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Identifying Speculative Demand Shocks in Commodity Futures Markets through Changes in Volatility*

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Abstract

This paper studies the effects of financial speculation on commodity futures returns, using publicly available data from the US Commodity Futures Trading Commission, aggregated by trader groups. We exploit the heteroskedasticity in the weekly data to identify exogenous variation in speculators' positions. The results suggest that idiosyncratic net long demand shocks of both index investors and hedge funds increase futures returns. They further indicate that these shocks are a relevant driver of returns, especially during periods of high speculative demand volatility. These findings confirm significant price effects of financial investments, complementing existing evidence based on disaggregated and proprietary daily data.

JEL-Classification: Q02, G13, E39.

Keywords: Financialization, hedge funds, index investors, market structure, liquidity, limits to arbitrage, heteroskedasticity.

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1 Introduction

The recent drastic boom-bust cycles in commodity prices spurred an intense debate about the increased presence of financial investors in commodity markets. The discussion revolves around whether investors are responsible for the large price swings and, more generally, whether they drive prices away from fundamentals, distort price signals, and reduce welfare. Growing concerns among policy makers already led to initiatives of stronger futures market regulation.¹ The empirical literature, on the other hand, has reached no consensus on whether and how financial investment affects commodity prices. Many studies use publicly available data on futures market positions aggregated by groups of traders, provided by the US Commodity Futures Trading Commission (CFTC) at a weekly or lower frequency. Only a few of these papers document positive effects of investor flows on futures returns for specific sample periods and markets (see Singleton, 2014, and Gilbert and Pfuderer, 2014). Most of them, however, find no effect of speculators' position changes on futures prices (see, among others, Stoll and Whaley, 2010, Büyüksahin and Harris, 2011, Irwin and Sanders, 2012, Aulerich et al., 2013, Hamilton and Wu, 2015).²

The main challenge in this literature is identification. Specifically, it is necessary to isolate variation in investors' positions due to trades actually initiated by speculators from variation due to trades initiated by other market participants, such as producers, to which speculators only respond by taking the counter-side. This distinction is important because only the former trades induce a positive correlation between speculators' long positions and futures prices, whereas the latter trades imply a negative correlation as producers need to compensate speculators for taking the risk by setting the futures price at a discount. A lack of identification might thus imply an insignificant correlation, as both types of trades are averaged.

Two recent studies address the identification issue using daily proprietary or disaggregated data and find significant positive price effects of financial investments. Henderson et al. (2015) use detailed issuance data on commodity-linked notes and show that futures prices increase when the financial institutions issuing the notes hedge their short exposure vis-à-vis the holders of the securities through long positions in the futures market. Cheng et al. (2015) have access to the CFTC's Large Trader Reporting System which provides private account-level data on individual traders' positions. The authors show that increases in the VIX, that are associated with lower futures prices, lead to a reduction in financial traders' exposure, and to an increase in producers' net long positions. This is consistent with financial traders initiating the trades.

In this paper, we provide new evidence on the price effects of financial investments in commodity futures markets by proposing an approach to address the identification issue in the publicly available aggregated weekly CFTC data. Specifically, we identify a system of simultaneous equations, modeled

¹In the US, the Dodd-Frank act granted the Commodity Futures Trading Commission (CFTC) the responsibility for additional regulations of commodity derivative markets. In the European Union, the European Commission set up an expert group on the regulation of commodity derivatives.

²See also Fattouh et al. (2013) and Cheng and Xiong (2013) for overviews of the literature.

as a vector autoregression (VAR), through the heteroskedasticity that is present in the weekly data to isolate exogenous variation in speculators' net long positions. Following Sentana and Fiorentini (2001) and Rigobon (2003), the approach exploits the fact that changes in the volatility of the structural shocks in the system contain additional information on the relation between the endogenous variables. For example, in a period of high speculative demand volatility, we learn more about the response of returns to positions as the covariance between both variables temporarily increases. Then, speculative demand shocks are more likely to occur and can be used as a 'probabilistic instrument' (see Rigobon, 2003).

The model includes three endogenous variables: commodity futures returns and net long positions of 'index investors' and 'hedge funds', respectively, who are both financial speculators.³ We use position data from the CFTC Supplemental Commitments of Traders (SCOT) reports, which contain a proper category for 'index investors'. Both groups are important in terms of market share and have received considerable attention in the academic debate (see Büyüksahin and Robe, 2014, Singleton, 2014, Cheng et al., 2015, Basak and Pavlova, 2016). The reports cover eleven agricultural markets, but exclude energy and metal markets. For the core analysis, we compute an aggregate index for each endogenous variable and apply a statistical approach to the reduced-form residuals of the model to detect changes in the volatility of the structural shocks. These changes in volatility, together with the assumption of time-invariant impact effects, are central to achieving identification. Formal tests support the necessary assumptions and indicate that identification has been achieved from a statistical point of view.

Our results suggest that the identified exogenous position changes of speculators have significant contemporaneous price effects and that they are a relevant driver of futures returns. In particular, we find that demand shocks of both index investors and hedge funds impact positively on returns. A one standard deviation shock to index investors' net long positions increases futures returns significantly by 0.15 standard deviations on impact. The contemporaneous effect of hedge funds' demand shocks on returns is 0.39 standard deviations. These results are qualitatively and quantitatively robust to various alterations of the model and the data. Specifically, we assess the sensitivity of the estimates to changing the definition of volatility regimes, to adding another trader group to the model, and to splitting the sample. Our results also hold on the single markets underlying the aggregate indexes used in the main specification.

We further assess the economic importance of the identified speculative demand shocks for commodity price fluctuations with variance and historical decompositions. The variance decompositions suggest that the shocks account for roughly one fifth of the variation in returns on average. Moreover, their importance increases during periods of high speculative demand volatility. Then, demand shocks of hedge funds account for 30 percent of the variation in futures returns, and demand shocks of index investors explain up to 10 percent. By means of historical decompositions, we also quantify the relevance of fundamental

³The latter group actually contains positions of hedge funds, commodity pool operators, and commodity trading advisors. For brevity, we refer to this category as hedge funds in the following.

demand and supply conditions as well as changes in the VIX and oil prices for explaining agricultural futures prices. The results suggest that these forces account for the largest part of commodity price fluctuations, and in particular explain their secular dynamics. Speculative demand shocks, on the other hand, seem to mainly contribute to short-run price movements.

Overall, the results support existing studies that detect significant impacts of financial investments on commodity returns based on highly disaggregated or proprietary data. Using a structural VAR approach allows quantifying the statistical significance of speculative demand shocks and their economic importance - both on average and during specific time periods - with publicly available aggregated data. The documented price effects are consistent with two recent strands of theoretical models. The first strand emphasizes the existence of limits to arbitrage. When financial intermediaries are funding constrained, position changes of other market participant can have price effects (see He and Krishnamurthy, 2013, Acharya et al., 2013, Hamilton and Wu, 2014). The second strand stresses the role of informational frictions. Under asymmetric information, trades can transmit private signals to the market and thereby affect prices (see Goldstein and Yang, 2015, 2016, Sockin and Xiong, 2015).

Methodologically, our paper connects to a fast-growing line of research that investigates the role of financial investors in commodity markets using time-series models. Irwin and Sanders (2012), Aulerich et al. (2013), or Gilbert and Pfuderer (2014) rely on bivariate Granger-causality tests or similar techniques. Other authors use structural VAR models. Ederer et al. (2013) and Bruno et al. (2017) employ Cholesky identification schemes. Zero restrictions, however, seem difficult to defend when working with weekly or lower frequency financial market data. Alternatively, Kilian and Murphy (2014) use sign restrictions that allow for an instantaneous response of all endogenous variables. Different to our focus, they analyze the impact of speculation tied to physical inventories. Moreover, sign restrictions do not allow us to disentangle the main shocks of interest, as theory gives similar predictions regarding the sign of the impact of several of the model's structural shocks on the endogenous variables. Therefore, we apply an agnostic identification approach using changes in volatility, without additional sign or zero restrictions.

The remainder of the paper is structured as follows. Section 2 outlines a simple theoretical framework to develop a notion about the structural shocks driving the systems of equations and to derive testable hypotheses. Then, we describe the data and the identification strategy in Section 3. Section 4 contains the main results, while their sensitivity and robustness is evaluated in Section 5. The last section concludes.

2 Theoretical framework

Our model of simultaneous equations contains three endogenous variables: the commodity futures return and net long positions of index investors and hedge funds, respectively. The variables are assumed to be contemporaneously driven by three uncorrelated structural shocks as well as exogenous variables. To

develop a notion about the three structural shocks, we employ a simple theoretical model of the futures market which also allows us to derive some hypotheses about the contemporaneous impacts of the shocks on the endogenous variables. As in Cheng et al. (2015), we consider a one period model with different groups of market participants, hedgers and—in our case—two groups of financial investors. The hedgers are commodity producers (pr) who need to hedge their price risk in the futures market. Financial investors are speculators without an interest in the physical delivery of the commodity, consisting of index investors and hedge funds ($f1$ and $f2$).

Speculative demand of the two groups of financial investors is driven by two idiosyncratic shocks, v_{f1} and v_{f2} , that motivate them to change their positions. Additionally, there is a shock η which commonly affects demand of all three groups. As we will exogenously control for physical supply conditions and financial market risk in the model (see Section 3.3), the common shock is unrelated to these two driving forces. Instead, it can be thought of as capturing changes in demand in the spot market which are transmitted to the futures market. The demand curves for producers and financial investors are

$$\Delta x_{pr} = -\beta_{pr}\Delta F - \gamma_{pr}\eta, \quad \Delta x_{f1} = -\beta_{f1}\Delta F + \gamma_{f1}\eta + v_{f1}, \quad \Delta x_{f2} = -\beta_{f2}\Delta F + \gamma_{f2}\eta + v_{f2},$$

where ΔF is the change in the futures price, Δx_{pr} , Δx_{f1} , and Δx_{f2} is the change in net long demand of hedgers and financial investors, respectively, and it is assumed that $\beta_{pr}, \beta_{f1}, \beta_{f2} \geq 0$ and that $\gamma_{pr}, \gamma_{f1}, \gamma_{f2} \geq 0$. The first assumption implies that all demand curves are downward sloping. The second assumption relates to the common shock. To meet higher physical demand, commodity producers increase their output, which in turn raises their hedging needs. The common shock therefore causes a decline in net long demand of producers in the futures market. We further assume that the common shock increases speculative net long demand of financial investors as the physical demand for commodities rises. This reaction can be motivated by, for example, trend-following behavior as speculators expect further price increases (see Rouwenhorst, 1998, Bhardwaj et al., 2014, Kang et al., 2017).

Market clearing imposes that $\Delta x_{pr} + \Delta x_{f1} + \Delta x_{f2} = 0$ where the equilibrium price balances the three groups' net demand. Solving the model with respect to the underlying shocks yields the following equation for the change in the futures price:

$$\Delta F = \frac{1}{\beta_{pr} + \beta_{f1} + \beta_{f2}} v_{f1} + \frac{1}{\beta_{pr} + \beta_{f1} + \beta_{f2}} v_{f2} + \frac{\gamma_{f1} + \gamma_{f2} - \gamma_{pr}}{\beta_{pr} + \beta_{f1} + \beta_{f2}} \eta$$

According to the price equation $\partial \Delta F / \partial v_{f1} > 0$ and $\partial \Delta F / \partial v_{f2} > 0$ if $\beta_{pr} + \beta_{f1} + \beta_{f2} < \infty$. For the empirical model this implies the testable hypothesis:

Hypothesis 1 *Positive speculative demand shocks lead to an increase in net long positions of financial investors and contemporaneously increase commodity futures returns.*

The alternative is to find no significant effect of speculative demand shocks on futures returns. This result would indicate that some or all of the β_i are so large that $1/(\beta_{pr} + \beta_{f1} + \beta_{f2})$ is statistically indistinguishable from zero. Economically, this means that idiosyncratic position changes by financial investors are absorbed by other market participants with nearly infinitely elastic demand curves and have no price effects.

While Hypothesis 1 is derived from a highly stylized model, it is consistent with more sophisticated asset pricing models. Shleifer and Summers (1990) and Shleifer and Vishny (1997), for example, show that large position changes can influence prices through an effect on the order book if the instantaneous supply of counterparty orders is low. Such problems of illiquidity might arise if there are limits to arbitrage which deter risk averse arbitrageurs from taking the counter-side. Positions changes can also influence futures market risk premia and thereby drive up prices (see Acharya et al., 2013, and Hamilton and Wu, 2014, 2015).⁴ If producers want to hedge their price risk, the futures price needs to include a risk premium and, hence, to be set at a discount to induce speculative traders to take the price risk. The higher is the provision of hedging liquidity through speculators, the lower is the risk premium and, hence, the higher the futures price. Additionally, financial investors could affect prices through informational channels. If some investors possess private information, their trades might communicate this information to the market and change the price (see Grossman and Stiglitz, 1980, Hellwig, 1980, Goldstein and Yang, 2015). Private information could be due to better forecasting abilities, different costs of private information production, or divergent interpretations of public information (see Singleton, 2014).

The effect of the common shock on the futures price depends on the relative size of γ_{pr} , γ_{f1} , and γ_{f2} . If long demand of investors increases by more than short demand of producers in response to the shock, that is, if $\gamma_{f1} + \gamma_{f2} > \gamma_{pr}$, then $\partial \Delta F / \partial \eta > 0$. Solving the model yields the following equation for changes in net long positions of financial investor group $i = 1, 2$

$$\Delta x_{fi} = \frac{\beta_{pr} + \beta_{fj}}{\beta_{pr} + \beta_{f1} + \beta_{f2}} v_{fi} - \frac{\beta_{fi}}{\beta_{pr} + \beta_{f1} + \beta_{f2}} v_{fj} + \frac{(\beta_{pr} + \beta_{fj})\gamma_{fi} + \beta_{fi}(\gamma_{pr} - \gamma_{fj})}{\beta_{pr} + \beta_{f1} + \beta_{f2}} \eta,$$

where j denotes the other investor group. The sign of the effect of physical demand shocks on financial investors' demand, $\partial \Delta x_{fi} / \partial \eta$, depends on the relative sizes of the parameters. However, as long as no group reacts extremely to the common shock (γ_{fi} very large) and no group reacts extremely to price changes (β_{fi} very large), it follows that $\partial \Delta x_{f1} / \partial \eta > 0$ and $\partial \Delta x_{f2} / \partial \eta > 0$. For the empirical model these observations can be translated to

⁴Following the theory of normal backwardation, going back to Keynes (1930), the spot and the futures price are related according to $F_{i,T} - S_t = [\mathbb{E}(S_T) - S_t] - \pi_{i,T}$, where S_t and S_T are the spot price at t and T , respectively, $F_{i,T}$ the T -periods ahead futures price and $\pi_{i,T}$ the risk premium. If short hedging demand exceeds long supply, the risk premium will be positive. 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 counter-party 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 can lead to an increase in futures prices if they affect risk premia.

Hypothesis 2 *Positive physical demand shocks have a positive contemporaneous effect on commodity futures returns and drive up net long positions of financial speculators.*

The alternative is that physical demand shocks have no significant effect on or even lead to a decrease in speculators' net long positions. This could be the case if, for example, $\gamma_{fj} \gg \gamma_{pr}$ and $\beta_{fi} \gg 0$. In the next section, we outline how we specify the empirical model to test the two hypotheses.

3 Empirical model, data, and estimation methodology

3.1 Empirical model

The structural VAR model is given by

$$Ay_t = \tilde{c} + \tilde{A}_1 y_{t-1} + \dots + \tilde{A}_p y_{t-p} + \tilde{\Lambda} x_t + \varepsilon_t, \quad (1)$$

with the vector of endogenous variables

$$y_t = \begin{pmatrix} \Delta \log(\text{Agricultural futures price})_t \\ \Delta(\text{Net long positions index investors})_t \\ \Delta(\text{Net long positions hedge funds})_t \end{pmatrix},$$

x_t a vector of exogenous variables, and \tilde{c} , \tilde{A}_p , and $\tilde{\Lambda}$ parameter matrices. The vector ε_t contains the structural shocks with regime-dependent diagonal covariance matrix in regime k

$$\Sigma_{\varepsilon,k} = E(\varepsilon_t \varepsilon_t') = \begin{pmatrix} \sigma_k^F & 0 & 0 \\ 0 & \sigma_k^I & 0 \\ 0 & 0 & \sigma_k^H \end{pmatrix}.$$

In its reduced-form, the model in equation (1) can be re-written as follows

$$y_t = c + \Pi_1 y_{t-1} + \dots + \Pi_p y_{t-p} + \Lambda x_t + u_t, \quad (2)$$

where $\Pi_p = A^{-1} \tilde{A}_p$ and $\Lambda = A^{-1} \tilde{\Lambda}$. The vector of reduced-form residuals $u_t = (u_t^F, u_t^I, u_t^H)'$ is related to the structural shocks through matrix A^{-1} : $u_t = A^{-1} \varepsilon_t$.

The focus of the empirical analysis is on the impact matrix A^{-1} that contains the contemporaneous effects of the structural shocks on the endogenous variables. Specifically, the hypotheses outlined in Section 2 can be assessed based on the estimated A^{-1} . Assuming that the identified structural shocks in the two equations with investors positions are speculative demand shocks of the different investor

groups, Hypothesis 1 comes down to testing $\alpha_{1,2}, \alpha_{1,3} > 0$, where $\alpha_{j,k}$ is the corresponding element in A^{-1} . Similarly, if the structural shock in the futures price equation of the estimated structural VAR model is the physical demand shock, Hypothesis 2 can be tested by analyzing whether $\alpha_{2,1}, \alpha_{3,1} > 0$. Therefore, after the estimation, we first assess how the estimated structural shocks can be interpreted with the outlined theoretical model in mind, before evaluating the estimated parameters in A^{-1} . For our baseline model, we will also assess the *direct* effects of structural shocks captured in A . They differ from the *overall* effects in A^{-1} as they do not take instantaneous feedback among endogenous variables into account. Instead, parameters in A can be interpreted as effects of shocks keeping all other variables constant and showing both is thus indicative of shock amplification among endogenous variables.

3.2 Identification

Equation (2) and the regime-dependent covariance matrix of the reduced-form shocks, $\Sigma_{u,k}$, can be estimated consistently by ordinary least squares. Specifically, we specify the model in first (log) differences to account for the non-stationarity of the data.⁵ Moreover, we standardize all variables prior to the estimation.⁶ We include two lags of the endogenous variables to obtain residuals free from autocorrelation and to strike a balance between the usual lag length selection criteria. From (1) and (2), it follows that $\Sigma_{u,k} = A^{-1}\Sigma_{\varepsilon,k}(A^{-1})'$. This relation illustrates how different volatility regimes contain additional information that can be exploited to identify the impact matrix A (or equivalently A^{-1}). With $k = 1$ we would only have six moments on the LHS that can be estimated but nine parameters that need to be determined on the RHS (three structural shock variances and six off-diagonal elements in A , with the main diagonal normalized to unity). For $k \geq 2$, however, the system has at least as many moments that can be estimated (for instance, twelve if $k = 2$) as unknowns (six structural shocks variances and six off-diagonal elements if $k = 2$).

The approach of identification through heteroskedasticity has been developed by Sentana and Fiorentini (2001) and Rigobon (2003) and applied in the context of financial markets and asset price co-movements by, among others, Bouakez and Normandin (2010) and Ehrmann et al. (2011). The idea is that changes in the relative variances of the structural shocks over time, that is, changes in $\sigma_k^S/\sigma_k^{S'}$ across k with $S = F, I, H$ contain additional information which allows determining the entries in A . If, for example, the variance of index investor position changes increases in a certain period ($\sigma_k^I/\sigma_k^F > \sigma_{k'}^I/\sigma_{k'}^F$), speculative demand shocks coming from that group help tracing out the demand curve of other market participants, and thereby

⁵Augmented Dickey-Fuller and Phillips-Perron tests on the level of the agricultural futures price and investors' net long positions do not reject the null hypothesis of a unit root, irrespective of whether we include a drift term. Returns and first differences of positions, in contrast, are found to be stationary.

⁶Specifically, we subtract the mean and divide by the standard deviation. This facilitates a direct comparison of the effects across variables and markets. Moreover, it reduces the computational challenges of the minimization procedure as the parameters to be estimated are of similar order of magnitude. For the main specification, we have verified that the results are robust to using non-standardized data.

the price effect, because large speculative demand shocks of index investors are more likely to occur during this period. Rigobon (2003) refers to these relative changes in volatility as ‘probabilistic instruments’. The identification strategy relies on two assumptions. First, the structural shocks are uncorrelated. This is commonly assumed in the structural VAR literature. Second, the matrix of contemporaneous impacts A is constant across volatility regimes. This is a standard assumption for instance in (G)ARCH models. Moreover, we formally test the assumption and cannot reject it.

Alternatively, identification is often achieved by imposing zero or sign restrictions. Zero restrictions would imply a delayed response of some endogenous variables to some structural shocks. This seems too restrictive, however, as futures prices and positions are likely to respond to shocks and each other contemporaneously at the weekly frequency. Sign restrictions, on the other hand, allow for an immediate impact among variables. Yet, they are not helpful in disentangling the shocks in our model as these shocks all imply the same sign pattern (compare Section 2), and it would thus take further strong assumptions, for instance on the relative magnitude of their impact, to disentangle them.

3.3 Data

To measure positions of the trader groups, we use publicly available data from the CFTC Supplemental Commitments of Traders (SCOT). In the reports, traders are classified into four categories: ‘commercial’ (producers, processors, and merchants), ‘non-commercial’ (commodity trading advisors (CTAs), commodity pool operators (CPOs), hedge funds, and other reportables), to which we for brevity mostly just refer as hedge funds, ‘non-reporting traders’, and ‘index investors’. Both index investors and non-commercial traders are financial investors without an interest in the physical delivery of the commodity. There are, however, some differences in their characteristic trading strategies (see Masters and White, 2008, Mou, 2010, Heumesser and Staritz, 2013). Traders in the non-commercial category actively gather and process commodity-specific information and base their trades thereon. CTAs and CPOs have an insightful knowledge of specific agricultural markets and hedge funds often take directional views by exploiting high-frequency cross-market information. These investors are typically active on both sides of the market. In contrast, index investors essentially use commodities to diversify portfolio risk, but have no particular interest in specific commodities. Their trades are based on re-balancing, rolling, or weighting considerations and occur at lower frequencies. They are typically only active on the long side of the market.

The SCOT reports cover all eleven agricultural commodities in the S&P Goldman Sachs Commodity Index (GSCI), one of the most widely used investible commodity indices, but exclude energy and metal futures markets. Reports start in July 2006, so that our sample runs from 04 July 2006 to 29 March 2016. The data frequency in the reports is weekly. To measure futures prices, we use corresponding nearby

futures contracts available from Thompson Reuters Datastream. For the core analysis, we construct one aggregate index for each endogenous variable. The weights of the individual commodities in each index are based on the commodities' yearly varying weights in the S&P GSCI. In a robustness analysis, we also investigate the relations among the endogenous variables on the individual markets using market-specific price and position data, that is, we estimate one three-variable model for each of the eleven agricultural futures markets separately. Table 1 lists the commodities and their average weights in our sample.

Table 1: Average commodity weights used for construction of aggregate futures market indexes

<i>Corn</i>	<i>SRW Wheat</i>	<i>Live Cattle</i>	<i>Soybeans</i>	<i>Sugar</i>	<i>Lean Hogs</i>
20.9%	18.1%	12.9%	12.5%	9.1%	7.4%
<i>Cotton</i>	<i>HRW Wheat</i>	<i>Coffee</i>	<i>Feeder Cattle</i>	<i>Cocoa</i>	
6.1%	4.7%	4.1%	2.3%	1.4%	

The table lists the commodities used for construction of aggregate futures price, position, and spread indexes and their average weights in these indexes. The weights are updated yearly and based on the reported weights in the S&P GSCI. Differences to 100% are due to rounding errors.

While the SCOT reports have the advantage of being publicly available and distinguishing between index investors and other speculators, they also have notable drawbacks. The data might contain reporting errors due to potential missclassification of traders for several reasons. First, financial investors have incentives to try being classified as hedgers, since this entails them for preferential treatments like exemption from positions limits or posting lower margins to clearinghouses. These incentives might have even increased after the the Dodd-Frank Act in 2010, when additional regulatory measures started to get implemented. Second, in particular large financial entities might trade for different reasons, like setting up a trade for a customer, proprietary trading, or index trading. The reports, however, are based on aggregated total end-of-day positions of individual traders and not on the underlying motifs behind their specific trades. Third, the CTFC itself changes the classification of traders from time to time, for instance, if additional information on a trader is available or when its client base changes.

Overall, these potential reporting errors in the data could show up in the estimated VAR model. With speculators being partly classified as hedgers, our results might actually represent a lower bound for the impact of speculators' position changes on futures price formation and any detected significant impact should still be supportive for the hypotheses. We also explicitly control for the impact of the Dodd-Frank act on our results by splitting the sample at this point in the sensitivity analysis, and we ensure that the changes in volatility used to identified the model are not solely driven by specific re-classification of traders by assessing the robustness of the results to various definitions of volatility regimes.

We add several exogenous variables to the model. First, we control for physical supply in the US as most of the included commodities are to a large extent produced there. Specifically, we build an index of crop conditions following Bruno et al. (2017) for this purpose. Second, changes in uncertainty

and risk aversion can have an impact on commodity futures prices and financial investors' risk bearing capacity. Cheng et al. (2015) show that speculators adjust positions to changes in the CBOE Volatility Index (VIX). We thus control for changes in the VIX. Third, changes in the price of oil can affect the price of agricultural products (see Baffes, 2007). One argument is that oil prices are part of production costs. Wang et al. (2014) find effects of oil shocks on agricultural commodity prices. As oil prices are highly correlated with the VIX including both of them jointly into the model would lead to problems of multicollinearity and therefore would make it difficult to interpret significance levels. We therefore use changes in the oil price orthogonal to changes in the VIX, computed as the residuals from a regression of oil returns on VIX changes. Fourth, we add the size of the Federal Reserve balance sheet as a measure of aggregate liquidity. Finally, the model contains monthly dummy variables to capture seasonal effects, following Kilian and Murphy (2014). All exogenous variables enter the model contemporaneously. As explained in Section 2, the estimated structural shocks in equation (1) thus explain the variation in the data that is left after controlling for the exogenous variables, and have to be interpreted accordingly. We provide a detailed description of the data in Appendix A.

3.4 Estimation

Before the estimation, we need to determine the volatility regimes used to identify the model. Following Ehrmann et al. (2011), we apply a statistical approach. Specifically, we compute the rolling standard deviation for each reduced-form residual in u_t . We then calibrate a threshold for the rolling standard deviations above which the corresponding residual is classified into a high volatility regime. In particular, we use a window of 15 weeks to compute the rolling standard deviations and a threshold of one standard deviation. We define regime 1 as a low volatility regime, where the standard deviation of all three residuals is below one. Regimes 2 to 4 are characterized by high volatility of only one of the residuals, while the other two residuals display low volatility.

The approach of defining one high volatility regime for each residual is motivated by the identification idea that a relative volatility shift of the underlying structural shock helps to trace out the effects of that shock on the other variables. The choice of the window and the threshold is then largely dictated by the need to have sufficient observations in each regime and the objective of minimizing the number of observations which do not fit into any regime, for example, because two reduced-form errors are in the high volatility regime simultaneously. We drop these observations from the estimation of the regime-specific reduced-form covariance matrices. Finally, note that the approach generates four volatility regimes, while two regimes are in principle enough for identification. Hence, the model is overidentified and the overidentifying restrictions implied by a regime-invariant A can be tested.

Table 2 shows the estimated variances of the residuals and the number of observations per regime. It

also contains the regime-specific estimated covariances between the residuals. The latter illustrate the idea underlying identification through heteroskedasticity. In regime 3, for example, where the reduced-form errors of the index investor equation display high volatility, the covariance between these residuals and those of the futures returns equation increases strongly relative to the regime 1, where both residuals show low volatility. Similarly, the covariance between the residuals of the hedge funds equation and of the futures return equation increases substantially in regime 4. These changes in the covariances provide the additional information needed for identification.

Table 2: Variance-covariance of the reduced-form shocks in the different regimes¹

Regime	(1) All low volatility	(2) Return high volatility	(3) Index inv. high volatility	(4) Hedge funds high volatility
$V(u_t^F)$	0.47	1.17	0.38	0.52
$V(u_t^I)$	0.42	0.57	1.68	0.48
$V(u_t^H)$	0.49	0.49	0.58	1.25
$C(u_t^F, u_t^I)$	0.13	0.11	0.26	0.14
$C(u_t^F, u_t^H)$	0.27	0.47	0.25	0.54
Observations	152	59	51	96

¹ The table shows the estimated variances and covariances of the reduced-form errors in the different volatility regimes. The sample period is 04 July 2006 - 29 March 2016.

To see whether our regime definition is supported by the data, we test formally for the constancy of the reduced-form covariance matrix. Recall that for identification we not only require changes in the volatility of the reduced-form residuals, which we expect given our construction of regimes, but in particular significant changes in the covariances between residuals across regimes. Following Lanne and Lütkepohl (2008), we thus perform pairwise likelihood ratio tests on the null hypothesis that two regimes have the same covariance matrix. Moreover, we test the joint null hypothesis that all four covariance matrices are the same. Table 3 shows that all null hypotheses are strongly rejected by the data. It is known that such likelihood ratio tests do not have optimal small sample properties. The null might be rejected too often. However, our test statistics are large, so that we reject the equality of the matrices with confidence, and in particular the joint equality of all matrices. The data prefer a model with changes in volatility over the assumption of homoskedasticity.

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

$$\|g'g\| = \sqrt{\text{tr}[gg']} = \sqrt{\text{vec}(g)\text{vec}(g)'}, \quad \text{with} \quad g = \sum_{k=1}^4 [A\Sigma_{u,k}A' - \Sigma_{\varepsilon,k}] \quad (3)$$

and $\Sigma_{u,k}$ the regime-specific covariance matrix of the reduced-form residuals. Statistical inference is based on bootstrapping. Specifically, we generate 200 draws of the data using the regime-specific covariance

Table 3: Tests for constancy of reduced-form covariance matrix¹

H_0	$\Sigma_{u,1} = \Sigma_{u,2} = \Sigma_{u,3} = \Sigma_{u,4}$	$\Sigma_{u,1} = \Sigma_{u,2}$	$\Sigma_{u,1} = \Sigma_{u,3}$	
LR statistic	746.82	31.86	46.46	
p -value	(0.00)	(0.00)	(0.00)	
H_0	$\Sigma_{u,1} = \Sigma_{u,4}$	$\Sigma_{u,2} = \Sigma_{u,3}$	$\Sigma_{u,2} = \Sigma_{u,4}$	$\Sigma_{u,3} = \Sigma_{u,4}$
LR statistic	30.68	43.82	48.22	38.93
p -value	(0.00)	(0.00)	(0.00)	(0.00)

¹ The table shows results of likelihood ratio tests on the null hypothesis that all regimes have the same reduced-form covariance matrix and that pairwise regimes have the same reduced-form covariance matrix. p -values are in parentheses.

matrices and for each draw we estimate the coefficients by minimizing (5). We compute p -values as the share of estimates beyond zero.

3.5 Identification and parameter stability tests

As outlined above, we use changes in volatility for identification. To uniquely determine A with this method, that is, to achieve identification in a statistical sense, the estimated variance-ratios of the uncorrelated structural shocks have to be sufficiently distinct across regimes (see Lütkepohl and Netšunajev, 2014). To check whether this is the case, we first study the variance-ratios $\phi_k^{S,S'} = \sigma_k^S / \sigma_k^{S'}$ for each pair of shocks (S, S') , which are given in Table 14 in Appendix B. The estimated ratios and standard errors suggest that for each pair there is at least one regime where the ratio changes sufficiently relative to the other regimes, that is, where the one-standard error intervals do not overlap. While these changes are indicative of statistically significant changes in volatility ratios, we also test formally for identification. For each shock pair, we use a linear Wald test on the joint null hypothesis that the variance-ratio is the same across regimes, that is, that $\phi_1^{S,S'} = \phi_2^{S,S'} = \phi_3^{S,S'} = \phi_4^{S,S'}$, which would invalidate the identification of A . Inference in these tests is based on 200 bootstrap replications. Table 4 contains the Wald test statistics and the associated p -values. It shows that for each pair of shocks the null hypothesis of no changes in volatility is strongly rejected by the data. The model is statistically fully identified.

Table 4: Identification tests

H_0	$\phi_1^{I,F} = \phi_2^{I,F} = \phi_3^{I,F} = \phi_4^{I,F}$	$\phi_1^{H,F} = \phi_2^{H,F} = \phi_3^{H,F} = \phi_4^{H,F}$	$\phi_1^{H,I} = \phi_2^{H,I} = \phi_3^{H,I} = \phi_4^{H,I}$
Wald statistic (bootstrapped)	22.96	27.19	28.92
p -value (bootstrapped)	0.00	0.00	0.00

The table shows the Wald statistics and associated p -values of linear Wald tests on the joint null hypothesis that the estimated variance ratios of two structural shocks, $\phi_k^{S,S'} = \sigma_k^S / \sigma_k^{S'}$, are the same across volatility regimes, for each pair of structural shocks. Here, σ_k^S is the estimated variance of shock $S = F, I, H$ in regime $k = 1, \dots, 4$. The tests are based on 200 bootstrap replications.

Having established statistical identification, we can test the assumption of a time-invariant impact

matrix A as it becomes overidentifying with more than two regimes. For this we perform the following Likelihood ratio test: $LR = 2(\log L_T - \log L_T^r)$, where L_T^r is the maximum of the likelihood under the H_0 of time-invariant A and L_T is the maximum likelihood under H_1 , which corresponds to the maximum likelihood of the reduced-form model with changes in volatility (compare Herwartz and Lütkepohl, 2014). The LR-statistic is 5.32 and the corresponding p -value is 0.50, not rejecting the constancy of A at conventional significance levels.

Finally, we investigate whether there is a break in the relation between the exogenous and endogenous variables on 21 July 2010. This date splits the sample into a crisis and post-crisis half. It is, first, motivated by Cheng et al. (2015) who show, based on different position data however, that the behavior of financial investors can change in crises. Hedge funds, for example, may be more sensitive to prices or may increasingly trade for reasons unrelated to agricultural commodities, such as losses in other markets. Second, the date corresponds to the day of the Dodd-Frank act. The following regulations of commodity derivative markets may have changed the functioning of futures markets. However, joint Chow tests for the three parameters of interest, referring to oil prices, the VIX, and crop conditions, do not reject the hypothesis of constant parameters across subsamples in the three equations. Moreover, all Chow tests of individual coefficient are insignificant, except for the effect of the VIX on hedge funds positions, where the null hypothesis of no break can be rejected at the 10% level. To account for the latter observation, we report subsample estimates in the robustness analysis of Section 5, which confirm our main results. All in all, the tests in this subsection indicate that the data support the assumptions of changing volatility during the sample period and time-invariant slope coefficients.

4 Empirical results: demand shocks and commodity futures returns

4.1 Interpretation of structural shocks

While we have shown that the model is statistically identified, our agnostic identification strategy has a well-known drawback. The structural shocks are more difficult to interpret since they are not based on a priori (zero or sign) assumptions or disaggregated data. We address this issue in several ways, in particular with the model outlined in Section 2 in mind.

First, we explore the significance of the exogenous control variables, meant to capture common factors affecting both futures prices and positions, to obtain an impression of the variation that remains in the reduced-form errors which are decomposed into the structural shocks. Table 5 shows the estimated effects of the most significant exogenous variables on the endogenous variables, corresponding to the entries in Λ in the *reduced form* model (2). Standard errors are robust to heteroskedasticity and statistical significance is denoted by a , b , c for the 1%, 5%, and 10% level, respectively. The index of crop conditions has the

expected negative effect on prices and is highly statistically significant. Better weather conditions lead to lower returns. While index investor positions are insensitive to crop conditions, net long positions of hedge funds decrease in response to improved physical supply conditions. Moreover, all three endogenous variables respond strongly to changes in the VIX and oil prices. In line with Tang and Xiong (2010) and Cheng et al. (2015), these responses suggest that changes in the risk bearing capacity of financial investors, as proxied by changes in the VIX, or re-balancing motives, induced by oil price changes, are important drivers of financial investors' positions that induce similar movements in agricultural commodity futures returns. This co-movement indicates that changes in these variables are to a large extent transmitted to futures returns through financial investors.

Table 5: Effects of selected exogenous variables on the endogenous variables^{1,2}

	Exogenous variable		
	Index of crop conditions	VIX	Oil price (orthogonal to VIX)
Futures returns	-0.36 ^a (0.00)	-0.30 ^a (0.00)	0.31 ^a (0.00)
Index inv. positions	0.09 (0.40)	-0.16 ^a (0.00)	0.26 ^a (0.00)
Hedge funds positions	-0.23 ^a (0.01)	-0.13 ^a (0.00)	0.15 ^a (0.00)

¹ The table shows the effects of selected exogenous variables on the endogenous variables from the baseline VAR, obtained from estimating the rows of the reduced-form model (2).

² a, b, c denote significance at the 1%, 5%, 10% levels. Heteroskedasticity robust p -values below point estimates.

Given that the crop condition variable has a strong effect on returns and therefore appears to be a good measure of physical supply, we interpret the *structural shock* to the equation for futures returns, ε_t^F , that explains the largest part of the remaining variability in futures returns (see the forecast error variance decompositions in Section 4.3), as shifts in physical demand for agricultural commodities. In the notation of the theoretical model, the shock ε_t^F thus is interpreted as corresponding to the shock η . The interpretation of ε_t^F as a physical demand shock is also supported by model-external information. Figure 1 shows the cumulative effect of ε_t^F on futures prices, obtained from a historical decomposition, and the (inverted) level of agricultural stocks in the US.⁷ The variables display a strong co-movement for most of the sample, indicating that they are driven by similar underlying demand shifts, with changes in stocks leading the relation. As intuition would suggest, physical demand shifts tend to be buffered by inventories first and then show up in prices over time.

With physical demand as well as supply, financial market risk, and oil price changes accounted for, we interpret the remaining two structural shocks as investor-specific speculative demand shifts in line

⁷The stock variable is based on data from the US Department of Agriculture and described in Appendix A. We do not include it into the model as it is only available at a monthly frequency. The stocks variable is not available for sugar, coffee, and cocoa that constitute close to 15 % of the aggregates. The relationship depicted in 1, however, is robust to excluding these commodities from the estimations.

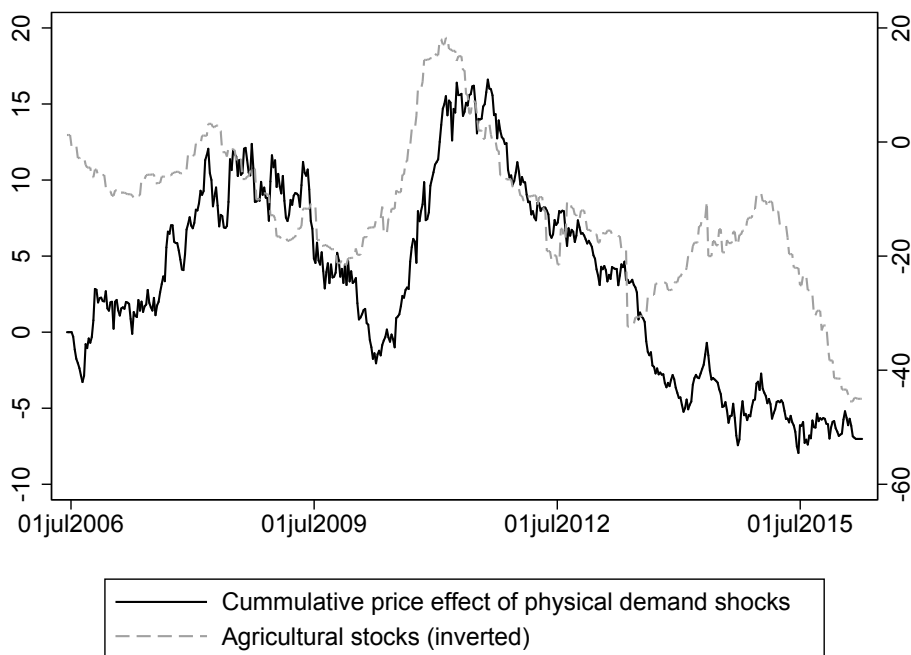


Figure 1: Agricultural stocks and cumulative effect of estimated agricultural specific demand shocks on the futures price. The figure shows the level of agricultural stocks as reported by the US Department of Agriculture (grey line, right scale inverted) and the agricultural futures price implied by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

with the theoretical model. Specifically, structural shocks to the equation for index investor positions, ε_t^I , are interpreted as idiosyncratic shifts in their speculative demand. Analogously, we interpret structural shocks to the equation for hedge funds, ε_t^H , as demand shifts of hedge funds. Both ε_t^I and ε_t^H thus capture speculative demand shocks unrelated to changes in the risk bearing capacity or re-balancing motives as captured by VIX or oil price movements. This orthogonality allows complementing the analysis of Tang and Xiong (2010) and Cheng et al. (2015) by focusing on changes in speculative demand unrelated to these motives. Index investors, for example, may adjust positions in response to demand changes of their institutional or retail clients, and hedge funds might trade based on private information, say.

To further assess our labeling of these two structural shocks, we follow Herwartz and Lütkepohl (2014) and evaluate whether the structural shocks display distinct volatility patterns and higher volatility during those periods that we expect, given our shock interpretation. Figure 2 shows the structural shocks (grey line) and their centered 52-weeks rolling standard deviation (black line). The shocks ε_t^I display higher volatility during the first sample half and in 2014/15, whereas the volatility of ε_t^H -shocks increases sharply towards the very end of the sample. These changes in volatility correspond to the time-varying importance and activity of the two investor groups on commodity futures markets. While index investors were relatively more active in the first part of the sample, and in particular in 2007/08 where many institutional and retail investors sought exposure to commodities as a new asset class, a significant portion of these investors left the market afterwards when long-only strategies were no longer profitable as commodity

prices experienced sharp boom-bust cycles. Their share in total long positions, for instance, declined from 32% in 2008 to 25% in 2014. In contrast, hedge funds employ trading strategies which allow them to earn positive returns in periods of both rising and declining prices (see Mayer, 2009). Their activity was relatively stable during most of the sample and only started to intensify when commodity prices began a steady decline from 2014 onwards.

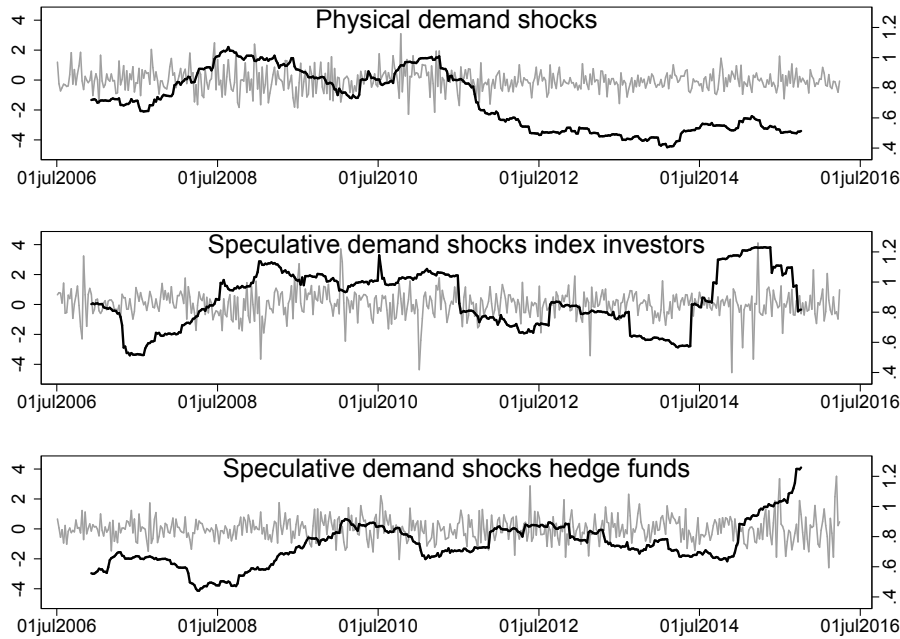


Figure 2: Interpretation of structural shocks. The figure shows the estimated structural shocks (grey line, left axis) together with their (centered) 52 weeks rolling standard deviations (black line, right axis). The estimated shocks are based on a structural VAR identified through heteroscedasticity.

4.2 Contemporaneous shock propagation

Having labeled the structural shocks, we now present their effects on the endogenous variables. Table 6 shows the estimated contemporaneous impact matrices A and A^{-1} . We do not show impulse response functions, as they do not provide additional insights given that there is virtually no persistence in the differenced data. To evaluate Hypothesis 1, we focus on the impact of speculative demand shocks on futures returns, that is, on parameters $\alpha_{1,2}$ and $\alpha_{1,3}$. According to the direct effects, demand shocks of both investor groups lead to a significant contemporaneous increase in commodity futures returns. The point estimates are both significant at the one percent level. A similar conclusion can be drawn from the overall effects which take into account all contemporaneous feedback among the endogenous variables. The overall effects imply that an exogenous increase of index investors' net long demand by one standard deviation leads to an increase in commodity futures returns by 0.15 standard deviations within the same week. The effect for hedge funds is even stronger. Here, a demand shock increases returns by

0.39 standard deviations. Together, the estimates support Hypothesis 1. Speculative demand shocks that increase net long positions impact positively on futures returns. Returning to the motivating theoretical model, these results imply that the demand curve of hedgers (or the respective counter-party in a general setting) is not infinitely elastic with respect to changes in the futures price and that exogenous changes in speculative demand consume liquidity. In other words, hedgers require a compensation for meeting speculators net long demand.

Table 6: Contemporaneous effects among endogenous variables^{1,2}

Response	Impulse		
	Futures return	Index inv. positons	Hedge funds positions
<i>Direct effects (A)</i>			
Futures Return	1.00	-0.16	-0.33
	.	.a	.a
Index inv. positons	0.03	1.00	-0.16
	.	.	.
Hedge funds positions	-0.29	0.08	1.00
	.a	.	.
<i>Overall effects (A⁻¹)</i>			
Futures Return	1.11	0.15	0.39
	.a	.b	.a
Index inv. positons	0.01	0.99	0.16
	.	.a	.
Hedge funds positions	0.32	-0.04	1.10
	.a	.	.a

¹ The table shows the estimated impact effects of structural shocks of one standard deviation on the endogenous variables, based on a structural VAR identified through heteroskedasticity. Impulse variables are in columns, response variables are in rows. The sample period is 04 July 2006 - 29 March 2016. The number of observations used for identification is 358.

² .a, .b, .c below point estimates denote significance at the 1%, 5%, 10% level, respectively.

Regarding Hypothesis 2, the point estimates for the effect of physical demand shocks on speculators' positions provide mixed evidence (parameters $\alpha_{2,1}$ and $\alpha_{3,1}$). Positions of index investors do not respond significantly to physical demand shocks, whereas for hedge funds we find a significant positive effect. For this trader group, a physical demand shock of one standard deviation leads to an increase in net long positions by 0.32 standard deviations. Through the lens of the theoretical model, the significant response of hedge funds' net long positions to physical demand shocks suggests that - through their increased net long demand - they provide liquidity to producers who have higher hedging needs.

4.3 Drivers of commodity futures prices

We next assess the relevance of alternative explanations for the commodity price swings contained in our sample by means of a historical decomposition of the futures return series. The upper left panel of Figure 3 contains the cumulated changes in the futures price and the cumulative effect of the exogenous variables on the futures price. It shows that the exogenous variables are an important driver of futures

prices and explain in particular the secular price movements well. There is a strong co-movement between both series. Local supply conditions as well as changes in the VIX and oil prices explain about half of the boom-bust cycle of commodity prices in 2008/09, and a relevant part of the steady price decline from 2012 onwards.

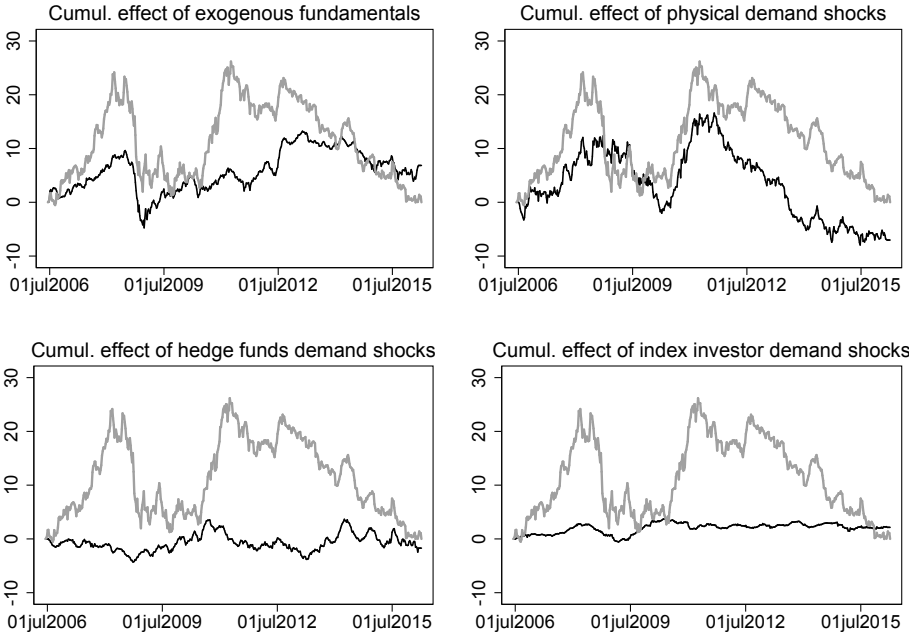


Figure 3: Cumulative effects of exogenous variables and structural shocks on agricultural futures prices. The figure shows the cumulative change of the agricultural futures price (grey line) and the cumulative effect of the exogenous variables and of the structural shocks (black lines) on agricultural futures prices over the sample 04 July 2006 - 29 March 2016.

The figure also shows the cumulative effects of physical and speculative demand shocks on futures prices. The cumulative effects are based on a historical decomposition of the futures return series which yields the weekly contribution of each structural shock to the futures return. The top right panel reveals that, next to the exogenous variables, physical demand shocks are the other main driver of futures prices. They explain approximately the other half of the boom-bust cycle in 2008/09, nearly the entire price surge in 2010/11, and account for a major fraction of the subsequent decline. Together, the top two panels suggest that the exogenous variables and physical demand shocks are the main drivers of prices and in particular explain the longer-term price movements.

Compared to these main forces, the effects of speculative demand shocks on futures prices appear more modest, but are not negligible. Especially speculative demand shifts of hedge funds explain the higher frequency (that is, short term) movements in returns well, in particular in the second sample half. Speculative demand shocks of index investors, on the other hand, seem to play only a limited role. This preliminary conclusion does not imply, however, that index investors are unimportant for commodity price formation in general. First, our results indicate that they transmit changes in the VIX or price of oil to

futures prices (see Section 4.1). Second, while their impact is apparently small on average, they might have relevant effects when their volatility increases. We investigate this issue next.

Specifically, we compute one week ahead forecast error variance decompositions to quantify the regime-specific and average economic significance of the different types of structural shocks. Since we have four different volatility regimes, we obtain four decompositions. They yield the percentage contribution of each shock to the variance of the endogenous variables in each regime. In addition, we compute a weighted average of the regime-specific decompositions to measure the average importance of the shocks over the full sample, using the number of observations per regime as weights. Table 7 shows that speculative demand shocks explain 15 percent of the variability in futures returns in regime 1, where all shocks display low volatility. Shocks of hedge funds are important, whereas index investor demand shifts play a more limited role. The positions of index investors, in turn, are almost entirely driven by own shocks, consistent with their trading strategies. Hedge funds positions, on the other hand, are also respond to physical demand shocks.

Table 7: Forecast error variance decompositions¹

	Impulse		
	Futures return	Index inv. positions	Hedge funds positions
<i>Regime 1</i>			
Futures return	0.85	0.02	0.13
Index investor positions	0.00	0.98	0.02
Hedge funds positions	0.07	0.00	0.93
<i>Regime 2</i>			
Futures return	0.95	0.01	0.04
Index investor positions	0.00	0.98	0.02
Hedge funds positions	0.19	0.00	0.81
<i>Regime 3</i>			
Futures return	0.73	0.09	0.18
Index investor positions	0.00	0.99	0.01
Hedge funds positions	0.04	0.00	0.95
<i>Regime 4</i>			
Futures return	0.68	0.02	0.30
Index investor positions	0.00	0.95	0.05
Hedge funds positions	0.02	0.00	0.98
<i>Weighted FEVD</i>			
Futures return	0.80	0.03	0.17
Index investor positions	0.00	0.97	0.03
Hedge funds positions	0.07	0.00	0.93

¹ The table shows the forecast error variance decompositions over the horizon of one week for volatility regimes 1-4 and a weighted average of these, using the number of observations per regime as weights, based on a structural VAR identified through heteroskedasticity. In regime 1 all structural shocks have low volatility. In regimes 2-4 the volatility of shocks to, respectively, physical demand, index investor demand, and hedge funds demand is high relative to the other structural shocks.

This asymmetry between investors increases in regime 2, where physical demand shocks are more volatile relative to the other shocks. Physical demand shocks now explain 19 percent of the variation in hedge funds positions and still nothing of the changes in index investor positions. Reversely, the

importance of speculative demand shocks in futures price determination increases and becomes important when positions are more volatile. In regime 3, demand shifts of index investors explain 9 percent of the variation in futures returns. In regime 4, hedge funds demand shocks account for nearly one third of the fluctuation. Finally, the weighted forecast error variance decomposition reveals that taking into account these changes in volatility increases the importance of speculative demand shifts relative to their importance in the tranquil period. Financial demand shocks on average account for almost one fifth of the variance of futures returns. All in all, however, the decompositions show that, next to exogenous fundamentals, shocks to physical demand are the main driver of commodity prices.

5 Sensitivity analysis

5.1 Alternative definitions of volatility regimes

As a final step in the analysis, we assess the sensitivity of our main results to various modifications of the model. First, we analyze the robustness of the results to changing the calibration and definition of the volatility regimes. In the baseline specification, we use 15-weeks rolling standard deviations of the residuals and a threshold of 1 standard deviation above which underlying observations are classified into volatility regimes. We investigate how the results change when we modify either the threshold (from 1 to 1.1 and 1.2 standard deviations, respectively) or the length of the window (from 15 weeks to 10, 12, and 18, respectively). Table 8 shows that the main results are robust to these alterations.

Also note that in the main specification we drop some observations from the computation of the regime-specific covariance matrices as they do not fit into any of the four volatility regimes. As a further robustness check, we adjust the regime definitions so that only a few observations are discarded. In contrast to the baseline definitions, now the second regime contains all observations where the residuals for the futures returns are volatile and the residuals for index investor positions tranquil, independent of the volatility of hedge fund positions, and vice versa for the third regime. Again, our main results are insensitive to these changes.⁸

5.2 Additional group of traders

Second, aside from commercials, non-commercials, and index investors, the SCOT reports contain the additional category of traders called ‘non-reportables’ (see above). To assess the sensitivity of our estimates for index investors and hedge funds to including another trader group, we add the net long positions of non-reportables as a fourth endogenous variable to the baseline model. Adding this fourth

⁸The same holds when, instead of the volatility in hedge fund positions, the volatility in futures returns or index investor positions is disregarded for the computation of the other two volatility regimes, respectively. With the reported combination, however, the lowest number of observations is discarded.

Table 8: Effects among endogenous variables with different regime definitions^{1,2}

Alternative regime definitions		1	2	3	4	5	6
Index Inv -> Fut Return	0.15	0.17	0.20	0.14	0.20	0.24	0.14
	.b	.b	.a	.b	.a	.a	.b
Hedge funds -> Fut Return	0.39	0.45	0.44	0.41	0.39	0.49	0.39
	.a	.a	.a	.a	.a	.a	.a
Fut Return -> Index Inv	0.01	-0.08	-0.07	0.04	0.00	-0.09	-0.02

Fut Return -> Hedge funds	0.32	0.26	0.33	0.30	0.31	0.18	0.38
	.a	.a	.a	.a	.a	.b	.a
Window	15	15	15	10	12	18	15
Threshold	1	1.1	1.2	1	1	1	1
Regime definition		main	main	main	main	main	adjusted

¹ 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 04 July 2006 - 29 March 2016.

² .a, .b, .c denote significance at the 1%, 5%, 10% levels.

variable requires adjusting the volatility regime definition slightly. To account for the additional shock, we add a fifth regime where only the reduced-form residuals of the new equation display volatility above the threshold. To obtain a sufficient number of observations per regime, we use 12-weeks instead of 15-weeks rolling standard deviations of the residuals.

Table 9 contains the results. It shows that the contemporaneous structural relations between futures returns, hedge fund positions, and index investor positions are robust to this model alteration. Speculative demand shocks still impact significantly positive on returns, with the size of the coefficients being comparable to the baseline case. On the other hand, net long positions of hedge funds, but not of index investors respond significantly to the physical demand shock.

Table 9: Contemporaneous effects in a model with non-reportables^{1,2}

	baseline	model with non-reportables
Index Inv. -> Fut Return	0.15	0.25
	.b	.b
Hedge funds -> Fut Return	0.39	0.32
	.a	.a
Fut Return -> Index Inv.	0.01	-0.04
	.	.
Fut Return -> Hedge funds	0.32	0.34
	.a	.a

¹ The table shows the estimated structural effects between futures prices and investors' positions, based on the a structural VAR model where non-reportables net long positions are added as a fourth endogenous variable. The arrows indicate the relation between impulse and response variable. The sample period is 04 July 2006 - 29 March 2016.

² .a, .b, .c denote significance at the 1%, 5%, 10% levels.

5.3 Alternative sample periods

Third, while statistical tests do not reject the assumption of a constant impact matrix A , one Chow test indicates the possibility that the impact of the VIX on hedge funds positions might vary between crisis and tranquil times (see Section 3.5). Also, financial speculators might have had stronger incentives to be classified as hedgers after the introduction of the Dodd-Frank act, possibly affecting the categorization of traders (see Section 3.3). Therefore, we split our sample in a pre-crisis/crisis sample and a post crisis sample and carry out individual estimations for the two samples. Specifically, we try two different break dates. The first is the implementation of the Dodd-Frank act on 07 July 2010. The second is 07 June 2011 following Cheng et al. (2015), who show that the behavior of financial investors can change between crisis and tranquil times.

Table 10 contains the parameters of interest for the different sub-sample estimations. It shows that the relation between structural shocks, hedge funds positions, and futures returns is basically the same across the two samples. The impact of index investors speculative demand shocks, on the other hand, is significant for the post-crisis samples, but less or not at all significant in the crisis. Whether this is indeed due to a less significant impact of shocks to index investors positions during the crisis, or due to more difficulties in identifying the shock in the particular sample, cannot be distinguished.

Table 10: Effects among endogenous variables in subsamples^{1,2}

	crisis		post-crisis	
	1	2	3	4
Index Inv. -> Fut Return	0.36 .c	0.23 .	0.18 .a	0.20 .b
Hedge funds -> Fut Return	0.33 .b	0.35 .a	0.39 .a	0.50 .a
Fut Return -> Index Inv.	-0.11 .	-0.13 .	-0.12 .	-0.10 .
Fut Return -> Hedge funds	0.27 .c	0.31 .b	0.37 .a	0.26 .c
Sample start	04jul2006	04jul2006	10aug2010	21jun2011
Sample end	27jul2010	07jun2011	29mar2016	29mar2016

¹ The table shows the estimated structural effects between futures prices and investors' positions, based on the baseline structural VAR model, for different start and end dates of the sample. The arrows indicate the relation between impulse and response variable.

² .a, .b, .c denote significance at the 1%, 5%, 10% levels.

5.4 Single markets

Fourth, we assess whether our main results based on the aggregated indexes reflect a general pattern on agricultural futures markets or whether they are driven by a few (dominant) markets. To this end, we estimate the structural model (1) for each individual market, that is, we replace the indexes in y_t by market-

specific variables and, regarding the exogenous variables, use market-specific crop conditions.⁹ For the market-specific models, we calibrate the thresholds and windows for the volatility regimes individually. This ensures that on each market there are enough observations per volatility regime and that statistical identification is achieved every time.

Table 11 shows the results which are ordered by market size. They closely mirror the findings for the aggregate level. The effect of demand shifts of hedge funds on futures returns is positive and highly statistically significant in all eleven markets. Quantitatively, the impact varies between 0.26 and 0.50, spanning the corresponding point estimate for the aggregate level of 0.39. Similarly, demand shocks of index investors impact significantly on returns in nine of eleven markets. Regarding the physical demand shocks, in ten of the eleven markets hedge funds systematically increase their long exposure in response to the shock. Index investors, in contrast, show significant reactions to the shock only in three markets.

Table 11: Effects between investors' positions and futures prices on individual markets^{1,2}

	<i>Corn</i>	<i>SRW Wheat</i>	<i>Live Cattle</i>	<i>Soybeans</i>	<i>Sugar</i>	<i>Lean Hogs</i>
Index Inv. -> Fut. Return	0.11	0.20	0.14	0.07	-0.00	0.20
	.c	.a	.c	.	.	.b
Hedge funds -> Fut. Return	0.47	0.37	0.26	0.46	0.42	0.30
	.a	.a	.a	.a	.a	.a
Fut. Return -> Index Inv.	0.11	-0.07	0.07	0.14	-0.07	-0.12
c	.	.c
Fut. Return -> Hedge funds	0.23	0.23	0.18	0.32	0.27	0.13
	.a	.a	.a	.a	.a	.c
	<i>Cotton</i>	<i>HRW Wheat</i>	<i>Coffee</i>	<i>Feeder Cattle</i>	<i>Cocoa</i>	
Index Inv. -> Fut. Return	0.12	0.25	0.11	0.10	0.11	
	.c	.b	.b	.c	.c	
Hedge funds -> Fut. Return	0.33	0.36	0.50	0.34	0.42	
	.a	.a	.a	.a	.a	
Fut. Return -> Index Inv.	-0.00	0.03	0.01	0.05	0.23	
a	
Fut. Return -> Hedge funds	0.18	0.17	0.28	0.13	0.16	
	.a	.b	.a	.	.a	

¹ The table shows the estimated structural effects between futures prices and investors' positions, based on market-specific structural VAR models. The arrows indicate the relation between impulse and response variable. The sample period is 04 July 2006 - 29 March 2016.

² .a, .b, .c denote significance at the 1%, 5%, 10% levels.

5.5 Narrative approach to identify volatility regimes

Fifth, in the baseline specification we have used a statistical approach to determine the volatility regimes. An alternative used in the literature is a narrative approach (see, Rigobon, 2003), which specifies volatility

⁹For the meat markets, we use crop conditions for corn. For sugar, coffee, and cocoa, no measure of crop conditions is available.

clusters based on a time line of major economic and political events. As a further sensitivity analysis, we thus apply such a narrative approach and then re-estimate our baseline model using the narratively-determined regimes. Specifically, we divide the sample into four volatility regimes. The first regime runs from the beginning of the sample until the bankruptcy of Lehman Brothers in September 2008. Regime 2 and 3 are then separated by the implementation of the Dodd-Frank act in July 2010, while the last Regime begins with the Federal Reserve ending its asset purchases in October 2014, corresponding to the end of quantitative easing. Table 12 displays matrix A^{-1} as estimated using the narrative volatility regimes. It shows that results of this exercise are similar to the baseline specification. Shocks to net long positions of both investor groups impact positively on futures returns, while only positions of hedge funds respond significantly to the physical demand shock.¹⁰

Table 12: Contemporaneous effects among endogenous variables^{1,2} - narrative regime definition

Response	Impulse		
	Futures return	Index inv. positons	Hedge funds positions
Futures return	1.11	0.22	0.43
	.a	.b	.a
Index inv. positons	-0.04	0.99	0.02
	.	.a	.
Hedge funds positions	0.32	0.06	1.12
	.a	.	.a

¹ The table shows the estimated impact effects of structural shocks of one standard deviation on the endogenous variables, based on a structural VAR identified through heteroskedasticity. Impulse variables are in columns, response variables are in rows. The sample period is 04 July 2006 - 29 March 2016.

² .a, .b, .c below point estimates denote significance at the 1%, 5%, 10% level, respectively.

6 Conclusion

This study provides new evidence on the impact of financial investment on price formation in commodity futures markets. We use publicly available data on net long positions of hedge funds and index investors on agricultural commodity futures markets from SCOT reports of the Commodity Futures Trading Commission, and include them in a vector autoregression along with the corresponding futures price. Controlling exogenously for physical supply and financial market risk and using the heteroskedasticity in the data, we identify idiosyncratic shocks to speculative demand of both investor groups.

Our results suggests that speculative demand shocks of both index investors and hedge funds impact significantly and positively on commodity futures returns. The shocks appear also economically relevant as they account for about one fifth of futures return fluctuations on average, and for up to one third of

¹⁰Results of the narrative approach are robust to the exact start and end date of the regimes. To assess this, we replaced one-by-one the bankruptcy of Lehman Brothers with the failure of Bear Stearns in March 2008, the implementation of Dodd-Frank with the second breakpoint used in Section 5.3, and the end of asset purchases with announcements of Federal Reserve official to taper quantitative easing.

the variability in returns during periods of high speculative demand volatility. Overall, physical demand shocks and exogenous variables explain most of the secular movement in commodity futures prices.

The findings complement recent studies that detect significant effects of financial investments on commodity futures prices based on highly disaggregated and partly private data (see Cheng et al., 2015, and Henderson et al., 2015). While these data potentially allow for a more precise estimation of the effects of speculative trading on commodity futures returns, and simpler and more transparent econometric approaches, one advantage of the statistical approach employed in this study is that it allows using publicly available data such that the analysis can be replicated and readily updated in the future. Moreover, the structural VAR model allows quantifying not only the statistical significance of the effects of speculative demand shocks, but also their economic importance both on average in the sample and during historical episodes.

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Appendix

A Data and sources

Table 13: Data construction and sources

Variable	Construction and source
Agricultural futures prices	Nearby (next-to-maturity) futures prices of eleven agricultural commodities. 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. Individual returns are computed as log differences and aggregated into one variable by multiplying them with their respective weights in the S&P GSCI. Our results are robust to first computing an aggregate futures price index with rescaled individual series and then taking the return of this index. Source: Datastream.
Investors' positions	Aggregated data on open positions of different trader groups on eleven agricultural markets. The underlying reports divide traders into four categories: index investors, non-commercial traders, non-reporting traders, commercial traders. The index investors category includes positions of managed funds, pension funds, and other investors that are generally seeking exposure to a broad index of commodity prices as an asset class in an unleveraged and passively-managed manner, as well as positions of entities whose trading predominantly reflects hedging of over-the-counter transactions involving commodity indices - for example, a swap dealer holding long futures positions to hedge a short commodity index exposure opposite institutional traders. Traders are classified as commercials if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3, 17 CFR 1.3(z). Examples are entities that predominantly engages in the production, processing, packing or handling of a physical commodity and use the futures markets to manage or hedge risks associated with those activities. The non-commercial category contains speculative traders like hedge funds, registered commodity trading advisors (CTAs), registered commodity pool operators (CPOs), or unregistered funds identified by CFTC. The non-reporting category contains traders that hold positions below specific reporting levels set by CFTC regulations. To construct aggregate position indexes, we combine net long positions in individual markets in two steps. First, we divide by average open interest in each market in 2010 to dispose of the underlying units (bushels, pounds, et cetera). Then, we average over markets with the respective weights. Source: CFTC SCOT reports.
Index of crop conditions	Weather conditions are measured following Bruno et al. (2017). 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 week, a percentage of crops is assessed to be in an '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 eight US based commodities using the (adjusted) S&P GSCI weights. Thereby, additional weight, namely that for live cattle, lean hogs, and feeder cattle, 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. For the included commodities not produced in the US (sugar, coffee, and cocoa) no such weather index is available. As they constitute less than 15 % of our aggregate, it is not surprising that the supply measure is, nevertheless, highly significant in the baseline estimations. Our main results are robust to dropping the non US commodities, the meat commodities, or even both. For the individual market estimates, we use the weather index for corn for live cattle, lean hogs, and, feeder cattle.
Oil Price	WTI oil price. Source: St. Louis Fed FRED database.
VIX	CBOE Volatility Index: VIX [®] , Source: St. Louis Fed FRED database.
Fed balance sheet	Total assets of the Fed. Source: St. Louis Fed FRED database.
Agricultural stocks	Actual agricultural stocks for eight US based commodities, constructed as in Bruno et al. (2017). Meat stocks: USDA total storage figures for beef and pork (excluding frozen ham). For grain and cotton stocks: monthly stock forecasts reported in the current USDA forecasts of US supply-use balances of major grains.

B Variance-ratios of the structural shocks

Table 14: Variance-ratios of the structural shocks per volatility regime k ¹

Regime	(1)	(2)	(3)	(4)
σ_k^I / σ_k^F	1.33 (0.24)	0.58 (0.16)	7.66 (2.39)	1.74 (0.39)
σ_k^H / σ_k^F	1.19 (0.24)	0.37 (0.11)	2.05 (0.61)	3.65 (0.88)
σ_k^J / σ_k^F	0.91 (0.18)	0.66 (0.21)	0.28 (0.08)	2.14 (0.52)
Observations	149	31	44	44

¹ The table shows the estimated volatility-ratios of the structural shocks of the endogenous variables in the different regimes. The shocks are named after the equation they appear in. Bootstrapped standard deviations of the ratios are reported in parentheses.