) |
| $\text{TED}_t$ | 0.0939** | 0.108* | 0.0846*** | 0.0840*** |
| | (0.019) | (0.073) | (0.001) | (0.002) |
| $\text{TED}_{t-1}$ | -0.0493 | -0.0874 | -0.0436* | -0.0629** |
| | (0.207) | (0.147) | (0.081) | (0.021) |
| $\text{TED}_t \cdot MM_t$ | 0.0479*** | 0.153*** | 0.0374*** | 0.0549*** |
| | (0.008) | (0.002) | (0.007) | (0.000) |
| $\text{TED}_{t-1} \cdot MM_{t-1}$ | -0.00788 | -0.0589 | 0.00508 | -0.0544*** |
| | (0.659) | (0.231) | (0.703) | (0.000) |
| $\text{TED}_t \cdot CIT_t$ | -0.0161 | 0.0776* | -0.0414* | -0.0434** |
| | (0.667) | (0.094) | (0.094) | (0.049) |
| $\text{TED}_{t-1} \cdot CIT_{t-1}$ | 0.0362 | -0.0541 | 0.0460* | 0.0588*** |
| | (0.336) | (0.257) | (0.069) | (0.008) |
| $\text{Lehman}_t$ | 0.400*** | 0.349*** | 0.137*** | 0.284*** |
| | (0.000) | (0.000) | (0.001) | (0.000) |
| $\text{Constant}_i$ | -0.120*** | -0.153*** | -0.0279 | -0.0632*** |
| | (0.000) | (0.003) | (0.208) | (0.000) |
| Observations | 394 | 394 | 394 | 394 |
| F | 2937.5 | 821.9 | 2176.5 | 6790.4 |
| $R^2$ | 0.987 | 0.955 | 0.983 | 0.994 |
| adj.$R^2$ | 0.987 | 0.954 | 0.982 | 0.994 |

$p$-values in parentheses

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

All variables were standardized (except the dummy accounting for the post-Lehman period)

Table 15: Determinants of the Dynamic Conditional Correlations with SP-500 - Other commodities

| | (1) DCC_cotton | (2) DCC_cocoa | (3) DCC_coffee | (4) DCC_sugar | (5) DCC_fc |
|---|---|---|---|---|---|
| AR(1) | 0.902*** | 0.986*** | 0.894*** | 0.805*** | 0.948*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $\text{SHIP}_t$ | 0.0515 | 0.0322 | 0.0408* | 0.0605 | 0.000383 |
| | (0.157) | (0.389) | (0.051) | (0.708) | (0.835) |
| $\text{SHIP}_{t-1}$ | -0.0622* | -0.0291 | -0.0244 | -0.0775 | -0.000619 |
| | (0.094) | (0.434) | (0.248) | (0.630) | (0.733) |
| $\text{TED}_t$ | 0.0890*** | 0.0678*** | 0.0607*** | 0.381*** | 0.00603*** |
| | (0.000) | (0.002) | (0.000) | (0.000) | (0.000) |
| $\text{TED}_{t-1}$ | -0.0664*** | -0.0609*** | -0.0391*** | -0.257** | -0.00449*** |
| | (0.007) | (0.004) | (0.002) | (0.010) | (0.000) |
| $\text{TED}_t \cdot MM_t$ | 0.0578*** | 0.0324** | -0.00582 | 0.168** | -0.00366*** |
| | (0.005) | (0.020) | (0.623) | (0.016) | (0.000) |
| $\text{TED}_{t-1} \cdot MM_{t-1}$ | -0.0646*** | -0.0337** | 0.0323*** | -0.153** | 0.00430*** |
| | (0.002) | (0.015) | (0.006) | (0.032) | (0.000) |
| $\text{TED}_t \cdot CIT_t$ | 0.00802 | 0.0718*** | 0.0208* | 0.212** | -0.00343*** |
| | (0.703) | (0.000) | (0.082) | (0.013) | (0.002) |
| $\text{TED}_{t-1} \cdot CIT_{t-1}$ | -0.0141 | -0.0360** | -0.00600 | -0.184** | 0.00436*** |
| | (0.502) | (0.024) | (0.621) | (0.032) | (0.000) |
| $\text{Lehman}_t$ | 0.306*** | 0.0779*** | 0.278*** | 0.295*** | 0.00389*** |
| | (0.000) | (0.006) | (0.000) | (0.006) | (0.004) |
| $\text{Constant}_i$ | -0.0711*** | -0.0283 | -0.00483 | -0.104 | 0.00155* |
| | (0.003) | (0.147) | (0.677) | (0.206) | (0.097) |
| Observations | 394 | 394 | 394 | 394 | 394 |
| F | 4160.1 | 1908.6 | 6794.2 | 120.4 | 1476.3 |
| $R^2$ | 0.991 | 0.980 | 0.994 | 0.759 | 0.975 |
| adj.$R^2$ | 0.991 | 0.980 | 0.994 | 0.752 | 0.974 |

$p$-values in parentheses

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

All variables were standardized (except the dummy accounting for the post-Lehman period)

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# Appendix A - Dataset and sources

**Agricultural futures prices** Futures prices for 16 agricultural commodities in US commodity exchanges were downloaded from Quandl (`http://www.quandl.com/futures`). In particular, we employ data on Corn, Wheat, Soybeans, Soybean Oil, Soybean Meal, Oats and Rough Rice Futures traded on the Chicago Board of Trade (CBOT); Sugar, Coffee, Cocoa, Cotton, Orange Juice traded on the Inter-Continental Exchange in the US (ICE-US),; Live Cattle, Lean Hogs, Feeder Cattle and Lumber Futures traded on the Chicago Mercantile Exchange;
For each commodity, the futures price time-series was obtained as an equally weighted average of the price for all contracts with maturity up to one year ahead (the same procedure adopted in [24] and [14]). Returns were calculated as percentage changes in prices.

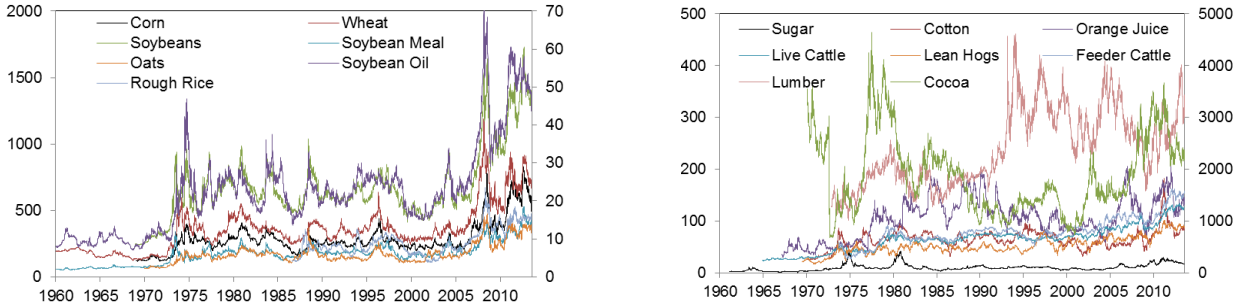


Figure 4: Average futures prices (daily data; Jan.1960 - Jul.2013)*Source: Author's own calculations on Quandl data*

Notes: Prices are quoted in cents of dollars per bushel for corn, wheat, soybeans and oats; in cents per short ton for soybean meal; in cents per pound for soybean oil, cotton, coffee, sugar, orange juice, feeder cattle, live cattle and lean hogs; in cents per hundredweight for rough rice; in dollars per metric ton for cocoa; in dollars per $1,000$ board feet for lumber. In the first panel, soybean oil and rough rice on the right axis; all other grains on the left axis. In the second panel, cocoa on the right axis, all other commodities on the left axis.

**Stock Market Returns** The S&P 500 index series was downloaded from Yahoo Finance (`http://finance.yahoo.com`)

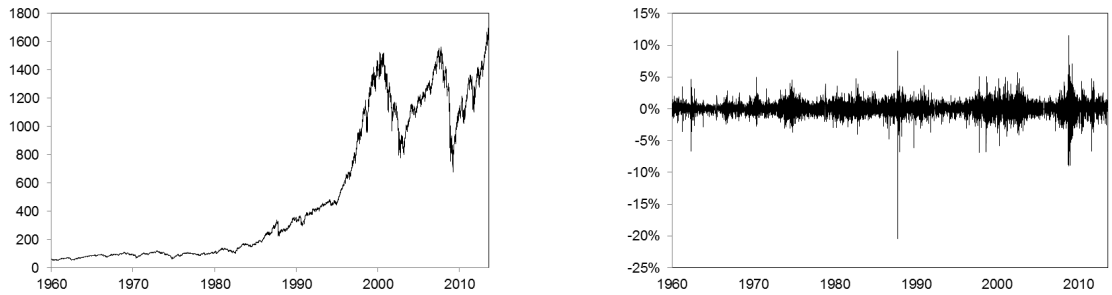

Figure 5: S&P 500 index (Daily data; Jan.1960 - Jul.2013) *Source: Yahoo Finance*

Note: Left panel depicts the value of the index. Right panel depicts percentage returns on the index.

**TED Spread** The TED spread is difference between the 3-Month London Interbank Offered Rate (LIBOR) and the 3-Month Treasury Bill secondary market rate. Both series were downloaded from the Federal Reserve Economic Data (FRED - `http://research.stlouisfed.org/fred2`).

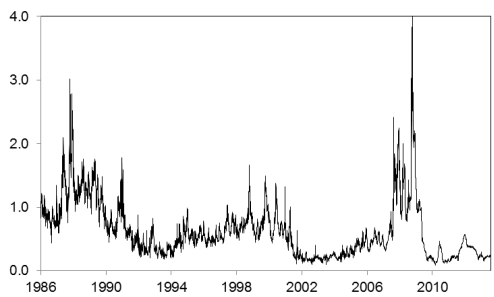

Figure 6: TED spread (daily data; Jan.1986 - Jul. 2013 *Source: Federal Reserve Economic Data (FRED)*

**Kilian index** The Kilian Index of global real economic activity in industrial commodity markets is downloadable from the website of Prof.Kilian at `http://www-personal.umich.edu/~lkilian/paperlinks.html`. It is calculated on the basis of dry cargo ocean freight rates (see [17] for details).

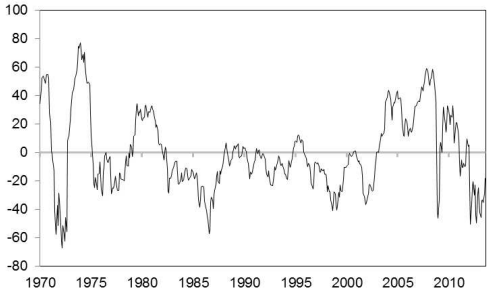


Figure 7: Kilian index of global demand for commodities
(monthly data; percent deviations from trend; Jan.1970 - Jul. 2013) *Source: Prof. Lutz Kilian*

**Composition of agricultural derivatives markets** Data about the share of financial investors in total reportable positions in US agricultural derivatives exchanges were calculated from the data made available by the Commodity Futures Trading Commission (CFTC) in its "Committment of Traders - Commodity Index Trader Supplement"(SCOT). The SCOT provides a breakdown of each Tuesdays open interest between non-commercial traders (excluding commodity index traders), commodity index traders and commercial hedgers. It is available only for the period since 2006 for 12 selected agricultural markets. The SCOT is an improvement over the COT, which is published since 1992 but in which commodity index traders' positions are not identifiable and they are attributed in part to commercial hedgers and in part to money managers (which means that a large part of the position taken by financial investors through commodity index trading is attributed to commercial operators). The SCOT is available at `http://www.cftc.gov/MarketReports/index.htm`

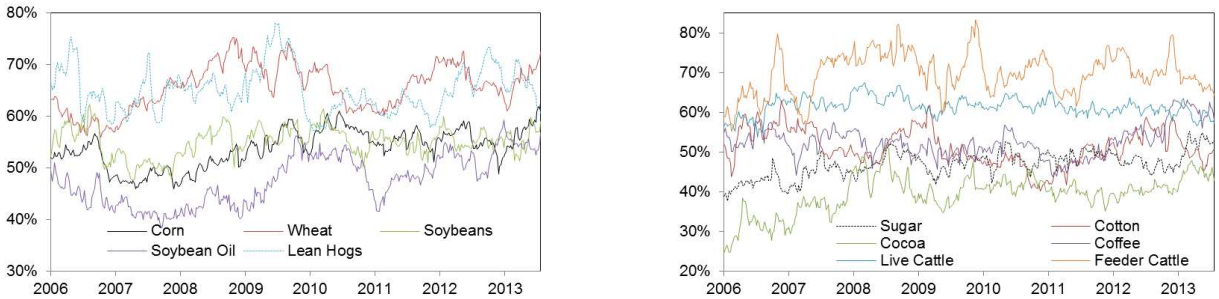


Figure 8: Share of financial investors in reportable positions in US agricultural exchanges
(weekly data; Jan.2007 - Jul.2013)
*Source: CFTC*

**Core inflation** Data on changes in the Consumer Price Index excluding food and energy for OECD countries were downloaded from the OECD database at `http://stats.oecd.org/Index.aspx?DatasetCode=MEI_PRICES`.

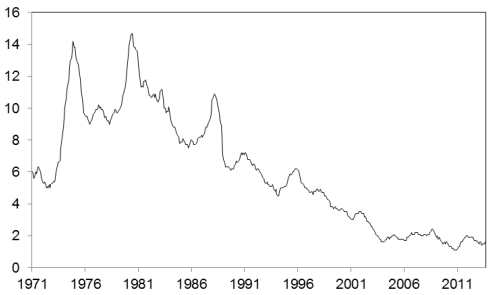


Figure 9: Core Inflation in OECD Countries. *Source: OECD Statistical Database*
Consumer Price Index excluding Food and Energy Items - % change on the same period of the previous year

**Broad Money** Data on changes in the broad monetary aggregate M3 in OECD countries were downloaded from the OECD database accessible on-line at `http://stats.oecd.org/Index.aspx?DatasetCode=MEI_FIN`

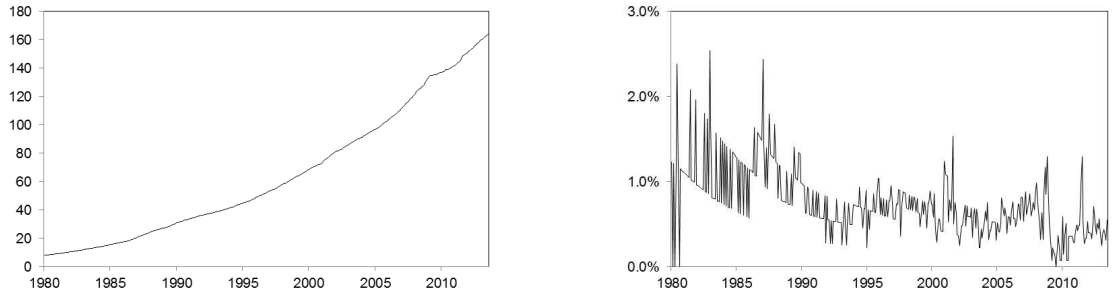


Figure 10: M3 Aggregate in OECD countries (monthly data; Jan.1980 - Jul.2013) *Source: OECD Statistical Database*

Notes: Index 2005=100, Seasonally Adjusted. Left panel depicts the value of the index. Right panel depicts percentage changes.

**US Dollar Exchange Rate** As a proxy for the US Dollar exchange rate, we employ the 'Trade Weighted US Dollar Index' against major currencies, calculated by the Federal Reserve and available at the FRED database (`http://research.stlouisfed.org/fred2`). In order to measure its volatility, we calculate 12-weeks standard deviations.

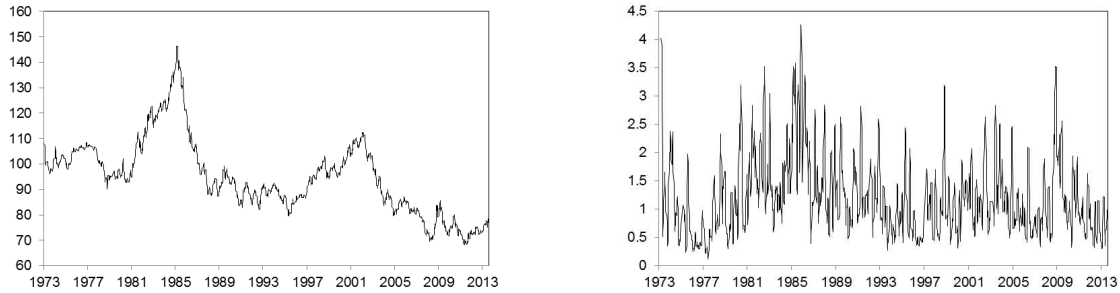


Figure 11: US Dollar exchange rate (left panel) and 12-weeks standard deviation (right panel) (weekly data; Jan.1973 - Jul.2013)
*Source: OECD Statistical Database*

Notes: Trade Weighted US Dollar Index against Major Currencies (TWEXM). Index, March 1973=100.
*Source: Federal Reserve Economic Data (FRED)*

All the on-line databases mentioned above were accessed between July and October 2013.