Information Discovery and Trend Following in Agricultural Futures Markets*

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April 2, 2015

Abstract

We develop a structural VAR model to analyze the relationship between financial speculation, agricultural futures prices, and other asset prices. We consider two important types of speculators and test if they affect futures prices and through which channels. Moreover, we study their trading strategies. We find that shocks to net long positions of index investors do not affect futures prices, whereas shocks to money manager positions increase futures prices. Our results suggests that shocks are transmitted through the information discovery channel and reflect private signals. Further, we find that both investors are trend followers. They increase exposure in response to futures price shocks. This strategy amplifies initial shocks and increases futures price volatility. Overall, however, fundamental demand and supply are the main drivers of agricultural commodity price cycles.

JEL-Classification: Q02, G13, E39.

Keywords: Commodities, financialization, futures markets, transmission channels, trading strategies, heteroscedasticity.

*We thank Stefan Ederer, Marcel Fratzscher, Hendrik Hakenes, Helmut Herwartz, Lutz Kilian, Markku Lanne, Helmut Lütkepohl, Dieter Nautz, and Michele Piffer, as well as participants at the DIW Macroeconometric Workshop 2014, Workshop Empirical Macroeconomics at Freie Universität Berlin, and of an internal seminar for helpful comments and suggestions.

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1 Introduction

Agricultural commodity prices experienced two pronounced cycles between 2005 and 2015. Prices surged to all-time highs in mid 2008, collapsed, and then rebounded sharply in the years that followed. The consequences of high prices were drastic for poorer households, which spend a large share of income on food, while producers and processors suffered from high price volatility. At the same time, there was a substantial participation of financial investors on agricultural futures markets which drew a lot of attention from researchers and policy makers. The discussion centers around whether financial speculation was behind the large price increases and fluctuations as well as, more generally, whether it drives prices away from fundamentals, distort price signals, and reduces welfare. For instance, agricultural prices were a leading topic of the 2011 G20 summit. In the US, the Dodd-Frank Act gave the Commodity Futures Trading Commission the responsibility for additional regulations of commodity derivative markets. In the European Union, the European Commission set up an expert group to provide legal advice on the regulation of commodity derivatives.

In this paper, we analyze if and how financial investors affect agricultural futures prices and what this implies for the role of futures markets in information aggregation and price discovery.[1] Specifically, we address two related questions: (1) Do speculators affect futures prices and, if so, through which channels? (2) How do speculators respond to futures price changes? To answer these, we develop a dynamic multi-equation model of the agricultural commodity futures market. We define speculation as holding a net long position without an interest in physical delivery and study two aspects of speculation: the effect of exogenous shifts in net long positions on futures prices and the endogenous response of investor's positions to futures price movements. We use weekly data from 2006-2014 for eight agricultural commodities, which we combine to aggregate indices, and employ a set of structural vector autoregressive (VAR) models.[2] To identify the structural relations, we use the heteroscedasticity in the data, following Sentana and Fiorentini (2001) and Rigobon (2003). The approach is agnostic with respect to sign and magnitude of contemporaneous effects, which is useful for our analysis as theory gives no clear guidance.

We include two important groups of speculators, each accounting for about one-fifth of total

[1]For final consumers, ultimately the spot price matters. Spot and futures price, however, are linked through an arbitrage relation.

[2]The eight markets account for more than 80 percent of the futures market volume of the agricultural commodities included in the Standard & Poor's Goldman Sachs Commodity Index (S&P GSCI), which is one of the main commodity indices used. Regarding positions, we follow the trader classification of the Disaggregated Commitments of Traders (DCOT) report of the Commodity Futures Trading Commission.

open interest in the analyzed markets: index investors, who typically seek passive long-only exposure to commodities as an asset class, and money managers, such as hedge funds, who trade actively in specific commodities and are present on both sides of the market. We find that unexpected changes in money managers positions increase futures prices, whereas those in index investor positions do not. We exploit this heterogeneity to disentangle three alternative transmission channels suggested in the literature. First, according to the information channel, if investors have different views about price fundamentals due to informational frictions, their trades can transmit private signals to the market and thereby affect prices (see Grossman and Stiglitz, 1980, Hellwig, 1980, Goldstein et al., 2014, Goldstein and Yang, 2014). Second, through the liquidity channel, large buy orders can increase prices through an effect on the order book if markets are not sufficiently liquid (see Grossman and Miller, 1988, De Long et al., 1990a, and Shleifer and Vishny, 1997). Third, according to the risk premium channel, financial investors can drive up futures prices by lowering the risk premium that commodity producers typically have to pay for hedging their price risk (see Keynes, 1930, Hicks, 1939, Acharya et al., 2013, Hamilton and Wu, 2015). Both the liquidity and the risk premium channel imply similar effects for both investors since they depend essentially on the size of position changes.[3] In contrast, the information channel allows for different effects between speculators as it functions through private signals. Our results thus suggest that shock transmission runs through this channel.

Regarding speculators' responses to futures price movements, they can trade in a contrarian fashion by selling high and buying low (see Chan, 1988, Lakonishok et al., 1994, Miffre and Rallis, 2007) and thereby stabilize prices. Alternatively, they can use trend following strategies by buying high and selling low (see Fung and Hsieh, 2001, Bhardwaj et al., 2014, Szymanowska et al., 2014), which could amplify price fluctuations. Our results show that both investors engage predominantly in trend following strategies. They raise net long exposure in response to futures price shocks. In case of money managers, this trading behavior amplifies initial shocks.

Our paper is related to a broad literature that seeks to quantify the effects of trading behavior on asset prices, for example, in stock markets (see Kaniel et al., 2008), foreign exchange markets (see Chang et al., 2013), and bonds markets (see Vayanos and Vila, 2009). It connects particularly to a fast-growing line of research that studies the role of financial institutions in commodity

[3]The econometric approach controls for the size of position changes. The risk premium channel could also depend on investors' risk aversion which potentially differs between groups. However, we show that both groups react qualitatively and quantitatively very similar to risk shocks. In addition, we control for futures market liquidity to rule out that the significant effect for money managers reflects the liquidity channel. This could be the case if there was a systematic relationship between their position changes and market liquidity.

(futures) markets.[4] A number of studies use Granger-causality or similar techniques to analyze the effect of speculation on futures prices (see, for instance, Sanders and Irwin, 2011, Irwin and Sanders, 2012, Aulerich et al., 2013, and, Gilbert and Pfuderer, 2014). Other authors rely on single-equation or forecasting models and focus on selected transmission channels (see Aulerich et al., 2013, Acharya et al., 2013, Büyüksahin and Robe, 2014, Henderson et al., 2014, Singleton, 2014, Hamilton and Wu, 2015). Several studies also use structural VAR analysis. Kilian and Murphy (2014) employ sign restrictions to analyze the impact of speculative activity, tied to physical inventories, on the price of crude oil. Bruno et al. (2013) as well as Ederer et al. (2013) focus on financial speculation and use Cholesky schemes to identify structural shocks. Overall, the results in the literature are ambiguous regarding the effect of positions changes on commodity prices. While several studies find no effect, some find a positive effect and others a negative one.

This paper contributes to the literature by estimating the contemporaneous bi-directional effects between agricultural futures positions and prices, while accounting for the endogeneity of positions, futures prices, and other asset prices. Moreover, our framework allows disentangling alternative transmission channels and trading strategies. We show that the consequences of speculation depend on the type of speculator and its underlying trading motive. Finally, we also quantify the effects of speculation to observed agricultural futures price dynamics.

As to the detailed results, we find that a shock of one standard deviation to net long positions of money managers increases futures prices by 1.2 percent on average. In contrast, shocks to index investor positions are not transmitted to prices. Reversely, a price shock of 10 percent leads to an increase in positions of money managers and index investors by 0.6 and 1.0 standard deviations, respectively. In case of money managers, this response creates a feedback loop between positions and futures prices (and other asset prices) that explains 0.2 percentage points of the effect of position shifts on prices. A historical decomposition of futures prices shows that speculative trading by money managers plays a non-negligible role, whereas positioning of index investors can be neglected. Overall, however, agricultural demand and supply conditions are the main price drivers. Concerning the average economic significance of specific shocks, those to money manager positions contribute 14 percent to futures price variability, while shocks to index investor position explain only two percent. Regarding variation over time, shock transmission from money manager positions to prices is similar before the Dodd-Frank Act and afterwards, whilst trend following strategies have gained importance recently. As to individual markets, the

[4] See Fattouh et al. (2013) and Cheng and Xiong (2013) for recent overviews of the literature.

results here largely mirror those for the aggregate level.

Our results show that the two investor groups are different in some respects but similar in others. The difference in the effect of shocks to positions on prices, points to the information channel as an important shock transmission mechanism. While money managers actively gather and process commodity-specific information and base their trades thereon, index investors derive trades typically from portfolio considerations that include a variety of asset classes (see, among others, Masters and White, 2008, Mou, 2010, Brunetti and Reiffen, 2014). We therefore interpret the consistently significant effect of position shifts by money managers as mirroring the transmission of private signals to the market that supports the role of futures markets in information aggregation and price discovery. On the other hand, both investors are similar regarding the systematic response to futures price changes. They are trend followers. For index investors, however, this finding is confined to the larger markets in our sample, which have higher weights in the commodity indices tracked by those investors. In case of money managers, trend following compounds price discovery as it amplifies the effects of initial asset price shocks on futures prices.

The remainder of the paper is structured as follows. Section 2 provides a conceptual discussion of the transmission channels between positions and futures prices, while also outlining potential drivers of futures prices. Section 3 presents the empirical methodology and the data. Section 4 contains the results. Section 5 provides a robustness analysis and Section 6 concludes.

2 Positions, futures prices, and other asset prices

In this section, we first outline different channels through which positions can affect futures prices, and vice versa. Then, we discuss other potential drivers of positions and futures prices.

2.1 Transmission channels and trading strategies

The following discussion serves to derive priors on the signs of the bi-directional effects between positions and futures prices and as a framework to disentangle alternative transmission channels and trading strategies empirically. Regarding the transmission of position shifts on futures prices, the literature identifies three main channels:

(1) According to the *information channel*, some traders could possess private information about the fundamental determinants of the futures price. Once their trade communicates

this information to the market, the price can change accordingly (see Grossman and Stiglitz, 1980, Hellwig, 1980, Goldstein and Yang, 2014). Private information could be due to better forecasting abilities, different costs of private information production, or a different understanding of macroeconomic trends or political processes (see Singleton 2014).[5]

(2) Following the *liquidity channel*, large position changes can influence prices if the market is not sufficiently liquid to absorb them. This can happen if the instantaneous supply of counterparty orders is low. Large buy orders would then raise the price through their effect on the order book. Such problems of illiquidity can arise if there are limits to arbitrage that deter risk averse arbitrageurs from taking the counterside (see De Long et al. 1990a, Shleifer and Summers, 1990, Shleifer and Vishny 1997).

(3) The *risk premium channel* relates to the costs of hedging and goes back to the theory of normal backwardation by Keynes (1930) and Hicks (1939).[6] Acharya et al. (2013) and Hamilton and Wu (2014, 2015) provide theoretical frameworks for this mechanism. If producers of a commodity want to hedge their price risk, they need to find a counterparty. To induce speculative traders to take the associated price risk, the futures price needs to include a risk premium and, hence, will be set at a discount. The higher short hedging demand by producers or the higher the risk aversion of speculators, the higher the risk premium will be.[7] Hence, if speculators' positions are a mere reflection of short hedging demand of producers, the relation between their positions and prices will be negative. Conversely, if speculators net long exposure increases due to shifts in their speculative demand, the futures price can increase as the risk premium declines.

Summarizing, the first two channels imply a positive effect of changes in speculators' positions on prices, while the sign of transmission through the risk premium channel depends on whether

[5]Even if traders do not posses private information in each instance, it is possible for position changes to affect prices if other traders have difficulty to distinguish between informed and uninformed trades. The latter might then perceive large order flows as a reflection of private information and adjust their own demand, which in turn can have an effect on prices (see Irwin and Sanders 2012).

[6]Following the theory of normal backwardation, the spot and the futures price are related according to:

$$F_{t,T} - S_t = [\mathbb{E}(S_T) - S_t] - \pi_{t,T}$$

where S_t is the current spot price, $F_{t,T}$ the T-periods ahead futures price and $\pi_{t,T}$ the risk premium. If short hedging demand exceeds long supply, the risk premium will be positive.

[7]Hamilton and Wu (2014, 2015) show that the same mechanism is at work if the market is characterized by long-pressure of speculators and not by short-pressure of producers. If speculators cannot find a counterparty to take the short side, the futures contract needs to include a risk premium on the short side. Therefore, an increase in speculators' long exposure will lead to an increase in futures prices through adjustments in the risk premium.

hedgers or speculators are the driving force behind observed position changes. We therefore leave the signs of the respective coefficients unrestricted in the empirical implementation. If they turn out to be negative, we interpret this as evidence for channel (3), with hedgers driving position shifts. If they are positive, this could mirror either of the three channels. Then, to discriminate between channels in a (conceptual) second step, we exploit potential heterogeneity across speculator types. If the effects are significant for both groups that we include, we conceive this as supporting channel (2) and (3), the latter with speculators driving position changes. Both channels rely on the size of position shifts but not on the type of speculator behind them and thus suggest similar effects across speculators. Conversely, if we find an effect only for one group, we read this as supporting channel (1), which is based on the presumption of an asymmetric information structure across investors and hence allows for differing effects.

This argumentation is valid under two assumptions. First, there is no systematic relation between identified position shifts and market liquidity. Otherwise a positive effect only for one group could also reflect the liquidity channel. Therefore, we control for futures market liquidity in the estimation. Second, both investor types have similar degrees of risk aversion. Otherwise, a positive effect only for one type could also mirror the risk premium channel if the required change in the risk premium differs between groups. However, we verify *ex-post* that both groups react qualitatively and quantitatively very similar to risk shocks.

In the other direction, the effect of futures price changes on speculators' positions depends on the trading strategy of investors. The literature discusses two main strategies.

(A) If investors use *contrarian strategies*, they try to buy low and sell high (see Chan, 1988, Lakonishok et al., 1994, Miffre and Rallis, 2007). An increase in prices will then induce a decline in investors' net long positions.

(B) If traders engage in *trend following strategies*, they buy when prices increase and sell when they fall (see De Long et al., 1990b, Rouwenhorst, 1998, Bhardwaj et al., 2014). An increase in prices would then prompt an increase in net long exposure.

Again, theoretical considerations give no clear prediction. We leave the sign of the effect of prices on positions unrestricted. We interpret a negative effect as evidence for investors using predominantly contrarian strategies and a positive effect as trend following. Finally, if the effects are significantly positive in both directions, that is, from positions to prices and vice versa, a feedback loop can emerge that might amplify initial movements in positions or prices.

2.2 Relation of agricultural prices and positions to other asset prices

We now discuss other asset prices that might potentially affect agricultural futures prices and speculators' positions or can be affected by those. First, the theory of storage implies a link between futures prices and inventories of a storable commodity (see Kaldor, 1939, Working, 1949). It predicts that a negative shock to inventories increases nearby futures prices, reflecting the scarcity for immediate delivery. Conversely, higher prices are likely to induce a depletion of inventories. Gorton et al. (2013) show that the futures spread, the difference between the nearby and deferred futures price, is a good proxy for commodity inventories.[8] We include it as a proxy for inventories into the model.

Furthermore, changes in the oil price can affect the price of agricultural products (see Baffes, 2007). One argument is that oil prices could influence agricultural prices through the cost of production. For instance, Wang et al. (2014) find effects of oil shocks on agricultural commodity prices. Another line of reasoning is based on substitution effects between biofuels and fossil fuel, which can run in either direction. Indeed, Tang and Xiong (2010) show that the correlation between non-energy commodities and oil prices increased significantly after 2004. Accounting for these findings, we add the oil price as an endogenous variable.

Finally, shocks to financial market risk can have an impact on commodity futures prices as they potentially affect the risk premium (see Beck, 1993). Moreover, a rise in risk might impact investors' positions if they shift their exposure into relatively safer assets during such periods. Empirically, Byrne et al. (2013) find that aggregate risk is one common factor driving primary commodity prices. Cheng et al. (2014) show that speculative traders on commodity futures markets adjust positions to changes in the Chicago Board Options Exchange Market Volatility Index (VIX). Reversely, in the presence of informational frictions, lower commodity price can be interpreted as signals of weaker aggregate demand (see Sockin and Xiong, 2013) and increase aggregate risk. Therefore, we incorporate the VIX into the model.

[8] According to the theory of storage, holders of inventories receive a benefit of storage, the 'convenience yield,' that declines as inventories increase. As the convenience yield only accrues to owners of inventories but not to owners of futures contracts, it is closely tied to the spread between the spot and futures price. It is also reflected in the futures spread as the nearby futures price still includes it to some extent while further-to-maturity contracts do not. Hence, if the deferred price is higher than the nearby price (upward sloping futures curve, 'contango') inventories are at high levels. On the contrary, a downward sloping futures curve ('backwardation') is associated with low levels of inventories.

3 Model specification, data, and estimation methodology

In this section, we describe the specification of the structural VAR model, the data, and the estimation methodology. Moreover, we present the interpretation of the identified shocks.

3.1 Model specification and data

The structural VAR model includes six endogenous variables: the agricultural futures price, net long positions of index investors and of money managers, respectively, the agricultural futures spread, the WTI oil price, and the VIX. It is given by:

$$Ay_t = \tilde{c} + \tilde{A}_1 y_{t-1} + \cdots + \tilde{A}_p y_{t-p} + \tilde{\Lambda}_1 x_t + \cdots + \tilde{\Lambda}_q x_{t-q} + \varepsilon_t \tag{1}$$

with y_t the vector of endogenous variables, x_t a vector of exogenous variables, $\tilde{c}$, $\tilde{A}_i$, and $\tilde{\Lambda}_j$ parameter matrices, and ε_t a vector of structural shocks with diagonal covariance matrix $\Sigma_\varepsilon = E(\varepsilon_t \varepsilon_t')$. The impact matrix A contains the *direct* contemporaneous effects of shocks on the endogenous variables, keeping all other variables constant.

The analysis includes eight agricultural commodities. For the core analysis, we compute aggregate indices for the first four variables in y_t. To investigate the individual markets, we use market-specific variables. The weights of the commodities in the aggregate indices are based on their yearly varying weights in the S&P GSCI, one of the most widely used investible commodity indices. Table 1 lists the commodities and the average weights over the sample period. We focus on commodities that are largely produced in the US because the futures contracts are traded on exchanges located in the US and, more importantly, comprehensive data on supply factors, which we use, are only available for the US. The US futures markets play a leading role in the determination of world prices. Moreover, the eight commodities account for more than 80 percent of the futures market volume of the agricultural goods included in the S&P GSCI.[9]

Table 1: Average commodity weights in the aggregate futures market indices

Corn	*SRW Wheat*	*Live Cattle*	*Soybeans*	*Lean Hogs*	*Cotton*	*HRW Wheat*	*Feeder Cattle*
24.6%	21.3%	15.1%	14.7%	8.7%	7.3%	5.5%	2.8%

The table shows the commodities used for construction of aggregate indices and their average weights. The weights are updated yearly and based on the reported weights in the S&P GSCI commodity price index. Differences to 100% are due to rounding errors.

[9]Coffee, cocoa, and sugar are the only S&P GSCI agricultural commodities that we do not include due to a lack of the data on supply factors that we use.

Regarding futures prices, we use nearby futures contracts and compute the aggregate index in two steps. First, we re-scale the individual series by their 2006 averages to make them comparable in size. Then, we average over markets, using the yearly varying weights. Regarding positions, we employ data from the Disaggregated Commitments of Traders report, publicly available from the Commodity Futures Trading Commission, which contains weekly open interest on US futures markets. Traders are classified into five categories in the report: commercial traders (producers, processors, and merchants), swap dealers, managed money, others, and non-reporting. We are particularly interested in swap dealers, our proxy for index investors, and money managers as both are financial investors (speculators) without an interest in physical delivery of the commodity. Swap dealers are large banks that take over exposure from counterparties, predominantly index investors, through swaps and hedge these positions on futures markets. Irwin and Sanders (2012) show that their positions are a good approximation of index investment in agricultural commodities. Money managers are speculative traders like hedge funds, registered commodity trading advisors, or commodity pool operators.

The reports are available from June 13, 2006, and our sample runs through August 15, 2014. Swap dealers constitute a significant part of total long contracts, although their share declined from 38 percent in 2006 to 25 percent in 2014. Their fraction in total short positions is negligible with only 2 percent on average, reflecting the long-only concept of index investment. Money managers, in contrast, are active on both sides of the market where they constitute important proportions. Their share of total long positions increased substantially from 20 percent in 2006 to 32 percent in 2014. The share in short contracts remained relatively stable at around 10 percent. To measure speculative demand, we compute the net long position of each investor group, following Sanders and Irwin (2011), Irwin and Sanders (2012), Mayer (2012), or Gilbert and Pfuderer (2014). For the aggregate index, we combine net long positions on individual markets in two steps. First, we divide by average open interest in each market in 2006 to dispose of the underlying units (bushels, pounds, et cetera). Then, we average over markets.

For futures spreads, we use the difference between the logarithm of the price of the next-to-maturity and of the second-next-to-maturity contract, respectively, and average over markets. Furthermore, we employ the spot price of WTI oil and the VIX. We also add several exogenous variables to the model. First, to control for the supply of agricultural commodities, we build an index of crop conditions using weekly reports on crop progress and conditions from the US Department of Agriculture, following Bruno et al. (2013). Second, to capture US aggregate demand at a weekly frequency, we use the number of initial jobless claims as it contains valuable information about the US business cycle (see Aruoba et al. 2009). Third, we include world demand by using an index of global real activity, as proposed by Kilian (2009). Fourth, to account for information transmission about macroeconomic conditions, we include the surprise components of data releases regarding 12 economic indicators for the US. Fifth, we include the US Federal Reserve balance sheet and dummies for the announcements of quantitative easing as measures of aggregate liquidity. Sixth, we control specifically for futures market liquidity. We follow Marshall et al. (2011) and add the average Amivest measure (see Amihud et al., 1997), which divides the volume on a trading day by the absolute return on that day. Lastly, the model contains dummy variables for month effects and for breakouts of swine-flu and mad-cow disease. We provide a detailed description of the data and their sources in Appendix A.

To account for non-stationarity of the data, we estimate the model in first log differences of the agricultural futures price and the oil price. For net long positions, the futures spread (already in logarithms), and the VIX we employ first differences.[10] Moreover, we standardize all variables prior to estimation. We include one lag of the endogenous variables, based on the Schwartz and Akaike information criterion. All exogenous variables enter the model contemporaneously, except for announcements regarding quantitative easing where we incorporate one additional lag to account for information processing in financial markets.

3.2 Estimation and identification

The structural VAR model in equation (1) can be rewritten in its reduced form as follows:

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \Lambda_1 x_t + \cdots + \Lambda_q x_{t-q} + u_t \tag{2}$$

where $A_i = A^{-1}\tilde{A}_i$ for $i = 1, ..., p$ and $\Lambda_j = A^{-1}\tilde{\Lambda}_j$ for $j = 1, ..., q$. The vector of reduced-form residuals u_t is related to the structural shocks through A as $u_t = A^{-1}\varepsilon_t$. The matrix A^{-1} contains the *overall* effects of the structural shocks. They differ from the *direct* effects in A in that they contain all contemporaneous feedback among the endogenous variables. Equation (2) and the covariance matrix of the reduced-form shocks can be estimated consistently by ordinary least squares. However, to identify the impact matrix A we need additional information. To this end,

[10]To asses the stationarity of the data, we perform augmented Dickey-Fuller and Phillips-Perron tests on the levels of the agricultural futures price and investors' net long positions. The tests do not reject the null hypothesis of a unit root, irrespective of whether we include a drift term.

we make use of the heteroskedasticity that is present in the data, following Sentana and Fiorentini (2001) and Rigobon (2003). This identification approach is proven to be useful in the context of asset price co-movements (see, among others, Andersen et al., 2007, Bouakez and Normandin, 2010, or Ehrmann et al., 2011). The intuition behind it is that changes in the ratio of the variances of two structural shocks carry additional information. Consider the relation between positions and futures prices: in a regime with high volatility in positions we learn more about the response of futures prices to positions as shocks to the latter are more likely to occur.

The identification strategy relies on two assumptions. First, the structural shocks are assumed to be uncorrelated, as it is commonly done in the structural VAR literature. Second, the matrix of contemporaneous impacts A is assumed to be constant over time (as are the matrices $\tilde{A}_i$). To assess the second assumption, we later conduct robustness analysis with rolling window estimations. Without any additional restrictions, however, the model is identified by heteroskedasticity only up to a rotation of A. To pin down the structural parameters that reflect the underlying economic model, we need one sign restriction on the parameters of A. We therefore assume that a shock to the VIX, which reflects aggregate risk, has a negative effect on the price of oil. The restriction is in line with recent findings on the effect of uncertainty shocks on oil prices (see Fratzscher et al., 2013). Moreover, it is not binding in the estimations.

Alternatively, identification is often achieved by imposing zero, long-run, or sign restrictions. Zero restrictions on A imply a delayed response of some endogenous variables to others. This seems unwarranted in our context since the included variables are likely to react to each other contemporaneously at the given weekly frequency. Similarly, long-run restrictions are not appropriate as there is hardly any persistence in the data. Sign restrictions, on the other hand, allow for the variables to have an immediate impact on each other but constrain this impact to be of a particular sign. However, as outlined in Section 2, theory gives no clear predictions for the signs of the bidirectional effects between investors' positions and prices.

Before the estimation, we need to determine the volatility regimes. Following Rigobon (2003), we apply a narrative approach. Our sample provides a natural framework for application of this approach as it covers two pronounced commodity price cycles as well as the Global Financial Crisis and, thus, is characterized by strong and persistent changes in volatility. Using media reports and previous studies (see, for instance, Adjemian and Plato, 2010, and Fawley and Neely, 2013), we construct a time-line of events that triggered changes in volatility. The events include both major economic as well as political triggers (for instance, the collapse of

Lehman Brothers, the introduction of quantitative easing, and the regulation of commodity markets through the Dodd-Frank Act). Based on the time-line, we divide the sample into six regimes. This number gives each shock variance the chance of a relative shift vis-à-vis the other shock variances. Our choice of regimes is supported by formal tests of constancy of the reduced form covariance matrices. Moreover, the standard deviations of the structural shocks display pronounced differences over the regimes. We provide the test results and a detailed account of the regimes in Appendix B. Additionally, in Section 5, we assess the sensitivity of our results to using a more statistical approach to define volatility regimes.

An alternative to defining regimes prior to estimation is to determine them jointly with the structural parameters of the model, as it is done in Markov-switching frameworks (see, for instance, Herwartz and Lütkepohl, 2014). However, due to the implied computational burden, these models allow typically only for a comparably small number of endogenous variables and regimes. For our analysis this is less than optimal given our focus on two investor groups and the aim of still accounting carefully for other contemporaneous relations between futures prices and asset prices, and given that our sample is difficult to characterize by a small number of regimes.

With the volatility regimes at hand, we estimate the model as in Ehrmann et al. (2011) by minimizing the following matrix norm:

$$||g'g|| = \sqrt{tr[gg']} = \sqrt{vec(g)vec(g)'}, \quad with \quad g = \sum_{k=1}^{6} [A\Sigma_{u,k}A' - \Sigma_{\varepsilon,k}] \tag{3}$$

with $\Sigma_{u,k}$ the variance of the reduced form shocks, $\Sigma_{\varepsilon,k}$ the variance of the structural shocks in volatility regime k, and A subject to the sign restriction on the impact of a VIX shock on the price of oil. We base statistical inference on bootstrap replications. We generate 200 draws of data using the regime specific covariance matrices and for each draw we estimate the coefficients by minimizing (3). We obtain p-values by computing the share of estimates beyond zero.

3.3 Interpretation of structural shocks

While our agnostic identification strategy gives full voice to the data regarding the sign and magnitude of impact effects, it has one drawback. It is more difficult to interpret the structural shocks since they are not based on *a priori* assumptions. We address this issue in several ways, in particular with regard to shocks to the futures price equation.

First, we explore the significance of our control variables to obtain an impression of the variation that remains in the endogenous variables and that is explained by the structural shocks. Table 2 shows the estimated effects of the exogenous variables on the aggregate futures price index. The crop index has the expected negative sign and is highly statistically significant. Better weather conditions lead to lower prices. The number of initial jobless claims is significant at the 5% level and the Kilian (2009) index only barely misses significance at the 10% level, both with the expected signs. Most of the macroeconomic news variables also display the expected signs. In particular, a positive surprise to consumer confidence increases prices. Given that our model captures supply and aggregate demand conditions well, we interpret the remaining structural variability in the futures price equation as shifts in the demand for agricultural commodities.

Table 2: Effects of exogenous variables on the agricultural futures price

Supply, Demand, and Liquidity		*Macroeconomic News*	
Crop Conditions Index	-0.53***	Current Account	-0.01
Kilian (2009) Index	0.07	Consumer Confidence	0.06***
Initial Jobless Claims	-0.09**	Consumer Price Inflation	-0.45
Fed Balance Sheet	-0.07	GDP	-0.35
Amivest Liquidity	0.00	Housing Starts	-1.86
		Industrial Production	0.03
Cumulative Effects and F-tests		Non-farm Payrolls	-0.02
Announcements of	-0.56	Purch. Managers Index	0.05
Quantitative Easing	[0.73]	Producer Price Inflation	0.12
Month Dummies	0.00	Retail Sales	-0.04
	[0.57]	Unemployment Rate	-0.17
		Av. Weekly Hours	0.61

[a] The table shows the estimated effects of the exogenous variables on the aggregate futures price index. Numbers in brackets refer to the p-values of F-tests of joint significance of the quantitative easing dummy and its first lag and of the monthly dummies.
[b] ***, **, * denote significance at the 1%, 5%, 10% levels, respectively.

This interpretation is supported by Figure 1. It shows the cumulative effect of structural shocks to the futures price equation, obtained from a historical decomposition, and the inverted level of actual agricultural commodity stocks in the US.[11] The variables display a strong co-movement. Intuitively, changes in agricultural stocks tend to lead price movements caused by identified demand shocks, in particular towards the second half of the sample. The common pattern indicates that both series are driven by similar underlying demand shocks.

To interpret the other shocks, we follow Fratzscher et al. (2013) and Herwartz and Lütkepohl

[11] The stocks variable is based on data from the US Department of Agriculture and described in Appendix A. We do not include it in the model as it is only available at a monthly frequency and, more importantly, captures only *ex-post* information about stocks. Instead, the futures spread is available at a weekly frequency and more closely related to – possibly rapidly changing – market perceptions about commodity shortages.

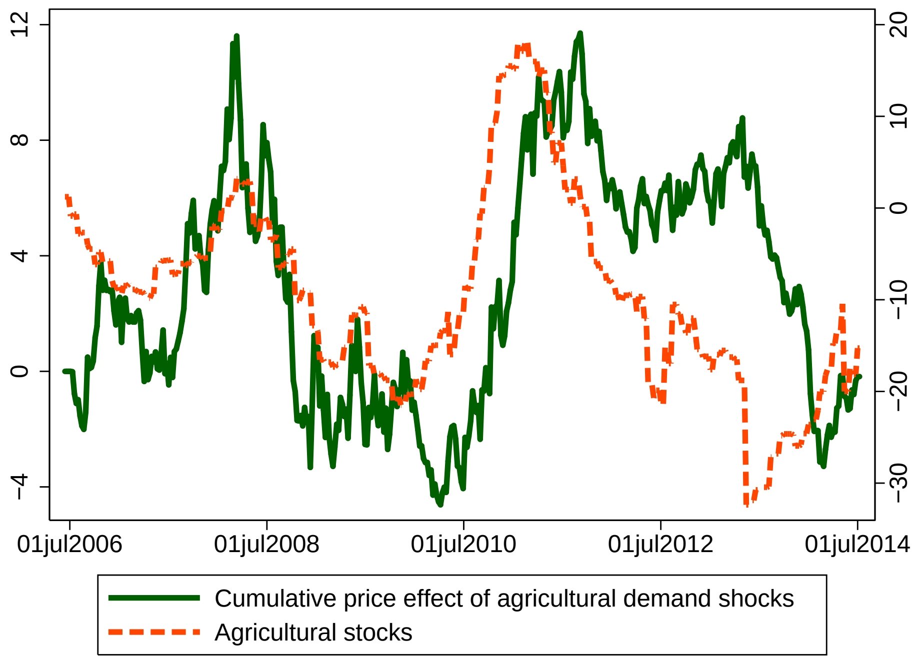

Figure 1: Actual agricultural stocks and cumulative effect of estimated agricultural specific demand shocks on the futures price. The figure shows the level of agricultural stocks as reported by the US Department of Agriculture (dashed orange line, right scale inverted) and the agricultural futures price implied by cumulated agricultural demand shocks (obtained from a historical decompositions, green line).

(2014) and evaluate whether they display higher volatility at times in which they are expected to, given their interpretation. We provide a detailed account of the volatility patterns in Appendix C. Overall, they align well with our shock interpretation. Shocks to index investor positions display greater volatility until 2010, whereas money manager shocks fluctuate more after. The volatility of shocks to the futures spread equation is high in harvesting periods, which are typically related to higher uncertainty in agricultural markets. Volatility in both the oil price and the VIX peaks during the Global Financial Crisis, but only the VIX displays a second volatility spike corresponding to fears of a recession in the US in 2011.[12]

4 Empirical results

In this section, we first present the estimated contemporaneous structural relations between the endogenous variables at the aggregate level. Then, we provide historical and variance

[12]Our shock interpretations are also supported by the estimated structural relations presented in the next section. For instance, if shocks to investors' positions would reflect general shifts in risk aversion instead of investor specific factors, they should also have an immediate impact on the VIX, which is not the case.

decompositions. Finally, we show estimation results for subsamples and for individual markets.

4.1 Contemporaneous shock propagation

Table 3 shows the estimated contemporaneous structural relations among the endogenous variables. The upper part displays the *direct* effects of a structural shock of one standard deviation (columns) on the endogenous variables (rows), keeping the other variables constant, as contained in A. For ease of interpretation, we reverse the signs of the off-diagonal elements. The lower part of the table displays the *overall* effects, which incorporate all contemporaneous feedback between variables and correspond to the elements in the A^{-1}-matrix.[13] We denote statistical significance at the 1%, 5%, and 10% level by *a*, *b*, *c*, respectively, below point estimates.

We first focus on shock transmission between positions and futures prices. There is a pronounced asymmetry in the effects of shocks to speculators' positions. Shocks to money manager positions significantly affect prices, whereas shocks to index investor positions do not. This observation holds both for the direct and overall effects. In case of money managers, the point estimate of the direct effect implies that a shock of one standard deviation to net long positions increases agricultural futures prices by 0.33 standard deviations on average or, equivalently, by one percent. On the other hand, there is a symmetry in the systematic part of position changes. Both investors use trend following strategies. On average, they increase net long exposure in response to futures price shocks by 0.26 and 0.16 standard deviations, respectively.[14] For money managers, this strategy implies a positive feedback loop between positions and prices, which amplifies the effect of initial position shifts on futures prices by 18%.

Regarding other shocks, they all affect futures prices significantly, both directly and overall. The signs correspond well to our theoretical priors. Shocks to the futures spread and to the price of oil both impact positively futures prices as they reflect lower inventories and higher costs of production, respectively. Risk shocks have the opposite effect, mirroring the perception of agricultural commodities as a risky asset class. Moreover, they are accentuated substantially through money managers' use of trend following strategies and through inter-market linkages. Furthermore, both types of investors react qualitatively and quantitatively very similar to risk

[13]As there is hardly any persistence in the data, impulse responses do not provide additional insights to the contemporaneous effects displayed in matrix A^{-1}.

[14]This finding is in line with Mayer (2012), who documents that speculators' net long positions are positively correlated with commodity futures returns, and Kang et al. (2014), who find that speculators as a whole use trend following strategies in commodity futures markets while hedgers rather trade in a contrarian fashion. In line with Sockin and Xiong (2013), we also detect a tendency of higher commodity prices to reduce aggregate risk.

Table 3: Direct and overall effects among endogenous variables (matrix A and A^{-1})

	Structural Shocks					
	Fut. Price	Index Inv.	Mon. Man.	Fut. Spread	Oil Price	VIX
			Direct effects (A-matrix)			
Fut. Price	1.00	-0.15	0.33	0.21	0.23	-0.22
	.	.	.a	.a	.b	.b
Index Inv.	0.26	1.00	-0.00	0.04	0.07	-0.04
	.c	.	.	.	.	.
Mon. Man.	0.16	-0.02	1.00	-0.09	0.08	-0.09
	.b	.	.	.	.	.
Fut. Spread	0.03	-0.07	0.20	1.00	-0.02	0.00
	.	.	.c	.	.	.
Oil Price	0.04	0.08	0.03	-0.01	1.00	-0.34
	.	.	.	.	.	.a
VIX	-0.19	0.01	0.04	0.04	0.06	1.00
	.c	.	.	.	.	.
			Overall effects (A^{-1}-matrix)			
Fut. Price	1.10	-0.17	0.39	0.17	0.25	-0.35
	.a	.	.a	.a	.b	.a
Index Inv.	0.30	0.95	0.11	0.08	0.14	-0.16
	.b	.a	.	.	.	.c
Mon. Man.	0.19	-0.06	1.04	-0.06	0.11	-0.17
	.b	.	.a	.	.b	.a
Fut. Spread	0.04	-0.09	0.22	0.99	0.00	-0.02
	.	.	.c	.a	.	.
Oil Price	0.13	0.06	0.06	0.00	1.02	-0.38
	.	.	.	.	.a	.a
VIX	-0.20	0.04	-0.02	0.00	0.02	1.04
	.c	.	.	.	.	.a

[a] The table shows the estimated *direct* (upper part) and *overall* effects of structural shocks of one standard deviation on the endogenous variables, based on a six-variable structural VAR. Impulse variables are in columns, response variables are in rows. The sample period is from June 13, 2006, through August 14, 2014. The number of observations is 420.
[b] .a, .b, .c below point estimates denote significance at the 1%, 5%, 10% level, respectively.

shocks. We conclude from this analogy that they have similar degrees of risk aversion. Finally, the effect of VIX shocks on the price of oil is significantly negative, which supports our identifying sign restriction.

Our results have important implications regarding both the transmission channels of speculative shocks to futures prices and the main trading strategies used by speculators as well as how these affect price discovery. Regarding the transmission of speculative shocks to futures prices, the asymmetry in the effects between investors suggest a limited role of the liquidity and the risk premium channel in our sample. Both channels imply similar effects for investor types, once we control for the size of position shifts and market liquidity as well as under the assumption that they have similar degrees of risk aversion. Instead, the results point to the information channel. The latter relies on the idea that who trades, and based on what information, matters for price discovery. In this respect, money managers and index investors differ substantially (see, among others, Masters and White, 2008, Mou, 2010, Heumeser and Staritz, 2013). The first group includes commodity trading advisors (CTA), commodity pool operators (CPO), and hedge funds. They all actively gather and process commodity-specific information and base their trades on that information. CTAs and CPOs have an insightful knowledge of the particular commodity markets they operate in and hedge funds often take directional views by exploiting cross-market information (see Büyüksahin and Robe, 2014). When these investors receive signals that the futures price is likely to rise, they bid prices up such that the equilibrium price conveys parts of their information – on average they are more often on the right side of the market (see Grossman and Stiglitz, 1980, Grossman, 1986). Thereby, they support one important function of futures markets, namely, that of information aggregation and price discovery. In contrast, position changes of index investors are unlikely to have the same informational content. These investors use commodities typically to diversify portfolio risk but have no particular interest in (specific) commodities themselves. Their trades are rather based on rebalancing, rolling, or weighting considerations. Finally, even if they base decisions on the same public information as money managers, their interpretation could differ (see Singleton, 2014).

Insights also emerge regarding the systematic response of positions to futures price movements. The estimates reveal that on average both types of investors engage in trend following strategies, while there is no evidence for contrarian investing. For index investors, the finding of trend following is less robust, however, and driven mainly by the larger markets, as we show below. For money managers, this finding qualifies the above assertion about their supportive role in price discovery to some degree. While unexpected changes in their positions are beneficial, the use of trend following strategies amplifies the effect of initial shocks on futures prices and thereby hampers price discovery.

4.2 Drivers of agricultural futures prices

In this subsection we analyze the contribution of the different types of shocks and of the exogenous variables to futures price fluctuations. We start with a decomposition of the historical price series to assess the relevance of alternative explanations in driving the booms and busts of 2008/09 and 2010/12. Figure 2 shows the cumulated changes in the futures price and the cumulative effect of the exogenous variables on those. There is a strong co-movement between both series. The exogenous variables capture the secular dynamics of the futures price well. About half of the price surge in 2008 and approximately one-third of the price increases over 2010 to 2012 can be explained by supply conditions, world and US aggregate demand, as well as by the remaining control variables. Overall, the figure suggests that physical and macroeconomic fundamentals already account for an important part of the past two agricultural commodity price cycles, which casts doubt on claims that financial investment was the major driving force (see Masters and White, 2008).

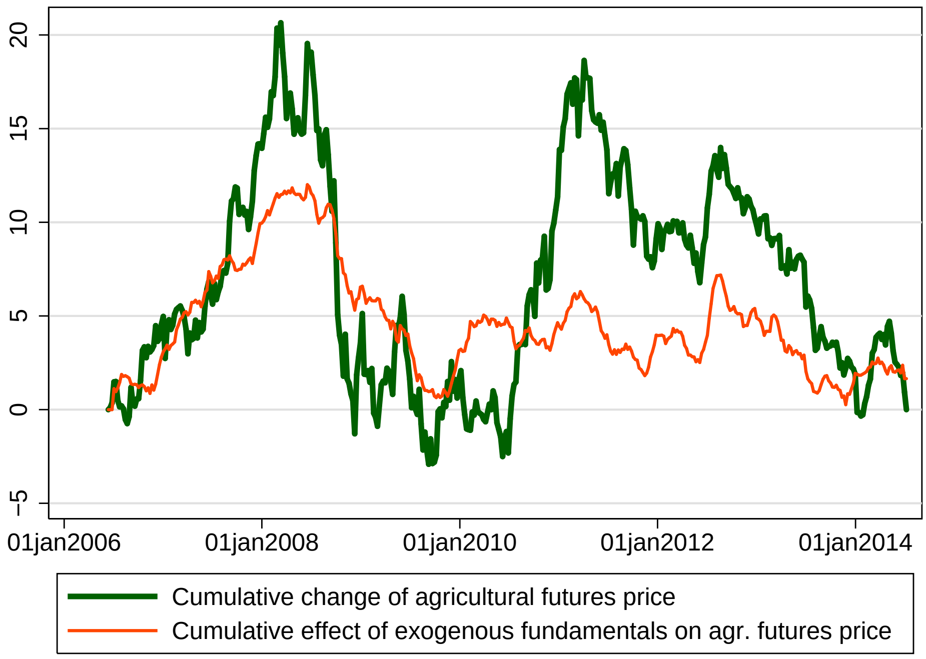

Figure 2: Agricultural futures prices and effects of exogenous fundamentals. The figure shows the cumulative change of the agricultural futures price and the cumulative effect of the exogenous fundamentals on the futures price from June 13, 2006, through August 14, 2014.

This conclusion is corroborated when looking at Figure 3. It shows the cumulative effect of shocks to futures prices, which we interpret as agricultural specific demand shocks based on Section 3.3, of shocks to money manager positions, and of shocks to index investor positions. They are based on a historical decomposition, which yields the weekly contribution of each structural shock to the evolution of the futures price. The figure reveals that, next to exogenous fundamentals, agricultural demand shocks are the other main driver of futures prices. They account roughly for the remaining half of the price boom in 2008 and for a similar fraction of the surge in 2010/2012. Shifts in money manager positions, while not playing a role in the first half of the sample, contributed to the price increases since 2010. Moreover, they seem to have led actual price movements during this period. In contrast, shocks to index investor positions explain hardly any of the fluctuation in futures prices.

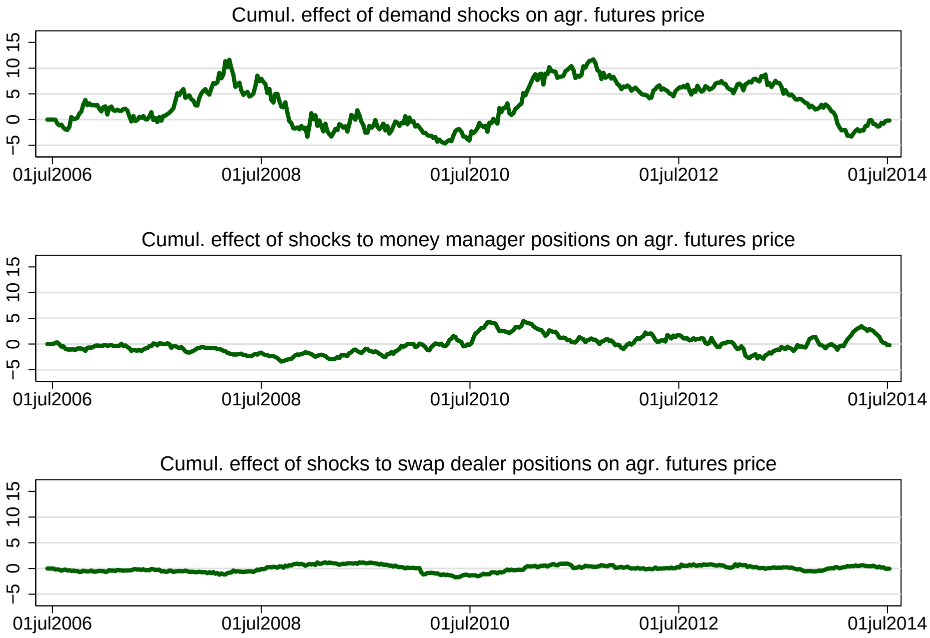

Figure 3: Cumulative effects of structural shocks on agricultural futures prices. The figure shows the cumulative effect of shocks to agricultural demand, to money manager positions, and to index investor positions, respectively, on agricultural futures prices from June 13, 2006, through August 14, 2014.

To quantify the average economic significance of the structural shocks over the sample period, we compute one week ahead forecast error variance decompositions. They yield the percentage contribution of each shock to the variance of the endogenous variables. Since the variance decompositions are regime-specific, we compute their average over the different volatility regimes, using the number of observations per regime as weights. Table 4 shows that other than own shocks explain 34 percent of the variability in futures prices. Among those, shocks to money manager positions are most important at 14 percent. Risk shocks and oil price shocks explain 10 and 5 percent, respectively. In contrast, shocks to index investor positions and to the futures spread play a negligible role. Regarding the drivers of investors' positions, apart from own shocks, they are affected mainly by futures price shocks, reflecting the use of trend following strategies. Oil price shocks and risk shocks also have some explanatory power for position shifts. Overall, the results of this subsection show that money manager positions are an important determinant of agricultural futures prices, whereas index investor positions are not. However, changes in demand and supply conditions are the main explanation behind the observed agricultural commodity price cycles.

Table 4: Weighted average of variance decompositions over different regimes

	Contribution of Shocks					
	Fut. Price	Index Inv.	Mon. Man.	Fut. Spread	Oil Price	VIX
Fut. Price	0.66	0.02	0.14	0.03	0.05	0.10
Index Inv.	0.07	0.85	0.01	0.01	0.02	0.03
Mon. Man.	0.03	0.00	0.89	0.00	0.02	0.04
Fut. Spread	0.00	0.01	0.04	0.95	0.00	0.00
Oil Price	0.01	0.00	0.01	0.00	0.84	0.14
VIX	0.03	0.00	0.00	0.00	0.00	0.97

The table shows the forecast error variance decompositions over the horizon of one week. Values are a weighted average of the variance decompositions of the different regimes, using the number of observations per regime as weights.

4.3 Rolling window and single market estimations

We now go into detail and analyze whether there is time-series or cross-sectional variation in the relation between positions and agricultural futures prices. First, we investigate whether the structural relations have changed over time, in particular after the introduction of the Dodd-Frank Act in 2010. To this end we estimate the model over rolling windows of three consecutive volatility regimes. In this way, the first window corresponds to the period before the Dodd-Frank Act and the last window to the time afterwards.[15] Prior to estimation, we standardize the endogenous variables over each window to facilitate a direct comparison of the point estimates. Table 5 shows the results. For brevity, we only display the overall bidirectional effects between futures prices and positions.

The main results hold largely over the different subsamples. The statistical significance of the point estimates tends to be somewhat lower, which likely mirrors the reduced number of observations. In some cases they loose significance. Demand shifts by money managers raise agricultural futures prices in all subsamples. The effect is qualitatively similar and highly statistically significant before (Regime 1-3) and after the Dodd-Frank Act (Regime 4-6). Shocks to index investor positions, on the other hand, have no effect on prices in any of the subsamples. In the other direction, shocks to futures prices raise net long positions of money managers in three out of four subperiods, whereas the effect on index investor positions is no longer significant.

[15] Given our identification strategy, it would also be possible to estimate the model over rolling windows of only two volatility regimes. This approach, however, does not yield meaningful results, most likely due to the resulting low number of observations per window and the lack of sufficient changes in volatility within the smaller subperiods.

Table 5: Effects between investors' positions and futures prices over rolling subsamples

	Regime 1-3	*Regime 2-4*	*Regime 3-5*	*Regime 4-6*
Index Inv. → Fut. Price	0.20	-0.03	-0.12	0.08
	.	.	.	.
Mon. Man. → Fut. Price	0.47	0.54	0.46	0.32
	.a	.b	.a	.a
Fut. Price → Index Inv.	0.29	0.38	0.08	0.03
	.	.	.	.
Fut. Price → Mon. Man.	0.20	0.08	0.34	0.27
	.c	.	.b	.b
Observations	213	149	196	206

[a] The table shows the estimated structural *overall* effects between futures prices and investors' positions over rolling subsamples of three consecutive volatility regimes. Estimates are obtained from a six-variable structural VAR. The arrows indicate the relation between impulse and response variables. The full sample period is from June 13, 2006, through August 14, 2014.

[b] .a, .b, .c denote significance at the 1%, 5%, 10% levels.

Next, to see which markets drive our main results, we return to the full sample period and estimate a set of VAR models for the eight individual futures markets that underlie the aggregate indices. Specifically, we replace the first four aggregate variables with market-specific variables and, regarding the exogenous variables, we use market specific crop conditions. Otherwise we leave the specification unchanged.[16] Table 6 shows the results which are ordered by market size.

Generally, they mirror the findings for the aggregate level. In all eight markets we find a positive and highly significant effect of shocks to money manager positions on futures prices. The point estimates are roughly similar across markets and comparable to the benchmark specification. They tend to be stronger in the (larger) grain markets. For index investor positions, we now find a significant effect in two of the smallest markets. Regarding the impact of prices on positions, money managers react to price shocks in most of the individual markets. Again, we find the strongest effects in the grain markets. Index investor positions, on the other hand, react to price shocks only in the larger markets. This pattern likely reflects one of the principles of index investment, where exposure is spread over a large number of commodity markets such that index investors' positions are only influenced by markets that constitute a large index share.

[16]For the meat markets, we use crop conditions for corn.

Table 6: Effects between investors' positions and futures prices on individual markets

	SRW Wheat	*Corn*	*Live Cattle*	*Soybeans*
Index Inv.→ Fut. Price	0.08	-0.02	0.02	0.01
	.	.	.	.
Mon. Man.→Fut. Price	0.34	0.52	0.27	0.46
	.a	.a	.a	.a
Fut. Price→Index Inv.	0.27	0.13	0.04	0.14
	.b	.c	.	.b
Fut. Price→Mon. Man.	0.32	0.22	0.05	0.31
	.a	.a	.	.a
	Lean Hogs	*Cotton*	*HRW Wheat*	*Feeder Cattle*
Index Inv.→Fut. Price	0.05	0.22	0.01	0.30
	.	.a	.	.c
Mon. Man.→Fut. Price	0.32	0.28	0.39	0.25
	.a	.a	.a	.b
Fut. Price→Index Inv.	0.01	-0.15	0.04	-0.17
	.	.	.	.
Fut. Price→Mon. Man.	0.06	0.04	0.29	0.16
	.	.	.a	.a

[a] The table shows the estimated structural *overall* effects between futures prices and investors' positions, based on market-specific six-variable structural VAR models. The arrows indicate the relation between impulse and response variable. The sample period is from June 13, 2006, through August 14, 2014. The number of observations for each market is 420.

[b] .a, .b, .c denote significance at the 1%, 5%, 10% levels, respectively.

5 Alternative volatility regime definition

In this section, we further assess the robustness of the main results for the aggregate level by using an alternative, more statistical approach to define volatility regimes. Specifically, following Fratzscher et al. (2013), we compute rolling standard deviations of the estimated reduced form residuals and calibrate thresholds above which underlying observations are classified into volatility regimes. Since we are particularly interested in the bi-directional effects between speculators' positions and futures prices, we group observations into five different volatility regimes based on the 13 weeks rolling standard deviations of the residuals of the respective equations. We employ a threshold of 1.2 standard deviations. In regime 1, no residual displays volatility above the threshold, while regimes 2 to 4 are characterized by increased volatility in only one of the three residuals. In regime 5 the standard deviation of at least two residuals exceeds the threshold.[17]

The results for the overall effects are presented in Table 7. The main findings are robust to the alteration. Shocks to money manager positions raise futures prices while shocks to index investor positions do not. On the other hand, futures price shocks induce an increase in net long positions of both types of investors. The bi-directional effects are similar in size to our main specification. The effects of shocks to the other endogenous variables, on the other hand, display a slightly different pattern. The difference originates in our choice of using only the three main variables of interest to define volatility regimes which means that shocks to the other variables are less precisely identified.

Table 7: Effects among endogenous variables with statistical regime definitions

	Structural Shocks					
	Fut. Price	Index Inv.	Mon. Man.	Fut. Spread	Oil Price	VIX
	Overall effects					
Fut. Price	1.11	-0.16	0.24	0.22	0.03	-0.24
	.a	.	.a	.a	.	.c
Index Inv.	0.38	0.93	0.15	0.11	0.09	-0.01
	.b	.a	.	.	.	.
Mon. Man.	0.34	-0.06	1.06	0.15	0.07	-0.12
	.a	.	.a	.	.	.
Fut. Spread	0.09	-0.05	-0.09	1.01	0.00	0.08
	.	.	.	.a	.	.
Oil Price	0.47	0.13	0.05	0.03	0.96	-0.43
	.a	.	.	.	.a	.a
VIX	-0.21	-0.18	-0.04	-0.05	0.15	0.97
	.	.	.	.	.	.a

[a] The table shows the estimated *overall* effects of structural shocks on the endogenous variables, based on a six-variable structural VAR. Impulse variables are in columns, response variables are in rows. The sample period is from June 13, 2006, through August 14, 2014. The number of observations is 420.

[b] .a, .b, .c denote significance at the 1%, 5%, 10% levels, respectively.

6 Conclusion

Using a structural VAR with weekly data for 2006-2014, this paper assesses the relationship between financial investors' positions, agricultural futures prices, and other asset prices. We

[17] While this approach is a useful tool to check the robustness of the results, we do not apply it for our main analysis as it has several drawbacks. First, calibrations need to be market and subsample specific to yield meaningful results, whereas with the narrative approach the definition of volatility regimes can be kept constant across specifications. This facilitates a straightforward comparison of results across specifications. Second, the statistical approach with thresholds for all six variables implies that some observations do not fit into any of the specified regimes. This would reduce the number of observations considerably.

include two important types of speculators jointly into the model: index investors and money managers. This approach allows us to test specific hypotheses in the literature of how financial investors can affect futures prices.

Our analysis shows that unexpected changes in net long positions of money managers raise futures prices, whereas there is no effect for index investors. Reversely, both investor groups react to futures price shocks by increasing their exposure. The results highlight the role of the information discovery channel in the transmission of speculative demand shocks to prices. Unexpected changes in money manager positions seem to transmit price signals to the market. In principal, they thereby support information aggregation and price discovery in futures markets. What seems more of a concern is that money managers also use trend following strategies. These in turn can amplify the effects of initial shocks on futures prices.

Regarding the historical evolution of agricultural futures prices, we find no evidence that speculative demand shocks of money managers contributed to the boom and bust in 2008/2009 but that they played a role in the price surge in 2010. Shifts in index investor positions in turn had no material effects on prices in either episode. Overall, the results suggest that demand and supply are the fundamental determinants of agricultural commodity price cycles.

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Appendix

A Data and sources

Table 8: Data construction and sources

Variable	Construction and source
Agricultural futures prices	Nearby (next-to-maturity) futures prices of eight agricultural commodities which are aggregated to an index as described in the main text. As position data measure open positions on each Tuesday, we use Tuesday futures prices. If Tuesday is not a trading day, we use the closing price of the trading day before. Source: Datastream.
Investors' positions	Swap dealers and money managers. Source: CFTC DCOT reports.
Futures spread	Difference between (log) of the nearby futures contract and the second-to-maturity futures contract. Source: Datastream.
Oil Price	WTI oil price. Source: St. Louis Fed FRED database.
VIX	CBOE Volatility Index: VIX©, Source: St. Louis Fed FRED database.
Index of crop conditions	Weather conditions are measured following Bruno et al. (2013). We use weekly crop conditions reports of the US Department of Agriculture (USDA) which survey the condition of cotton, corn, soybeans, and wheat plants in major producing US states. On a given weak, a percentage of crops is assessed to be in a 'excellent', 'good', 'fair', 'poor', or 'very poor' condition. We weight the assessments using a linear scheme to construct a measure of individual crop conditions. The resulting series are set to zero when no information is available, that is when there is nothing yet in the ground. We construct a weather conditions index based on the commodities included in the report using the S&P GSCI weights as with the futures price index. Thereby, additional weight is given to corn as it is the most import source of feed for cattle and pigs. As a robustness check, we also exclude the weights for meat commodities, as they are not directly affected by the weather. This yields very similar results.
Macroeconomic news shocks	Difference between announced realization and median forecast of surveyed forecasters for the variables contained in Table 2. Source: Datastream.
Announcements of quantitative easing	Dummies for announcement dates of quantitative easing. Source of dates: Fawley and Neely (2013).
Fed balance sheet	Total assets of the Fed. Source: St. Louis Fed FRED database.
Market liquidity	Amivest measure (Amihud et al., 1997): volume of open contracts in a trading week divided by the absolute return in that week. Source: datastream / CFTC.
Initial jobless claims	Number of initial jobless claims, seasonally adjusted. Source: St. Louis Fed FRED database.
Index of global economic activity	Kilian's (2009) index of dry cargo shipping rate. Source: Lutz Kilian's webpage.
Agricultural stocks	Actual agricultural stocks, constructed as in Bruno et al. (2013). Meat stocks: USDA total storage figures for beef and pork (excluding frozen ham). For grain stocks: monthly stock forecasts reported in the current USDA forecasts of US supply-use balances of major grains.

B Definition of volatility regimes

We define volatility regimes based on events that triggered major changes in the volatility of our endogenous variables, and in particular in the agricultural futures market (see Figure 4). Regime 1 ends with the bankruptcy of Lehman Brothers. Subsequent major stress in financial markets affected the volatility of all endogenous variables. Regime 2 ends with last announcement regarding the first program of Quantitative Easing, which calmed financial markets. To illustrate this, Figure 4 also contains the 52 weeks rolling standard deviations of changes in agricultural futures prices and in investors' positions. The volatility of the price series (thick green line) increased strongly after Lehman Brothers and is later reduced by the unconventional monetary policy measures. The fourth regime starts with the Dodd-Frank Act in 2010, which regulated agricultural derivative markets and, thereby, affected the volatility of investors' positions (see blue and red line). Regime 5 starts with the rating downgrade of US government debt by S&P in August 2011. This coincided with fears of a US recession. The last regime starts with the announcement by the Fed to taper the Quantitative Easing Program.

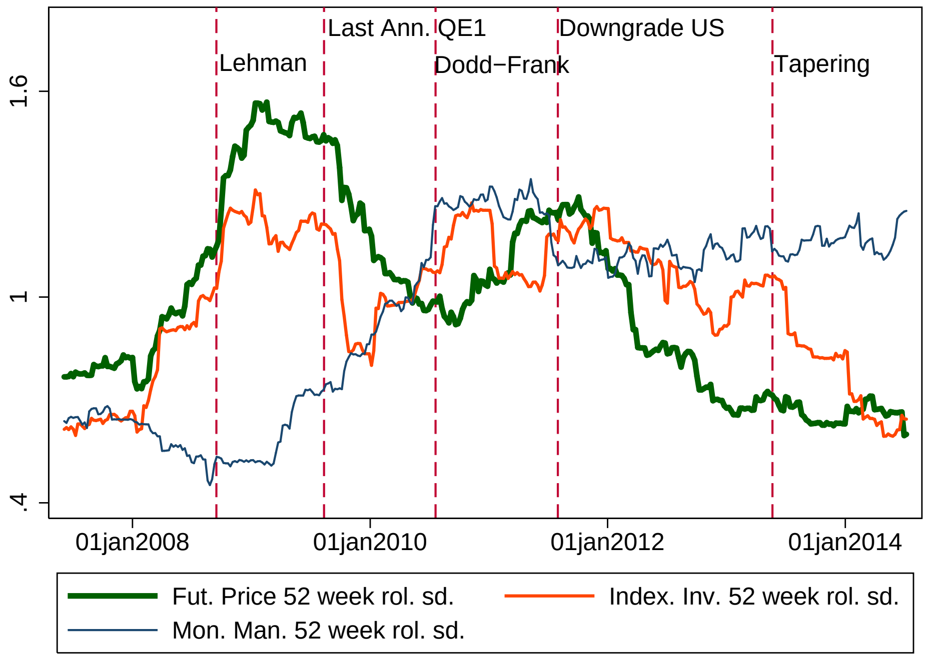

Figure 4: Major events, volatility regimes, and rolling standard deviations. The figure shows (a) major political and economic events affecting agricultural commodities and other asset markets, (b) the definition of volatility regimes 1-6 (vertical dashed lines), and (c) the 52 weeks rolling standard deviations of the first (log) difference of the agricultural futures prices index (green line), of index investors' positions (orange line), and of money managers' positions (blue line).

To see if our regime definition is supported by the data, we test formally for the constancy of the reduced form covariance matrix (see Table 9). We follow Lanne and L´utkepohl (2008) and perform likelihood ratio (LR) tests on the null hypothesis that every two neighboring regimes have the same covariance matrix. The null hypothesis can be strongly rejected for each pair of regimes. It is known that such LR tests do not have optimal small sample properties. The null might be rejected too often. However, our test statistics are so large that we can reject the equality of the variance matrices with confidence. Moreover, the changes in volatility are also reflected in the regime-specific variances of the structural shocks. Table 10 shows that there are shifts in the ratio of variances between at least two regimes for every pair of structural shocks. This illustrates the idea behind identification through heteroskedasticity: an increase in the relative variance of shocks to, say, money manager positions affects the covariance between positions and prices in a way that gives us additional information about the responsiveness of prices to position shifts. Finally, the events affect all agricultural markets included in our price index, giving no additional weight on one market or the other, such that the regimes can be kept constant across single market specifications. Moreover, the regimes define natural subperiods of sufficient and similar length which allows us to perform subsample estimations to check the robustness of the results.

Table 9: Tests for constancy of reduced form covariance matrix between regimes

H_O	LR test statistic	p-value
$\Sigma_1 = \Sigma_2$	83.55	$2.04e^{-09}$
$\Sigma_2 = \Sigma_3$	204.65	0
$\Sigma_3 = \Sigma_4$	248.99	0
$\Sigma_4 = \Sigma_5$	343.62	0
$\Sigma_5 = \Sigma_6$	370.55	0

Table 10: Variances of the structural shocks in the different regimes

Regime	1	2	3	4	5	6
Fut. Price	0.69	1.03	0.41	0.73	0.33	0.23
Index Inv.	0.56	0.68	1.12	1.10	0.79	0.41
Mon. Man.	0.30	0.32	0.94	0.76	1.11	0.99
Fut. Spread	0.82	0.44	0.62	0.77	1.34	1.07
Oil Price	0.64	3.30	0.51	0.51	0.39	0.27
Vix	0.53	2.41	1.09	0.28	0.65	0.39
Observations	28 %	11 %	12 %	13 %	22 %	14 %

C Additional interpretation of structural shocks

To check whether the structural shocks correspond to our interpretation, we evaluate whether they display higher volatility in those periods the interpretation suggests. Figure 5 shows the structural shocks (grey lines) along with their centered 52 weeks rolling standard deviations (black lines). Shocks to investors' positions increase in volatility around the Dodd-Frank Act in 2010. Resulting regulations required many derivatives, which had been traded over-the-counter, to be traded on commodity exchanges, increasing the observed volatility in positions. Moreover, a clear difference between investors is visible towards the end of the sample where agricultural prices stagnated or declined. This development mainly affected the volatility in swap dealers' shocks as they proxy index investors whose activity in commodity markets relies on steadily rising prices. Money managers, on the other hand, take positions an both sides of the market and trade actively also in an environment with falling prices.

The volatilities of the agricultural specific demand shock, the oil price shock, and the uncertainty shock all peak during the Global Financial Crisis. Apart from that, however, there are pronounced differences between the series. Demand shock volatility reaches another local maximum around the tipping point of the second boom in agricultural commodities in 2012, whereas this peak is absent from the oil shock series while uncertainty shocks peak again twice. This is because oil prices did not experience a second cycle but fluctuated around a high level from 2011 onwards. Uncertainty in turn increased when the US economy was feared to enter recession and during the announced end of Quantitative Easing. For shocks to the futures spread, volatility seems to reflect harvesting periods.

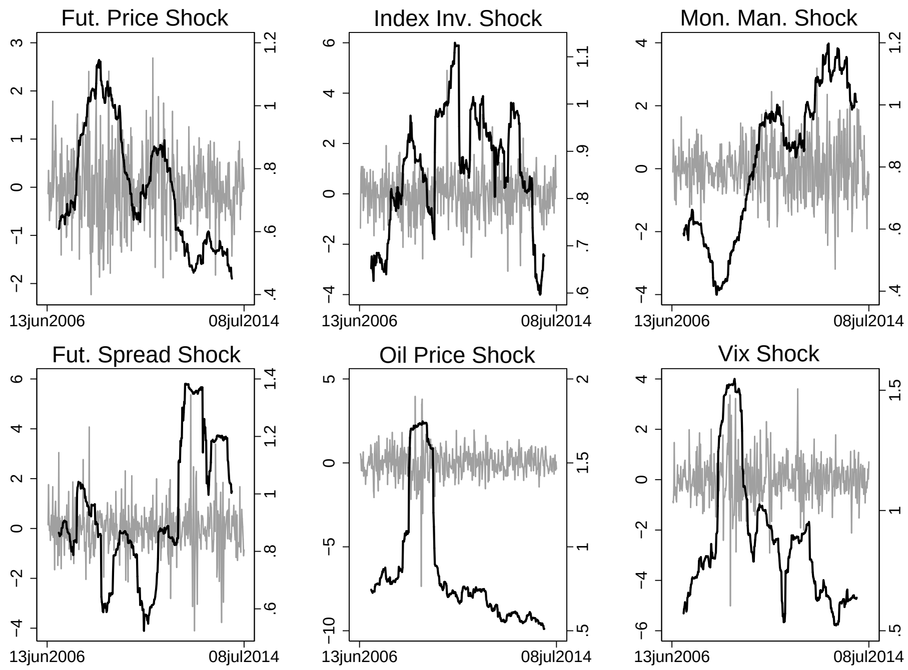

Figure 5: Interpretation of structural shocks. The figure shows the estimated structural shocks (grey bars, left axis) together with their (centered) 52 weeks rolling standard deviations (black lines, right axis). The estimated shocks are based on a six-variable structural VAR for the agricultural futures market.