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Financialization of food. Modelling the time-varying relation between agricultural prices and stock market dynamics

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This article studies the correlation of agricultural prices with stock market dynamics. We discuss the possible role of financial and macroeconomic factors in driving this time-varying relation, with the aim of understanding what 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 agricultural prices, in order to assess patterns that are specific to agricultural commodities but also differences across markets. We show that an explanation based on a combination of financialization and financial crisis is consistent with the empirical evidence in most markets, while global demand factors don't appear to play a significant role. The correlation between agricultural prices and stock market returns tends to increase during periods of financial turmoil. The impact of financial turmoil on the correlation gets stronger as the share of financial investors in agricultural derivatives markets rises. Our findings suggest that the influence of financial shocks on agricultural prices should decrease as global financial tensions settle down but also that, as long as agricultural markets are 'financialized', it might rise again when it is less needed, i.e. in the presence of new financial turmoil.

Keywords: Asset Price Speculation; Financial Liberalisation

AMS Subject Classifications: Q11; Q13; G12; G13

1. Introduction

Until recent years, commodity price dynamics had usually been regarded as largely independent of short-run fluctuations in financial markets (Gorton and Rouwenhorst 2004). 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 commodity futures since the early 2000s (Basu and Gavin 2011).

Since the burst of the global financial crisis, however, 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. The transmission of financial shocks could significantly add to the volatility of commodity prices in periods of financial turmoil.

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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 (Bicchetti and Maystre 2013), that financial shocks appear to be important predictors of correlation dynamics (Silvennoinen and Thorp 2013) 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 (in particular hedge funds that are active also in the stock market) in commodity derivatives market (Büyükşahin and Robe 2013). Basak and Pavlova (2013) 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).

We focus here on agricultural commodities. In a working paper which was released while the present work was in progress, Bruno et al. (2013) study two price indices, composed respectively by grains and livestocks, through a structural VAR model. They argue that increasing correlation of these indices with the S&P500 stock market index is mainly due to the evolution of market fundamentals, while financialization played a limited role, if any. In this article, by studying agricultural prices instead of price-indices, we provide evidence supporting a different view, namely that a combination of financial turmoil and financialization is at the root of the recent increase in correlation between agricultural prices and stock market dynamics.

In particular, we analyse 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 (Engle 2002) 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 caused positive correlation in recent years. We discuss the possible role of macroeconomic fundamentals, monetary expansion, financial turmoil and the financialization of agricultural derivatives markets (Section 3). Then 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 to estimate the pattern of a time-varying correlation coefficient are moving-window analysis and Kalman filters (Meinhold and Nozer 1983). However, both rolling correlations[2] and Kalman filtering can be seriously biased in the presence of volatility clustering[3] (Lebo and Box-Steffensmeier 2008). For this reason, since it is well-known that both stock market returns and agricultural prices display heteroskedasticity (Schwert and Seguin 1990; Stigler 2011), we employ a Dynamic Conditional Correlation (DCC) approach.

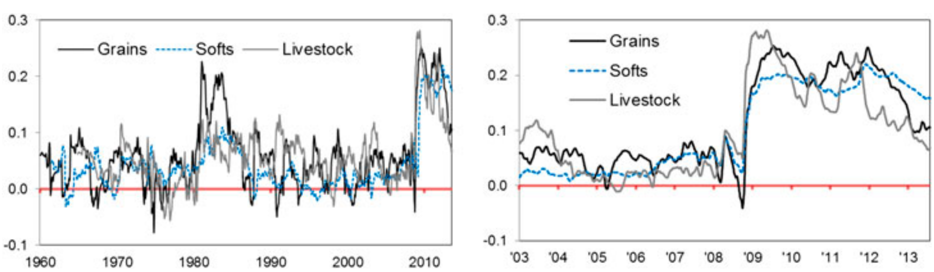
The DCC is estimated in two steps (Engle 2002). First, the mean and the variance of each variable are modelled as Garch (Engle 1982; Bollerslev 1986) processes. Standardized residuals from the first step are then used in order to estimate a time-varying correlation matrix. This procedure yields a consistent estimation of the likelihood function (Engle and Shepperd 2001). 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 correlation between agricultural price changes and returns on the S&P500 stock market index is depicted in Figure 1, which presents average DCCs for grains, softs and livestocks. DCCs for each single commodity are shown in Figure 2.

Before the recent financial crisis the correlation of agricultural price changes with stock market returns appears to have fluctuated mildly, mainly in the range between zero and 0.1, with the only exception of the early Eighties. Strikingly, the correlation 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 (Figure 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. The only commodities in our sample that behave in a different way are lean hogs and lumber. The correlation of lean hogs price with S&P500 fluctuates much more wildly in the whole sample, and several periods of positive correlation are displayed. The price of lumber, instead, has 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[4] (Figure 2).

In order to complete the picture, it is useful 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[5] by estimating the following OLS regressions for the sub-period September 2008-July 2013:



(a) Jan.1960-Jul.2013 *(b)* Jan.2003-Jul.2013

Figure 1. Dynamic Conditional Correlation (DCC) between agricultural prices and S&P500
Notes: 20-days moving averages. Lean hogs is excluded from livestocks, because its DCC follows a very different pattern from that of other commodities in this group.

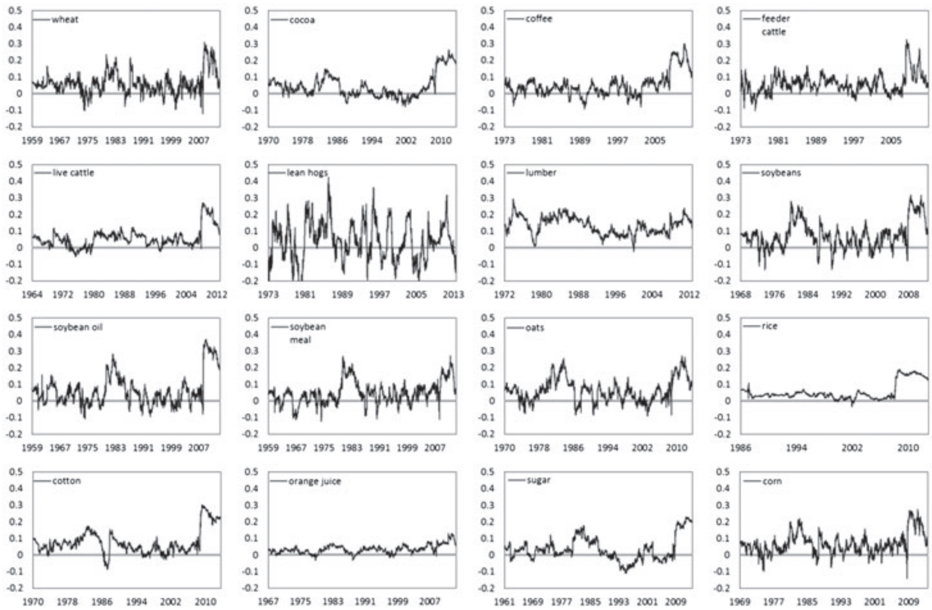


Figure 2. Dynamical Conditional Correlation (DCC) with S&P500.

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

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 Table 1, indicate that stock market returns tend to lead agricultural prices in most markets, while the reverse is not true in any market. β_2 is indeed significant at the 0.05 level for 11 agricultural commodities out of 16, while γ_2 is never significant at any conventional level.[6] The sign of β_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 given that 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.

Table 1. Granger causality tests – (subsample Oct.2008–Jul.2013).

	(1) Corn	(2) Wheat	(3) Soybeans	(4) Soyb. Oil	(5) Soyb. Meal	(6) Oats	(7) Rice	(8) Cotton
AR(1)	0.0138	−0.0692**	−0.0170	−0.0658**	−0.0124	0.123***	0.0930***	0.0549*
	(0.641)	(0.020)	(0.572)	(0.034)	(0.671)	(0.000)	(0.002)	(0.065)
$SP500_{t-1}$	0.0706*	0.102***	0.0785**	0.134***	0.0425	0.0965***	0.0208	0.0883**
	(0.067)	(0.009)	(0.011)	(0.000)	(0.202)	(0.010)	(0.448)	(0.013)
Const.	0.0119	0.0139	0.0228	0.00433	0.0421	0.0102	−0.00228	0.0366
	(0.839)	(0.816)	(0.620)	(0.923)	(0.412)	(0.860)	(0.957)	(0.497)
Obs.	1213	1213	1213	1213	1213	1213	1213	1213
F	2.135	4.870	3.293	9.538	0.832	15.31	6.168	6.542
R^2	0.00352	0.00799	0.00541	0.0155	0.00137	0.0247	0.0101	0.0107
adj. R^2	0.00187	0.00635	0.00377	0.0139	−0.000277	0.0231	0.00846	0.00906

	(9) Cocoa	(10) Coffee	(11) Or. Juice	(12) Sugar	(13) Live Cattle	(14) Lean Hogs	(15) Feeder Cattle	(16) Lumber
AR(1)	−0.0301	−0.0578*	0.116***	−0.0671**	−0.0246	−0.110***	0.109***	0.0792***
	(0.308)	(0.052)	(0.000)	(0.023)	(0.409)	(0.000)	(0.000)	(0.006)
$SP500_{t-1}$	0.134***	0.0983***	0.0836**	0.0826**	0.0351**	0.0479**	0.0214	0.00242
	(0.000)	(0.004)	(0.020)	(0.028)	(0.020)	(0.041)	(0.164)	(0.945)
Const.	0.00509	0.00711	0.0447	0.0327	0.0226	0.0245	0.0324	0.0466
	(0.924)	(0.891)	(0.424)	(0.568)	(0.322)	(0.506)	(0.168)	(0.390)
Obs.	1213	1213	1213	1213	1213	1213	1213	1213
F	7.444	4.855	12.24	4.059	2.715	8.961	9.614	3.859
R^2	0.0122	0.00796	0.0198	0.00666	0.00447	0.0146	0.0156	0.00634
$adj.R^2$	0.0105	0.00632	0.0182	0.00502	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 percent changes.

Financial turmoil The timing of the recent upward shift in the DCC series (Figure 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 (Büyükşahin and Robe 2013) that in recent years[7] 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 Figure 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 (FDIC 1997; IMF 1982). 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) 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

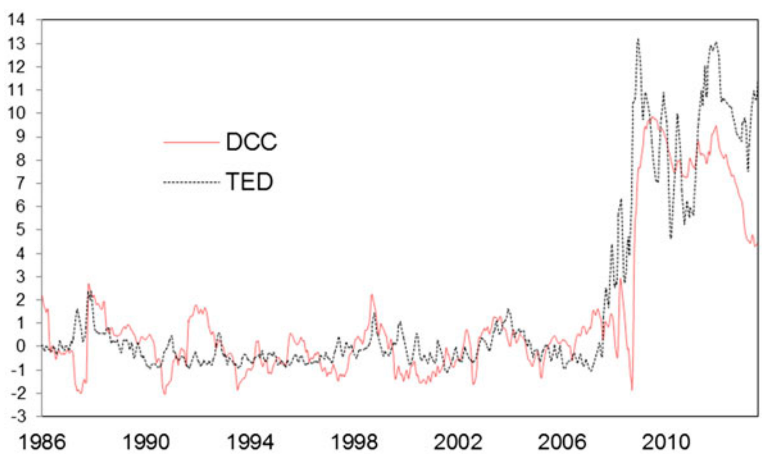


Figure 3. Average correlation of agr. commodities with equities (DCC) vs. financial turmoil (TED) (standard deviations from the mean; Jan.1986–Jul. 2013)

Notes: 20-days moving averages. DCC is averaged across our sample of agricultural commodities (excluding lumber because of its peculiar pattern); TED spread is expressed as a % of LIBOR.

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 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[8]).

From a theoretical point of view, how would financial turmoil result in positive correlation between agricultural and stock prices? A possible answer relies on commodity derivatives trading by financial institutions. We will discuss it after having briefly exposed the recent dynamics of agricultural derivatives 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 (Girardi 2012, pp.83–88).

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 (2010), 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. Tang and Xiong (2010, 2012) also argue that commodity index trading[9] contributed to the increase in correlation between oil and non-energy commodities and provide empirical evidence in support of that claim. Even more importantly from our point of view, Büyükşahin and Robe (2013) showed that the DCC between S&P-GSCI and S&P500 tends to increase amid greater participation of hedge funds in commodity derivatives markets.

However, the financialization of agricultural commodity markets started in the early 2000s and was already overwhelming in 2006–2007 (UNCTAD 2011; Girardi 2012), 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 a 'flight to liquidity', causing a decrease in prices. Moreover, the expectation that the financial crisis will affect negatively the real economy may lead investors to forecast a decline in commodity 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 (2010) 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. This reasoning implies that financialized commodity markets need not produce a commodity-equity correlation of a definite sign in tranquil periods, but they may do so amid financial turmoil. *Prima facie* evidence would appear consistent with this hypothesis: the relation between financial turmoil and our estimated DCCs appears to have been less tight before financialization (Figure 3).

Let us examine more closely the theoretical underpinnings of the hypothesis that a combination of financialization and financial turmoil can explain the recent increase in the correlation between agricultural prices and stock market returns. In periods of financial turmoil, the correlation between different financial assets can increase because of wealth effects: limited liquidity and borrowing constraints push financial intermediaries to liquidate positions simultaneously in all the markets in which they operate in response to significant losses incurred in one important market (Kyle and Xiong 2001; Danielsson et al. 2013). Financialization caused a change in the nature of agricultural derivatives markets: the share of positions held by financial intermediaries, who treat commodities as an asset class and operate also in the stock market, increased abruptly; the share of commercial traders, who employ agricultural derivatives to hedge their 'physical' trades in agricultural goods and are generally not exposed to stock market fluctuations, decreased dramatically (Büyükşahin and Robe 2013; UNCTAD 2011; Girardi 2012). In short, amid financial distress the correlation between different assets can increase because of 'contagion behavior' by financial intermediaries and financialization implied increasing involvement of financial intermediaries in agricultural futures markets. In this sense, financialization can have enhanced the transmission of financial turmoil to agricultural commodity markets.

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 (2010). 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 (Büyükşahin and Robe 2013) 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 Figures 1 and 4 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.

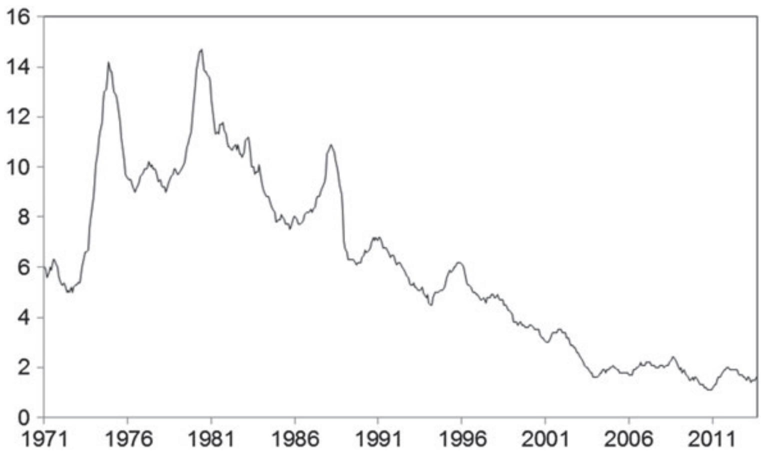


Figure 4. Core Inflation in OECD Countries. *Source: OECD Statistical Database* Consumer Price Index excluding Food and Energy Items – % change on the same period of the previous year.

Monetary policy The hypothesis that monetary policy affects stock prices has been advanced by several authors of different inspiration (see for example the review in Sellin 2001). Monetary policy is also mentioned in the literature on recent agricultural price trends. Sensitivity of agricultural prices to monetary policy can be motivated 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 expansive monetary policy is likely to result in a significant increase in prices. Furthermore, monetary policy could influence agricultural prices through the speculative channel: cheaper credit would increase demand for risky assets, including commodity derivatives (Basu and Gavin 2011, p.44). It is thus possible to hypothesize that the hyper-expansive monetary policy enacted in response to the recent financial crisis may have influenced demand for both stocks and agricultural goods, resulting in positive correlation between their prices.

Most economists today recognize that money is endogenous and that monetary policy is enacted through the interest rate, not the stock of money (Lavoie 2003; McLeay et al. 2014). So it appears more appropriate to study the role of the interest rate,[10] rather than focusing on the quantity of money as done by some previous studies on agricultural price trends (e.g. Gilbert (2010), which argues that monetary growth, measured through the M3 aggregate, has influenced agricultural price dynamics in the last four decades[11]).

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 agricultural prices both theory and empirical evidence largely point to a negative relation with the US Dollar exchange rate (as explained for example by Gilbert 2010), 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.

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 may have played a part in connecting agricultural prices to stock market dynamics in the first half of the Eighties. Volatility in 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. More plausibly, it was financial market dynamics that affected exchange rate movements immediately after the Lehman bankruptcy.

4. Empirical test

In what follows, we 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 risk-less 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 attributed to financial institutions in agricultural derivatives exchanges (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").[12]

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 (2009)[13] on the basis of dry cargo ocean freight rates.

Core inflation in OECD countries[14] is measured by percentage changes in the Consumer Price Index excluding food and energy. As a proxy for monetary policy, we employ the US Federal Funds Rate (i.e., the interest rate at which balances held at the Central Bank are traded overnight).[15]

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 the appendix. Some of these variables are available only at weekly or monthly frequencies. We take weekly observations of all variables,[16] after interpolating monthly series (the Kilian Index, and core inflation) by assuming linear growth between weeks of the same month. We limit our empirical analysis to the period 1986–2013, for which all our variables of interest are available.

Stationarity and structural breaks As suggested by visual inspection of Figures 1 and 2, almost all the DCCs present a structural break in late 2008. ADF unit-root tests (Said and Dickey 1984) reveal that we cannot reject at any conventional level the null of non-stationarity for 10 agricultural commodities out of 16 (Table 2). 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 3). 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.[17]

Estimation and results We estimate the following ARDL model:

$$\begin{aligned} DCC_{i,t} = {} & \beta_{0,i} + \beta_{1,i} DCC_{i,t-1} + \beta_{2,i} SHIP_t + \beta_{3,i} SHIP_{t-1} + \beta_{4,i} TED_t \\ & + \beta_{5,i} TED_{t-1} + \beta_{6,i} IR_t + \beta_{7,i} IR_{t-1} + \beta_{8,i} CPI_t + \beta_{9,i} CPI_{t-1} \\ & + \beta_{10,i} USD\_V_t + \beta_{11,i} USD\_V_{t-1} + \beta_{12,i} Lehman_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

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; *IR* is the US federal funds rate;[18] *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; ϵ 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). They will be introduced in the

Table 2. P-value for the null hypothesis of non-stationarity of the DCC series (Jul.1986–Jul.2013).

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	Or. Juice	Sugar	L.Cattle	Lean Hogs	F.Cattle	Lumber
0.38	0.65	0.77	$1.1 \cdot 10^{-15}$	0.04	0.06	0.02	$2.1 \cdot 10^{-30}$

(P-value computed through an Augmented Dickey Fuller (ADF) unit-root test.)

Table 3. 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).

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	Or. Juice	Sugar	L.Cattle	Lean Hogs	F.Cattle	Lumber
0.01	0.04	0.03	$2.9 \cdot 10^{-17}$	$1.3 \cdot 10^{-4}$	0.06	0.01	$2.1 \cdot 10^{-30}$

(ADF unit-root test on the residuals from the regression of the DCC series on the 'post-Lehman dummy').

next paragraph. Usual selection criteria (Schwartz and Akaike) suggested the introduction of just one lag of each variable. Results are summarized in Tables 4 and 5.

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

For those cases in which the contemporaneous effect of *TED* is positive and significant (13 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 (with the exception of cocoa, for which it is slightly larger). An adjustment process seems to be at work: a surge in the correlation, due to contemporaneous financial turmoil, tends to be partially corrected by a subsequent decrease. Long-run coefficients for the *TED* variable for those commodities for which β_4 was found to be significant are reported in Table 6. On average for all commodities for which the effect of *TED* is significant, the long-run multiplier is 0.48, which means that an increase of one standard deviation in the TED spread tends to be associated with a cumulated increase of 0.48 standard deviations in the weekly DCC.

Global macroeconomic conditions seem to exert a much weaker effect. The coefficient of the Kilian index 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.

Overall, exchange rates, inflation and monetary policy don't appear to exert a relevant effect on our DCCs. The coefficient of *CPI* is 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; that of *USD_V* is positive and significant at the 90% level only for lean hogs; the effect of the interest rate is negative and significant only in the markets for coffee, lean hogs and feeder cattle, and not significant for the remaining 13 commodities.

The dummy accounting for the post-Lehman period is positive and highly significant for all commodities except lean hogs, feeder cattle and lumber.

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 persistence of the phenomenon. This is revealed by differences among commodities: while most AR(1) coefficients are above 0.9, the ones

Table 4. Determinants of the Dynamic Conditional Correlations with S&P-500.

	(1) DCC_Corn	(2) DCC_Wheat	(3) DCC_Soyb.	(4) DCC_Soyb.Oil	(5) DCC_Soyb.Meal	(6) DCC_Oats	(7) DCC_Rice	(8) DCC_Cotton
AR(1)	0.973***	0.934***	0.968***	0.956***	0.972***	0.975***	0.982***	0.977***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SHIP_t$	−0.0354	−0.0641	−0.0733**	−0.0383*	−0.0796**	−0.0445	−0.0293	0.0173
	(0.169)	(0.304)	(0.015)	(0.086)	(0.025)	(0.162)	(0.140)	(0.535)
$SHIP_{t-1}$	0.0406	0.0828	0.0743**	0.0332	0.0826**	0.0573*	0.0241	−0.0261
	(0.116)	(0.186)	(0.014)	(0.138)	(0.020)	(0.074)	(0.226)	(0.348)
TED_t	0.0534***	0.0909***	0.0565***	0.0468***	0.0569***	0.0329**	0.0259***	0.0436***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.017)	(0.003)	(0.000)
TED_{t-1}	−0.0332***	−0.0554**	−0.0414***	−0.0373***	−0.0483***	−0.0188	−0.0207**	−0.0216*
	(0.003)	(0.040)	(0.002)	(0.000)	(0.002)	(0.171)	(0.016)	(0.072)
IR_t	−0.0923	0.0196	−0.0950	−0.0776	−0.0873	−0.0122	−0.0226	−0.0925
	(0.146)	(0.898)	(0.202)	(0.158)	(0.319)	(0.876)	(0.645)	(0.178)
IR_{t-1}	0.0756	−0.0446	0.0895	0.0672	0.0902	0.0000498	0.0221	0.0746
	(0.235)	(0.772)	(0.231)	(0.223)	(0.304)	(0.999)	(0.653)	(0.278)
CPI_t	0.0395	−0.299	−0.0277	0.107	−0.0605	0.0857	−0.000451	−0.0354
	(0.808)	(0.449)	(0.885)	(0.447)	(0.787)	(0.671)	(0.997)	(0.840)
CPI_{t-1}	−0.0297	0.340	0.0274	−0.0964	0.0536	−0.0678	−0.00289	0.0381
	(0.855)	(0.389)	(0.886)	(0.494)	(0.811)	(0.737)	(0.982)	(0.829)
USD_V_t	−0.00425	−0.000148	−0.00267	−0.0102	0.00466	0.00248	0.000182	0.00966
	(0.748)	(0.996)	(0.863)	(0.373)	(0.798)	(0.880)	(0.986)	(0.498)
USD_V_{t-1}	0.000179	−0.00878	0.00244	0.0134	−0.00352	−0.00781	0.00166	−0.0134
	(0.989)	(0.784)	(0.875)	(0.242)	(0.846)	(0.633)	(0.874)	(0.348)
Lehman	0.0796***	0.163***	0.0845***	0.138***	0.0764***	0.0720***	0.0476***	0.0579***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)	(0.003)
Const.	−0.0136***	−0.00894	−0.0159***	−0.0156***	−0.0150**	−0.00778	−0.00939**	−0.0125**
	(0.004)	(0.417)	(0.005)	(0.000)	(0.029)	(0.172)	(0.013)	(0.011)
Obs.	1437	1437	1437	1437	1437	1437	1404	1437
F	11549.8	1929.0	6979.6	15059.5	5929.7	7285.9	14007.0	9679.4
R^2	0.990	0.942	0.983	0.992	0.980	0.984	0.992	0.988
adj.R^2	0.990	0.942	0.983	0.992	0.980	0.984	0.992	0.988

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 5. Determinants of the Dynamic Conditional Correlations with S&P-500 (Continued).

	(9) DCC_Cocoa	(10) DCC_Coffee	(11) DCC_Or.Juice	(12) DCC_Sugar	(13) DCC_L.Cattle	DCC_L.Hogs	DCC_F.Cattle	DCC_Lumber
AR(1)	0.973***	0.960***	0.982***	0.805***	0.959***	0.982***	0.958***	0.509***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SHIP_t$	0.000141	0.0351*	−0.000683	−0.00230	−0.0439	−0.0961**	−0.0378	0.0811
	(0.996)	(0.055)	(0.969)	(0.984)	(0.238)	(0.030)	(0.375)	(0.661)
$SHIP_{t-1}$	0.000230	−0.0319*	0.000105	−0.0294	0.0557	0.0917**	0.0204	−0.0532
	(0.994)	(0.082)	(0.995)	(0.802)	(0.135)	(0.039)	(0.633)	(0.775)
TED_t	0.0206*	0.0146*	0.0148**	0.174***	0.00812	0.0156	0.0350*	0.00974
	(0.095)	(0.064)	(0.049)	(0.001)	(0.614)	(0.414)	(0.055)	(0.903)
TED_{t-1}	−0.0228*	−0.00166	−0.00927	−0.109**	−0.0136	−0.00431	0.0183	0.0445
	(0.065)	(0.833)	(0.220)	(0.033)	(0.400)	(0.822)	(0.321)	(0.578)
IR_t	0.0367	−0.0974**	−0.0681	−0.0838	−0.107	−0.208*	−0.254**	−0.585
	(0.603)	(0.031)	(0.115)	(0.772)	(0.245)	(0.057)	(0.015)	(0.200)
IR_{t-1}	−0.0286	0.0839*	0.0673	0.0755	0.0981	0.193*	0.204*	0.571
	(0.686)	(0.064)	(0.120)	(0.794)	(0.287)	(0.079)	(0.051)	(0.212)
CPI_t	0.171	0.0992	0.0918	−0.903	−0.527**	0.119	−0.119	−0.445
	(0.343)	(0.391)	(0.406)	(0.222)	(0.026)	(0.670)	(0.655)	(0.703)
CPI_{t-1}	−0.186	−0.113	−0.0915	0.879	0.564**	−0.121	0.111	0.460
	(0.304)	(0.329)	(0.407)	(0.235)	(0.017)	(0.666)	(0.678)	(0.694)
USD_V_t	0.00198	0.00433	−0.0109	0.0625	−0.0282	0.0376*	−0.00159	−0.0438
	(0.893)	(0.644)	(0.223)	(0.298)	(0.140)	(0.099)	(0.941)	(0.645)
USD_V_{t-1}	0.00673	−0.00360	0.00573	−0.0544	0.0199	−0.0484**	0.000638	0.00654
	(0.646)	(0.701)	(0.522)	(0.364)	(0.297)	(0.033)	(0.977)	(0.945)
Lehman	0.0745***	0.0847***	0.0430***	0.165***	0.0902***	−0.0173	−0.00490	0.0637
	(0.000)	(0.000)	(0.001)	(0.004)	(0.000)	(0.407)	(0.814)	(0.462)
Const.	−0.0149***	−0.0161***	0.00409	−0.0525**	0.00650	−0.00463	−0.0233***	−0.0482
	(0.008)	(0.000)	(0.253)	(0.012)	(0.333)	(0.556)	(0.002)	(0.141)
Obs.	1437	1437	1437	1437	1437	1437	1437	1437
F	8829.9	18924.9	14096.2	290.5	3457.8	3089.3	2772.7	43.40
R^2	0.987	0.994	0.992	0.710	0.967	0.963	0.959	0.268
adj.R^2	0.987	0.994	0.992	0.708	0.967	0.963	0.959	0.262

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 6. Long-run multiplier for the effect of TED spread on the DCC 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
0.75	0.54	0.47	0.22	0.31	0.56	0.29
Cotton	Cocoa	Coffee	Or. Juice	Sugar	Feeder Cattle	Average
0.96	−0.08	0.32	0.31	0.33	1.27	0.48

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

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 alone didn't imply increasing correlation between equities and agricultural 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). We exclude changes in interest rates, exchange rates and inflation from the analysis, since they were shown to have very little effect on the DCC. We thus estimate the following model

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

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 that 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 Table 7. 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 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).

Table 7. Determinants of the Dynamic Conditional Correlations with S&P500 and interaction with financialization (subsample Jan.2006–Jul.2013).

	(1) DCC_Corn	(2) DCC_Wheat	(3) DCC_Soyb.	(4) DCC_Soyb.Oil	(5) DCC_Cotton	(6) DCC_Cocoa	(7) DCC_Coffee	(8) DCC_Sugar	(9) DCC_F.Cattle
AR(1)	0.887***	0.907***	0.966***	0.918***	0.908***	0.982***	0.891***	0.802***	0.948***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SHIP_t$	0.00979	0.0739	−0.0415	−0.0456	0.0516	0.00962	0.0457**	0.132	0.000959
	(0.810)	(0.412)	(0.340)	(0.159)	(0.155)	(0.798)	(0.029)	(0.416)	(0.988)
$SHIP_{t-1}$	0.0297	−0.00752	0.0475	0.0388	−0.0623*	−0.0136	−0.0282	−0.141	−0.0142
	(0.465)	(0.933)	(0.276)	(0.231)	(0.087)	(0.719)	(0.183)	(0.385)	(0.816)
TED_t	0.137***	0.104*	0.0996***	0.126***	0.111***	0.0756***	0.0500***	0.275***	0.213***
	(0.000)	(0.088)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)
TED_{t-1}	−0.0836***	−0.0820	−0.0623**	−0.108***	−0.0887***	−0.0636***	−0.0301**	−0.185*	−0.153***
	(0.002)	(0.176)	(0.012)	(0.000)	(0.000)	(0.002)	(0.011)	(0.057)	(0.000)
$(TED \cdot Fin)_{i,t}$	0.0551**	0.166***	0.0272*	0.0463**	0.0475**	0.0623***	−0.00868	0.0605	−0.163***
	(0.016)	(0.007)	(0.076)	(0.040)	(0.023)	(0.000)	(0.364)	(0.465)	(0.000)
$(TED \cdot Fin)_{i,t-1}$	−0.00945	−0.0680	0.00499	−0.0403*	−0.0537**	−0.0472***	0.0288***	0.00684	0.189***
	(0.676)	(0.275)	(0.740)	(0.077)	(0.012)	(0.001)	(0.002)	(0.934)	(0.000)
$Lehman_t$	0.424***	0.387***	0.139***	0.276***	0.288***	0.0730**	0.282***	0.303***	0.127***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.012)	(0.000)	(0.002)	(0.005)
$Constant_i$	−0.132***	−0.183***	−0.0461**	−0.0562***	−0.0662***	−0.0155	−0.00427	−0.116	−0.0502
	(0.000)	(0.000)	(0.028)	(0.001)	(0.004)	(0.433)	(0.684)	(0.136)	(0.118)
Observations	394	394	394	394	394	394	394	394	394
F	3651.7	1020.7	2642.5	8064.4	5182.9	2285.8	8380.5	148.6	1848.6
R^2	0.987	0.955	0.982	0.994	0.991	0.979	0.994	0.755	0.975
adj.R^2	0.987	0.954	0.982	0.994	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.); Fin = share of financial investors in total reportable positions in US commodity futures exchanges.

Table 8. Long-run multiplier for the effect of TED spread on the DCC with S&P500 (expressed in standard deviations from the mean – sample period: Jan.2006–Jul.2013).

keeping *Financial* constant				
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 Equation (2).

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 8)

Commodity index traders and money managers Financial investors operating in commodity derivatives markets can be divided into two main 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 don't 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.

The strategies of both types of investors are likely to affect positively the transmission of shocks between commodity and equity markets, given that both money managers and index traders are typically exposed at the same time to stocks and commodities. Money managers – as hedge funds, commodity pool operators or commodity trading advisors – typically follow active investment strategies with shorter-term horizons. Index traders – which are mainly institutional investors as pensions funds, sovereign wealth funds or life insurance companies – follow passive strategies with longer-term objectives. The active behavior of money managers makes them more reactive to short-run fluctuations in the markets in which they operate. Furthermore, they are likely to be more affected by liquidity constraints. For these reasons they could be more important in connecting different markets. Büyükşahin and Robe (2013) argue 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. On the other hand, index traders' investments are typically larger in size and they account for the largest part of financial investments in agricultural markets (Girardi 2012, p.87).

Public data about the composition of agricultural derivatives markets (see Appendix) allow us to isolate, among positions of financial investors, the ones attributable to commodity index traders. 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

$$\begin{aligned} DCC_{i,t} = {} & \beta_{0,i} + \beta_{1,i}DCC_{i,t-1} + \beta_{2,i}SHIP_t + \beta_{3,i}SHIP_{t-1} \\ & + (\beta_{4,i} + \beta_{5,i}MM_{i,t} + \beta_{6,i}CIT_{i,t})TED_t \\ & + (\beta_{7,i} + \beta_{8,i}MM_{i,t-1} + \beta_{9,i}CIT_{i,t-1})TED_{t-1} + \beta_{10,i}Lehman_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

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 (β_5, β_6, β_8 and β_9) is totally analogous to the one that we put forward in discussing Equation (2).

Results, summarized in Table 9, 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 β_5 (related 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. β_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 β_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, β_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 (Table 10).

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.

Table 9. Determinants of the Dynamic Conditional Correlations and interaction with different kinds of financial investors (subsample Jan.2006–Jul.2013).

	(1) DCC_Corn	(2) DCC_Wheat	(3) DCC_Soyb.	(4) DCC_Soyb.Oil	(5) DCC_Cotton	(6) DCC_Cocoa	(7) DCC_Coffee	(8) DCC_Sugar	(9) DCC_F.Cattle
AR(1)	0.890***	0.909***	0.958***	0.918***	0.902***	0.986***	0.894***	0.805***	0.948***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SHIP_t$	0.0154	0.0776	−0.0416	−0.0458	0.0515	0.0322	0.0408*	0.0605	0.000383
	(0.706)	(0.388)	(0.344)	(0.147)	(0.157)	(0.389)	(0.051)	(0.708)	(0.835)
$SHIP_{t-1}$	0.0198	−0.0320	0.0310	0.0431	−0.0622*	−0.0291	−0.0244	−0.0775	−0.000619
	(0.628)	(0.723)	(0.475)	(0.172)	(0.094)	(0.434)	(0.248)	(0.630)	(0.733)
TED_t	0.0939**	0.108*	0.0846***	0.0840***	0.0890***	0.0678***	0.0607***	0.381***	0.00603***
	(0.019)	(0.073)	(0.001)	(0.002)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
TED_{t-1}	−0.0493	−0.0874	−0.0436*	−0.0629**	−0.0664***	−0.0609***	−0.0391***	−0.257**	−0.00449***
	(0.207)	(0.147)	(0.081)	(0.021)	(0.007)	(0.004)	(0.002)	(0.010)	(0.000)
$TED_t \cdot MM_t$	0.0479***	0.153***	0.0374***	0.0549***	0.0578***	0.0324**	−0.00582	0.168**	−0.00366***
	(0.008)	(0.002)	(0.007)	(0.000)	(0.005)	(0.020)	(0.623)	(0.016)	(0.000)
$TED_{t-1} \cdot MM_{t-1}$	−0.00788	−0.0589	0.00508	−0.0544***	−0.0646***	−0.0337**	0.0323***	−0.153**	0.00430***
	(0.659)	(0.231)	(0.703)	(0.000)	(0.002)	(0.015)	(0.006)	(0.032)	(0.000)
$TED_t \cdot CIT_t$	−0.0161	0.0776*	−0.0414*	−0.0434**	0.00802	0.0718***	0.0208*	0.212**	−0.00343***
	(0.667)	(0.094)	(0.094)	(0.049)	(0.703)	(0.000)	(0.082)	(0.013)	(0.002)
$TED_{t-1} \cdot CIT_{t-1}$	0.0362	−0.0541	0.0460*	0.0588***	−0.0141	−0.0360**	−0.00600	−0.184**	0.00436***
	(0.336)	(0.257)	(0.069)	(0.008)	(0.502)	(0.024)	(0.621)	(0.032)	(0.000)
$Lehman_t$	0.400***	0.349***	0.137***	0.284***	0.306***	0.0779***	0.278***	0.295***	0.00389***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.006)	(0.000)	(0.006)	(0.004)
$Constant_i$	−0.120***	−0.153***	−0.0279	−0.0632***	−0.0711***	−0.0283	−0.00483	−0.104	0.00155*
	(0.000)	(0.003)	(0.208)	(0.000)	(0.003)	(0.147)	(0.677)	(0.206)	(0.097)
Observations	394	394	394	394	394	394	394	394	394
F	2937.5	821.9	2176.5	6790.4	4160.1	1908.6	6794.2	120.4	1476.3
R^2	0.987	0.955	0.983	0.994	0.991	0.980	0.994	0.759	0.975
adj.R^2	0.987	0.954	0.982	0.994	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); MM = share of money managers in total reportable positions in US commodity futures exchanges; CIT = share of commodity index traders.

Table 10. Long-run multiplier for the effect of TED spread on the DCC with S&P500 (expressed in standard deviations from the mean – sample period: Jan.2006–Jul.2013).

keeping both *MM* and *CIT* fixed				
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 Equation (3). * Excluding cocoa.

5. 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 (Engle 2002). 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 empirical 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 (13 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). Interest rates are significant in even less cases (2 out of 16 at the 95% level), while inflation and exchange rates don't appear to influence the correlation with stocks in any market.

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 – Figure 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.

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Notes

1. Information about the data employed is provided in the appendix.
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 Lebo and Box-Steffensmeier (2008))
4. 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.
5. 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 $E(y_t|y_{t-1}, y_{t-2} \ldots x_{t-1}, x_{t-2}, \ldots) \neq E(y_t|y_{t-1}, y_{t-2} \ldots)$.
6. For the sake of brevity, we report in Table 1 only results showing that stock market returns Granger-cause agricultural price changes, not the ones showing that agricultural price changes don't Granger-cause stock market returns, but the latter are available upon request.
7. In particular, the analysis of Büyükşahin and Robe (2013) concerns the period 2000–2008
8. On September 16th 1992 the British sterling was forced out of the European Exchange Rate Mechanism
9. Defined as the exchange of financial instruments which passively track a commodity index, which is a weighted average of different commodity prices.

10. I'm grateful to the Editor Malcolm Sawyer for suggesting to stress the endogenous nature of money and to include the role of the Central Bank's interest rate in the analysis.
11. Indeed, if money is treated as endogenous, a positive correlation between the stock of money and commodity prices does not necessarily imply a causal effect of the first on the second. To the contrary, it is higher (cost-driven) inflation, due to rising commodity prices, which 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. Of course reverse causality affects also the relation between money expansion and stock prices: increases in equity prices can result in higher demand for money.
12. These two categories will be defined later.
13. As Kilian (2009) writes, his index is "a measure of the component of worldwide real economic activity that drives demand for industrial commodities in global markets."
14. We focus on OECD countries because we are using data on US commodity exchanges, mostly populated by Western actors.
15. Again, we focus on the US because we are employing data on US commodity exchanges.
16. In the case of the DCCs, we calculate them again on weekly returns on agricultural prices and on S&P500
17. 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 (1999), 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 (2013).) 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.
18. We don't directly correct the nominal rate for inflation, given that we are already controlling for the average inflation rate of OECD countries, which is included in the regression. In any case, when we tried substituting the nominal rate with the real rate (obtained by subtracting the US inflation rate from the US nominal rate), the coefficient of the real rate was found to be insignificant in all regressions and all other results remained unchanged.

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Appendix - Dataset and sources

Agricultural futures prices Futures prices for 16 agricultural commodities in US derivatives exchanges were downloaded from Quandl (https://www.quandl.com). 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 futures traded on the Inter-Continental Exchange (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 Silvennoinen and Thorp (2013) and Hong and Yogo (2012)). Returns were calculated as percentage changes in prices.

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

TED Spread The TED spread is the 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).

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 Kilian (2009) for details).

Composition of agricultural derivatives markets The share of financial investors in total reportable positions in US agricultural exchanges was calculated from the "Committment of Traders - Commodity Index Trader Supplement" (SCOT), released by the Commodity Futures Trading Commission (CFTC). The SCOT provides a breakdown of each Tuesday's open interest between non-commercial traders (excluding commodity index traders), commodity index traders and commercial hedgers. It is available 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 are attributed in part to commercial hedgers and in part to money managers (implying that a relevant part of the positions 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.

Core inflation 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.

Monetary policy Data on the US Federal Funds rate were downloaded from the FRED database at http://research.stlouisfed.org/fred2/series/FEDFUNDS

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.

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