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Price effects from the financialization of agricultural commodity markets

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Abstract

Supposed portfolio benefits of commodities and the increased availability of commodity linked investment products such as index funds contribute to a financialization of agricultural commodity markets. The parallel increase in price levels and short-term volatility for almost all major agricultural commodities and a growth in trading volume on their derivative markets triggered a debate about the underlying causal linkage. In particular, financial "index trading", i.e. taking long positions in the futures markets and rolling these forward, has been suspected to inflate prices above fundamentally justifiable levels by creating artificial demand on the futures markets.

The objective of this thesis is to investigate the price effects from the financialization of agricultural commodity markets, specifically focusing on (i) the robustness and interpretability of findings from previous empirical studies on direct price effects of index trading; (ii) volatility linkages between agricultural commodity and financial asset markets as a result of financial portfolio strategies; and (iii) direct price level or volatility effects on single agricultural commodity markets from portfolio inclusion of commodity index funds.

The thesis employs various methodologies, using a combination of a literature review with a theoretical assessment of the findings, an empirical calculation of rolling volatility spillover indices and a simulation-based Heterogeneous Agent Model (HAM). This implies a transfer of methodological knowledge from traditional financial market research to the area of agricultural economics.

Results show that the existing empirical evidence based on Granger-Causality tests between index trading activity and price levels, returns, volatilities or spreads in agricultural commodity markets does not permit conclusions on the presence or *absence* of a true underlying causal influence. Any definite conclusions based on these findings on index trading inflating price levels on agricultural commodity markets are likely premature. In fact, the HAM simulation reveals that index trading volume, despite being of a large magnitude and always net long, does not automatically inflate price *levels*. But, it may indeed transmit information shocks to the single agricultural markets and thus increase price *volatility*. And, the volatility spillover indices point to a stronger integration between agricultural and financial markets and an increase in volatility linkages after agricultural commodity markets have become more financialized.

Thus, the financialization of agricultural commodity markets can lead to events in other asset markets that have little or no real economic connection to agricultural commodity markets affecting the latter's price volatility, if commodity index funds are included in financial portfolio strategies. Especially in times of financial crises, these effects could be of substantial magnitude.

Key words: Financialization of commodity markets; commodity index trading; Granger Causality; volatility spillovers; Heterogeneous Agents

Zusammenfassung

Die vermuteten Vorzüge von Rohstoffen als Portfoliokomponenten und die erhöhte Verfügbarkeit von rohstoffbasierten Investmentprodukten wie Indexfonds tragen zu einer „Finanzialisierung“ der Agrarrohstoffmärkte bei. Das zeitgleiche Wachstum der Handelsvolumina auf den Derivatemärkten und die Erhöhung sowohl der Preisniveaus als auch der kurzfristigen Volatilität auf nahezu allen wichtigen Agrarmärkten löste eine Debatte über mögliche kausale Zusammenhänge aus. Insbesondere der sogenannte „Indexhandel“, sprich das Eingehen von Kaufpositionen in den Futuremärkten und das anschließende rollieren dieser Positionen, kam unter Verdacht, Preise über ihre fundamental vertretbaren Niveaus anzuheben, indem auf den Futuremärkten künstliche Nachfrage geschaffen wird.

Das Ziel dieser Arbeit ist eine Untersuchung der Preiseffekte aufgrund der Finanzialisierung der Agrarrohstoffmärkte, mit besonderem Fokus auf (i) der Robustheit und Interpretierbarkeit der Ergebnisse vorhergehender empirischer Studien zu direkten Preiseffekten des Indexhandels, (ii) Volatilitätsbeziehungen zwischen Agrarrohstoff- und Finanzmärkten durch finanzwirtschaftliche Portfoliostrategien und (iii) direkte Preisniveau oder -volatilitätseffekte auf einzelnen Agrarrohstoffmärkten aufgrund einer Aufnahme von rohstoffbasierten Indexfonds in Portfolios.

Die Arbeit verwendet verschiedene Methodiken: eine Kombination eines Literaturüberblicks mit einer theoretischen Beurteilung der Ergebnisse, eine empirische Berechnung von „Volatilitäts-Spillover-Indizes“ und ein simulationsbasiertes Heterogenes Agentenmodell (HAM). Dies beinhaltet einen Transfer von methodischem Wissen aus dem Bereich der traditionellen Finanzmarktforschung hin zur Agrarökonomie.

Die Ergebnisse zeigen, dass die bestehende empirische Evidenz, die auf Granger-Kausalitäts-Tests zwischen Indexhandelsaktivität und Preisniveaus, Returns, Volatilitäten oder Spreads in Agrarrohstoffmärkten beruht, keine Rückschlüsse über das Bestehen oder *Nichtbestehen* einer tatsächlichen Kausalität erlaubt. Auf dieser Basis sind definitive Aussagen darüber, dass der Indexhandel das Preisniveau auf Agrarrohstoffmärkten anhebt, wahrscheinlich zu voreilig. Tatsächlich zeigt die HAM Simulation, dass das durch den Indexhandel erzeugte Handelsvolumen nicht automatisch zu einer Erhöhung des *Preisniveaus* führt, selbst wenn es von substantieller Größe ist und stets einer Netto-Kaufposition entspricht. Allerdings kann der Indexhandel Informations-Shocks in die einzelnen Agrarmärkte tragen und so die *Preisvolatilität* erhöhen. Auch die „Volatilitäts-Spillover-Indizes“ zeigen eine stärkere Integration von Agrarrohstoff- und Finanzmärkten an. Die Volatilitätsbeziehungen verstärken sich, nachdem die Finanzialisierung der Agrarrohstoffmärkte stärker vorangeschritten ist.

Somit kann die Finanzialisierung von Agrarrohstoffmärkten dazu führen, dass Ereignisse in anderen Finanzmärkten, die kaum oder keine realökonomische Verbindung zu den Rohstoffmärkten haben, sich dennoch auf die Preisvolatilität der letzteren auswirken, wenn rohstoffbasierte Indexfonds in finanzwirtschaftliche Portfoliostrategien eingebunden werden. Insbesondere in Zeiten finanzwirtschaftlicher Krisen, könnten diese Effekte ein deutliches Ausmaß annehmen.

Schlagwörter: Finanzialisierung der Rohstoffmärkte; Indexhandel von Rohstoffen; Granger Kausalität; Volatilitäts-Spillover-Effekt; Heterogene Agenten

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Abbreviations

ACF	Autocorrelation Function
ACV	Autocovariance
ADL	Autoregressive Distributed Lag
bn	billion
BO	CBOT Soybean Oil Futures Contract
C	CBOT Corn Futures Contract
CBOT	Chicago Board of Trade
CC	ICE Cocoa Futures Contract
CFTC	Commodity Futures Trading Commission
CIT Report	Commodity Index Trader Report
CME	Chicago Mercantile Exchange
COT Report	Commitment of Traders Report
CPO	Commodity Pool Operator
CRB Index	Commodity Research Bureau Index
CT	ICE Cotton Futures Contract
CTA	Commodity Trading Advisor
DCA	Discrete Choice Approach
DCOT Report	Disaggregated Commitment of Traders Report
DGP	Data Generation Process
DJ UBS	Dow Jones UBS
ETF	Exchange Traded Fund
ETP	Exchange Traded Product
EU	European Union
FAO	Food and Agricultural Organization
FEV	Forecast Error Variance
FC	CME Feeder Cattle Futures Contract
FGLS	Feasible Generalized Least Squares
GC	Granger Causality
GDP	Gross Domestic Product
HAM	Heterogeneous Agent Model
ICE	Intercontinental Exchange
IFPRI	International Food Policy Research Institute
IID Report	Index Investment Data Report
KC	ICE Coffee Futures Contract
KCBT	Kansas City Board of Trade
KW	KCBT Wheat Futures Contract

LC	CME Live Cattle Futures Contract
LH	CME Lean Hogs Futures Contract
LPOI	Long Position Open Interest
m	million
MA	Moving Average
MSE	Mean Squared Error
MSM	Method of Simulated Moments
NGO	Non-Governmental Organization
NYMEX	New York Metal Exchange
OECD	Organization for Economic Cooperation and Development
OI	Open Interest
OTC	Over-the-counter
REIT	Real Estate Investment Trust
S	CBOT Soybean Futures Contract
SB	ICE Sugar No. 11 Futures Contract
SBC	Schwartz Bayesian Criterion
SPOI	Short Position Open Interest
SSV	Structural Stochastic Volatility
SUR	Seemingly Unrelated Regression
S&P GSCI	Standard & Poor's Goldman Sachs Commodity Index
TPA	Transition Probability Approach
UN	United Nations
U.S.	United States
VAR	Vector Autoregressive
W	CBOT Wheat Futures Contract
WTO	World Trade Organization

Chapter 1

Introduction and overview of the thesis

Over the past decade, agricultural commodity markets have experienced some profound structural changes. During and after the 2007/2008 food crisis, prices of major agricultural commodities rose to unprecedented levels. In the period 2006-2008, the Food and Agricultural Organization's (FAO) food price index increased by around 70% and, after a short period of recovery, surged again in the period 2010-2012 (FAO 2014). And, prices have become more volatile, not only in the sense of price spikes but also in terms of day-to-day or even intraday price fluctuations on the commodity exchanges (e.g. Tadesse et al. 2014; Diebold and Yilmaz 2012).

There is little doubt about changing market fundamentals contributing to the observed price developments. In 2007, stock-to-use ratios for corn and wheat were at low levels of around 13% and 18% respectively (USDA ERS 2012). Both the EU and U.S. policy regime had previously shifted towards reducing excess supply and their biofuel mandates promote growth of crops like corn or soybeans for energy rather than food production. Growing economies, most notably China and India, increase their demand for both food and non-food commodities. Also, weather patterns become more unpredictable and extreme, leading to droughts and floods, subsequent harvest failures and increased uncertainty (cf. Piesse and Thirtle 2009). Yet, there is more controversy concerning the role of "financialized" commodity markets in inflating price levels and increasing price volatility. While lacking a formal definition, "financialization" typically refers to the increased market presence of financial investors, the creation of new commodity-linked financial products and more trading activity on the derivative markets (cf. Domanski and Heath 2007; Redrado et al. 2009; UNCTD 2011; Silvennoinen and Thorp 2013). Commodity derivatives are now perceived as a financial asset class and the spread of electronic trading and creation of investment products facilitate market entry for financial investors who do not wish to handle the physical commodity. And, "traditional investors" such as commodity trading houses increasingly set up financial investment funds with commodity return exposure. These financial investors and their respective trading motives and investment strategies represent new trader types on the market.

Apart from benefiting from returns, a dominant commodity trading motive for financial investors is to diversify their portfolios (Fortenbery and Hauser 1990). Alleged portfolio benefits of commodities include low or negative return correlations with other financial assets and protection against unexpected inflation, as their prices may drive inflation but their holding is not associated with inflation-threatened cash flows (Bodie and Rosansky 1980; Ankrim and Hensel 1993; Satyanarayan and Varangis 1996; Anson 1999; Gorton and Rouwenhorst 2006; Daskalaki and Skiadopoulos 2011; Huang and Zhong 2013). From a portfolio perspective, it is beneficial to have exposure to the returns of a diversified commodity index, such as the S&P Goldman Sachs Commodity Index (S&P GSCI) or the Dow Jones UBS (DJ UBS) Commodity Index, rather than picking single commodities. But, since it is not possible to directly invest into one of these indices, suitable investment vehicles are needed. Commodity "index funds" fill this gap for the investor by replicating the return of a selected commodity index and paying that return to its shareholders.[1]

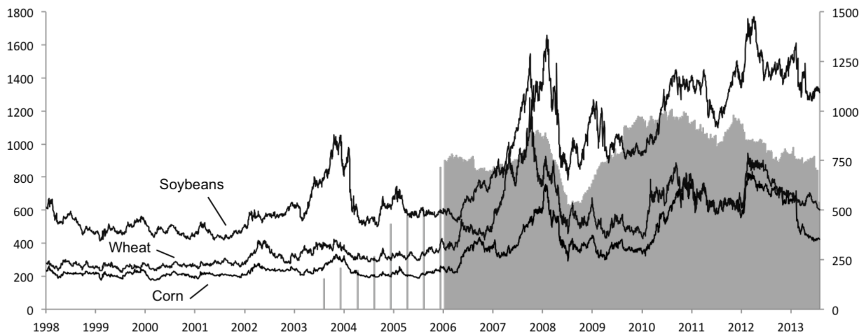
Index replication requires "index trading" strategies on the single commodity futures markets. According to the U.S. Commodity Futures Trading Commission (CFTC), commodity index trading refers to taking long (buy-side) positions in the commodity futures markets and rolling these positions forward as active contracts expire and first deferred contracts become active (CFTC 2014). This is necessary in order to gain constant exposure to the returns of all commodities that are included in the index. Irrespective of whether index funds choose a direct replication via futures contracts or a synthetic replication via index return swaps, which the swap dealer could also subsequently hedge via futures positions, an increase in financial investment into index funds likely leads to an increase in index trading activity on the commodity futures markets.

The discussion on the influence of financial (index trading) activity on price formation in agricultural commodity markets was sparked and fueled by a simultaneous growth in financial trading activity and an increase in price levels, as shown in Figure 1.1. Long position open interest (LPOI)[2] in CBOT corn, soybeans and wheat futures markets associated with index trading shows a steep growth between 2004-2006 and high levels between the years 2007-2008 and 2010-2012. These latter periods were generally characterized by spiking

[1] In the following, the term "index fund" is used for all financial products that have a passive index replication strategy, irrespective of their legal structure or whether they are exchange-traded or structured like a mutual fund.

[2] LPOI measures the amount of open positions on the buy-side, i.e. positions not offset with another transaction or closed via settlement.

Figure 1.1: Price development and index trader LPOI



Notes: Black lines, scaled on the left y-axis, represent CBOT closing prices (in U.S. Dollars) for corn, soybeans and wheat active contracts, grey columns, scaled on the right y-axis, is combined index trader LPOI (in thousand contracts) for the three futures contracts. Data points (bars) between 6 January 2004 and 13 June 2006 are approximated from a graphical presentation of non-public CFTC data in Irwin and Sanders (2011).

Source: Bloomberg, CFTC, Irwin and Sanders (2011)

prices for all three commodities. Reflecting this development, assets under management of commodity exchange-traded index funds increased from 1.2 to 45.7 billion U.S. Dollars in the period 2005-2010 (BlackRock 2011). General trading activity in the futures markets also increased significantly. Average daily trading volume in the Chicago Board of Trade (CBOT) corn, wheat and soybeans active contracts more than doubled from 67 thousand contracts in the period 2000-2005 to 167 thousand contracts in the period 2006-2010 (Bloomberg data).

Participants in the debate about the potential cause-and-effect relations underlying these parallel developments include academia, public bodies, governments and non-governmental organizations (NGOs) alike. During his frequently cited testimonies in front of the U.S. Committee on Homeland Security and Governmental Affairs and the U.S. Senate, and in front of the CFTC, hedge fund manager Michael W. Masters claimed that index trading contributed to inflated price levels by creating artificial demand for the commodities that could not be justified by market fundamentals (Masters 2008, 2009), a statement that later came to be known as the "Masters hypothesis" (eg. Irwin and Sanders 2012). Likewise, Oliver de Schutter, the United Nations Special Rapporteur on the right to food stated that "[a] significant contributory cause of the price spike was speculation by institutional investors [...] who invested in commodity index funds [...]" (De Schutter

2010). International institutions and governmental bodies such as the European Commission (European Commission 2008), the Organization for Economic Cooperation and Development (OECD) (Irwin and Sanders 2010) or the International Food Policy Research Institute (IFPRI) (Robles et al. 2009) published special reports that attempted to unravel the true role of financial (index) investment in agricultural commodity price formation. In Germany, NGOs such as Oxfam Germany and Foodwatch started to accuse companies like Allianz or Deutsche Bank of being "Hungermacher" ("Hunger-makers") or playing "hunger roulette" by maintaining and marketing commodity index funds (Foodwatch 2011; OXFAM 2013).

When research for this thesis began, academic studies on the price effects of financial (index) trading in agricultural commodities had primarily been conducted in the field of agricultural economics and concentrated on the assessment of direct price effects from index trading on agricultural futures markets (e.g. Irwin et al. 2009; Sanders and Irwin 2010; Aulerich et al. 2010; Gilbert 2010; Irwin and Sanders 2011; Sanders and Irwin 2011). From a methodological perspective, a strong focus was put on empirical work, in particular Granger Causality (GC) (cf. Granger 1969) tests, with few alternative approaches and a lack of transfer of theories and methodologies from general financial market research. It was neither clear whether the applied methods were really suitable to make definite statements about presence or absence of price effects from financial trading nor was there a consistent theory about the timing, character or degree of the expected price impact. There was thus a definite need for a critical evaluation of existing research and an extension of both theories and methodologies to assess the price effects from the financialization of agricultural commodity markets.

1.1 Research objective and structure of the thesis

The objective of this thesis is to investigate price effects from a financialization of agricultural commodity futures markets. These price effects could be direct price level or volatility effects on the agricultural commodity futures markets or a change in return or volatility linkages with other asset markets. The main focus is on effects from financial portfolio inclusion of commodities and therefore on futures markets. An assessment of the price transmission to spot markets was out of scope of this thesis. Also, when investigating single agricultural commodity markets, the focus is primarily on CBOT corn, wheat and soybeans as these are heavily traded futures contracts, have comparatively high weights in the most well-known commodity indices and a significant share in global food production.

1.1.1 Research questions

The thesis contributes to existing research by addressing the following three research questions:

(I) *How robust are the conclusions of previous studies that use GC tests to investigate direct price effects from index trading?*

The sampled studies conduct bivariate GC tests within either Vector Autoregressive (VAR) or Autoregressive Distributed Lag (ADL) models for an index trading activity variable (*Activity*) and a price variable (*Price*). *Activity* is approximated with index trader position holdings from CFTC reports while *Price* is either defined as the price level, returns, the spread between nearby and deferred contracts, or as the price volatility. The results are rather mixed and inconclusive. The few significant findings of GC from *Activity* to *Price* variables occur outside the large grains markets; the direction of the *Price* impact appears unclear; some results suggest an increase in *Activity* to Granger-Cause higher returns or volatilities, while others find the opposite. And, there is some evidence for reverse GC from *Price* to *Activity* variables. Since GC tests are statistical tests for the null hypothesis of no causal lead-lag relations between variables given a pre-specified information set, any true structural or causal inference from the test results is hindered. It needs to be investigated whether alternative ways to interpret the GC test results allow to make any inference on the presence or absence of a price impact of index trading activity on agricultural commodity markets.

(II) *Does an increased use of agricultural commodities in financial portfolio strategies affect linkages between commodity and traditional financial asset markets?*

The inclusion of commodities in financial portfolios next to assets like stocks, bonds, foreign exchange or real estate may contribute to a closer market integration of financial assets and commodities. Tactical portfolio management adjusts portfolio weights to changing return or volatility correlations, in particular as a response to shocks or extreme market regimes (Jensen et al. 2002; Conover et al. 2010). Financial crises may lead to portfolio managers shifting asset weights in favor of comparatively less risky and more liquid "refuge assets", leading to a "flight-to-quality" or "flight-to-liquidity" effect (Beber et al. 2007). The use of commodities as such refuge assets has been suggested e.g. by Chong and Miffre (2010); Silvennoinen and Thorp (2013). With an increased use of commodities in financial portfolios, there is need for an assessment of whether such portfolio strategies contribute to an increase in intra-commodity and commodity-financial market linkages.

(III) *What direct price effects emerge on single agricultural commodity markets as a result of portfolio inclusion of index funds?*

Inclusion of index funds in financial portfolios may not only depend on return or volatility correlations of the commodity index with other portfolio assets, but also on the expected returns of the single commodities within the index. The magnitude and changes of net long index trading volume in the single commodity markets are ultimately a consequence of portfolio attractiveness of commodities. If commodities are included in financial portfolios via index fund shares, then the index trading volume is the linkage channel between an increase or decrease of commodity exposure in financial portfolios and changes in trading volume on single commodity futures markets. It is to be investigated how these changes in trading volume will affect price levels and volatilities.

1.1.2 Structure

The remainder of this introductory section first describes the employed methodologies and data sources before it briefly summarizes the principal results from the three main parts of the thesis (chapters 2-4). The last section presents an overall conclusion and an outlook on future research needs and possibilities.

Chapters 2-4 contribute to the objective by focusing on specific research questions and can be read independently. The article included as chapter 2 of this thesis has been published as Grosche, S.C. (2014). What Does Granger Causality Prove? A Critical Examination of the Interpretation of Granger Causality Results on Price Effects of Index Trading in Agricultural Commodity Markets. *Journal of Agricultural Economics*, *65* (2), 279-302 and addresses research question (I) by conducting a literature review and discussing the GC test results on price effects from index trading based on an extended theoretical background. Chapter 3 contains an article previously published as Grosche, S.C. and T. Heckelei (2014): “Directional Volatility Spillovers between Agricultural, Crude Oil, Real Estate and other Financial Markets”, ILR Discussion Paper 2014:4 and addresses research question (II) with a short overview of the current literature on commodity-financial market linkages and an empirical investigation of changing short-term volatility spillovers during the two main financial and economic crisis periods of the last decade. Chapter 4 presents the article published as Grosche, S.C. and T. Heckelei (2014): “Price dynamics and financialization effects in corn futures markets with heterogeneous traders”, ILR Discussion Paper 2014:5, which concentrates on research question (III) by simulating price dynamics on the corn futures market emerging from the interaction of heterogeneous traders.

1.2 Data and methodologies

Methodologies have been chosen to best address the research objective and specific research questions. And, methodologies that have previously not been employed in this research context have been selected to transfer knowledge from traditional financial market research to the area of agricultural economics. Following a short description of the main sources for price data from the relevant exchanges and for position holdings for specific trader types, as published by the CFTC, this section briefly describes the chosen methodologies. More details can be found in the respective chapters.

1.2.1 Data sources

Price data for the futures contracts is obtained from Bloomberg. The focus is on the active contract (i.e. the contract that is next to expire) for which Bloomberg's first generic contract series is used. The active contract has the largest trading volume among the futures contracts and is used in index replication strategies (cf. S&P Dow Jones Indices 2014).The rolling procedure is "relative to expiration" where expiring active contracts are rolled to the first deferred contract on the last trading day to consider the price development over the contract's full trading period. More details on potential effects from the rolling procedure are included in the relevant chapters of the thesis.

The CFTC reports are currently the most comprehensive data sources available for trader-type-specific position holdings on U.S. commodity exchanges. All traders exceeding a specific reporting level have to file a report about their position holdings with the CFTC. The main reports are the weekly Commitment of Traders (COT) report, the Disaggregated Commitment of Traders (DCOT) report and the Commodity Index Trader (CIT) report, which are usually released each Friday at 3:30 pm Eastern time and report the previous Tuesday's state of traders' position holdings[3] in terms of open interest on both the long and short side of the market.

The COT report disaggregates traders of commodity futures and options into commercial traders, who have other (primary) business activities linked to the commodity market, and non-commercial traders. The DCOT report further disaggregates the position holdings into that of "producers/merchants/ processors", who hedge commercial risk from their primary business activities on the physical spot market, "swap dealers", mostly financial institutions, who hedge the risk associated with swap transactions with their clients, and "managed money" that includes Commodity Trading Advisors, Commodity

[3] The latest addition is the monthly Index Investment Data (IID) report, which is explained in more detail in chapter 2 of this thesis.

Pool Operators or actively managed funds such as hedge funds. With growing concern about the price influence of index traders on agricultural markets, the CFTC started to publish the CIT report as a supplement to the COT report where position data is split into that of commercial, non-commercial and index trader positions. Here, index traders are all traders with an index trading strategy as defined in CFTC (2014).

1.2.2 Methodologies

Research question (I) is addressed by conducting a thorough literature review of existing empirical studies that directly test for Granger Causality between index trading activity and prices on commodity futures and options markets, summarizing their results and examining their robustness and interpretability against an extended theoretical background. Fifteen empirical studies are selected that apply GC tests, focus on *agricultural* commodity markets and cover the time period of the 2007/08 price spike. They are grouped according to their variable specifications for price effects and index trading activity and their results are examined in detail and then summarized to obtain a synthesis of their combined findings. Finally, the existing theoretical approaches to interpret GC test results that can be found in the current literature are taken as a basis to critically examine the robustness and explanatory power of the obtained results and to assess to which extent they permit any conclusions about the presence or absence of a price impact of index trading on agricultural commodity markets.

Research question (II) is investigated with an econometric approach. The focus is on volatility rather than return linkages between commodity and financial asset markets as these are closer related to information flows (Chiang and Wang 2011; Cheung and Ng 1996). Diebold and Yilmaz (2012) develop total and directional (pairwise) volatility spillover indices based on *generalized* forecast error variance decompositions (Koop et al. 1996) within a Vector Autoregressive (VAR) model. These indices are applied to investigate volatility linkages between commodity and financial asset markets and between agricultural commodity and crude oil markets. The volatility proxy is the daily range (Parkinson 1980) that is based on the difference between high and low prices within a specific trading day. It complies with the null hypothesis that financial market linkages via portfolio reweightings will mostly affect short-term (intraday) volatility relations. The empirical data sample consists of daily high and low prices for CBOT corn, soybeans and wheat futures, NYMEX WTI crude oil futures, the S&P 500 U.S. equity index, the Dow Jones Equity all REIT index, CBOT 10-year U.S. Treasury Note futures and the Intercontinental Exchange (ICE) U.S. Dollar index over the time period 06/03/1998-12/31/2013. Previous studies investigating market linkages focus largely on GARCH-type models. The rolling spillover indices allow to include more variables and thus to consider a broad market network rather than bivariate or trivariate relations. And, the rolling estimation permits the consideration of gradual structural change rather than pre-imposing any specific structural breakpoint.

Research question (III) is addressed with a few-type heterogeneous agent model (HAM) for the CBOT corn futures market. This approach allows to simulate direct price effects from different trading strategies, which are unobservable variables in the currently available CFTC data and cannot be directly included in an empirical model. In a base scenario, corresponding to the period before the increased availability of index funds, the market is populated by fundamentalist-type commercial traders who believe that prices always revert back to their fundamental value and chartist-type speculators who extrapolate short-term price trends (cf. Zeeman 1974; Beja and Goldman 1980; Frankel and Froot 1990). Both trader types have, next to this deterministic demand component, a stochastic demand component and the model setup thus follows a structural stochastic volatility model as introduced in e.g. Franke and Westerhoff (2011, 2012). The traders' market weights are endogenously determined based on relative strategy attractiveness, which can vary, depending on the situation on the market. Markets can be in disequilibrium and price levels result from excess demand and supply. In a later financialization scenario, which models the time period after 2005, index funds become available and financial portfolio managers include the index fund shares in their portfolios. Parameters in the base scenario model are estimated with the Method of Simulated Moments (MSM) (cf. Lee and Ingram 1991; Duffie and Singleton 1993), following an approach developed in Winker et al. (2007); Franke (2009); Franke and Westerhoff (2011, 2012). Thereby, parameters are set such that moments calculated from simulated returns closely match the moments calculated from empirical CBOT corn returns over the time period 01/05/1970-12/31/2005. The moments are chosen to replicate the stylized facts of commodity markets such as the overall volatility level, fat-tailed returns, zero autocorrelation of relative returns, long-memory and volatility clustering effects. The moment-matching is achieved by minimizing a loss function that calculates the weighted squared deviations between empirical and simulated moments.

More details on the methodologies can be found in the respective chapters. Model documentations for the calculation of the volatility spillover indices and the HAM, including the MATLAB code, are available from the author upon request.

1.3 Summary of main findings

The main findings of each of the three articles that make up the main part of this thesis are first presented independently. The final section of this introductory chapter will then summarize and relate the single findings and give an overall conclusion.

(I) *Empirical results from GC tests on any direct index trader price impact cannot be interpreted as robust evidence for the presence or absence of a true causal or structural influence*

The statistical nature of GC requires alternative interpretations of GC test results other than as structural causal evidence. Three options are predominantly discussed in the literature: (i) as *prima facie* causal evidence; (ii) as a test for the informational efficiency of markets; (iii) as a test for the ability of one variable to improve the forecast of another variable.

In the first case, robustness of the *prima facie* causal evidence hinges on the likelihood of finding an alternative specification of the information set that would disprove the GC test results. The information sets of the sampled studies mostly consist of *Price* and *Activity* variables whereby *Activity* contains information on open interest at a specific point in time and its association with index trading activity, represented by the CFTC index trader or swap dealer categories. But, the trading motive and strategy behind the original investment into an index fund that ultimately led to the observed index trader or swap dealer open interest remain hidden. If, for example, the fund investor only partially bases the investment decision on the expected fundamental value of the commodity, then both *Price* and *Activity* are likely influenced by the same market fundamentals. Adding these to the information set would be a necessary robustness check before GC results can actually be interpreted as true *prima facie* causal evidence on the presence or absence of a price influence of index trading.

In the second case, strong-form informational efficiency of markets precludes any *ex ante* expectations of a price influence from *lagged Activity* on the current *Price*. The actual degree of informational efficiency that is assumed under the null hypothesis requires an assessment of the nature and timing of public information within the *Activity* variable. The information on open interest is related to trading volume. For price-volume relations on financial asset markets, contemporaneous, rather than lead-lag relationships are more plausible (e.g. Karpoff 1987; Chevallier and Sévi 2012) and even under weak-form informational efficiency one would expect no GC. But, *Activity* contains additional information on the associability of open interest with index trading, which is is for weekly data partly private and partly public information and for daily data fully private information. Presence of GC from *Activity* to

Price would in this case disprove semi-strong- or strong-form informational efficiency. But, *absence* of GC does not automatically disprove a structural influence but could merely show that the markets are efficient in incorporating the relevant information on index trading activity in the price.

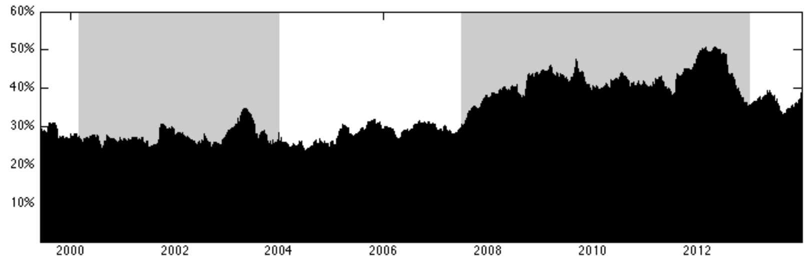
In the third case, presence of GC shows that information on lagged *Activity* helps to forecast *Price*. But, a logical extension of that argument is that market participants will attempt to not only forecast prices, but also index trading positions. If markets are informationally efficient with respect to these collective forecasts then these will be impounded in the market price, leading to GC in the "wrong" direction, i.e. from *Price* to *Activity* (cf. Hamilton 1994; Hoover 2001). As shown by Hoover (2001) and Timmermann and Granger (2004) for rational-expectations-type and more general forecasting models respectively, it is indeed plausible that some *Activity* forecast will be contained in *Price*. Thus, absence of GC from *Activity* to *Price* or detection of GC from *Price* to *Activity* may only prove informational efficiency of the markets with respect to the forecast for *Activity* and again should not be taken as proof against a structural influence from index trading on the price mechanism.

Thus, none of the three possibilities to interpret the GC test results allows to draw robust conclusions on either the presence or *absence* of a structural influence from index trading activity on agricultural commodity prices. An extended information set may disprove any *prima facie* causal evidence. Presence of GC could also be interpreted as a lack of informational efficiency of markets with respect to existing or forecast information, irrespective of the information's relevance. Likewise, *absence* of GC may merely indicate informational efficiency with respect to the information on index trading activity and should thus not be taken as a proof for a lack of its structural influence.

(II) *Volatility linkages between commodity and financial asset markets increase during and after the subprime crisis*

The development of the rolling spillover indices is compared for the two big crisis periods of this millennium. The first period between March 2000 and December 2003 is characterized by the burst of the dot.com bubble, the NASDAQ crash and an overall downturn in equity markets. Both the U.S. and EU economies experienced low GDP growth and the wars in Afghanistan and Iraq caused political turmoil. Agricultural commodity markets were affected by e.g. the EU's reduction

Figure 1.2: Total volatility spillover index



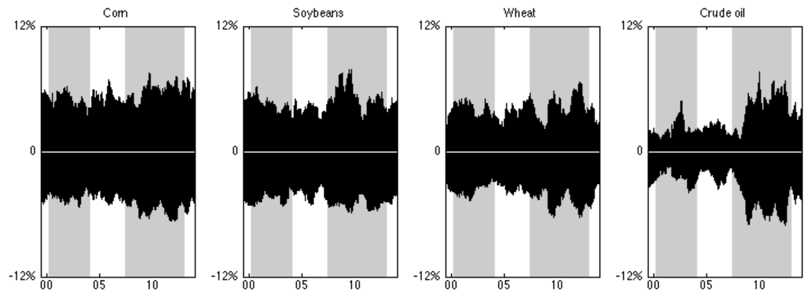
Notes: Grey shaded areas represent the two crisis periods.

of buffer stocks and China's WTO accession. The second crisis period between July 2007 and December 2012 was mainly shaped by the events of the subprime and global liquidity crisis and again low or even negative GDP growth rates in the EU and U.S. Agricultural markets saw an introduction of EU and U.S. biofuel mandates.

The total volatility spillover index is shown in Figure 3.2. Comparing the two crisis periods, there is a marked increase in range volatility interdependence between the included commodity and financial asset markets. The average total volatility spillover level rises from 26% in the first crisis period to 42% in the second crisis period. During the subprime crisis, individual asset market volatilities moved in sync and experienced significant parallel jumps, but the increase in volatility linkages even stretches beyond this period. The index peak is in May 2012 at a time when volatility levels in the single markets had declined again. This suggests an overall higher degree of interaction between the financial and commodity markets in the system.

Directional spillover indices from and to corn, soybeans, wheat and crude oil markets are presented in Figure 3.3. The magnitude of spillovers to and from the commodities also increases during the second, compared to the first crisis periods. But clearly, effects are most pronounced in the crude oil markets. Volatility relations are more closely investigated with pairwise spillover indices, which are shown in chapter 3 of this thesis. While there is no evidence for linkages between the agricultural commodities and crude oil to be affected by the introduction of biofuel mandates, some commodity-financial market linkages appear to be influenced by market crises and generally increase from the first to the second crisis period. The S&P 500 is the strongest volatility transmitter in the system with significant peaks during both crisis periods.

Figure 1.3: Directional volatility spillover indices



Notes: Positive values in upper graphs are spillovers *from*, negative values spillovers *to* the commodity, grey shaded areas represent the two crisis periods.

REITs volatility transmission, on the other hand, only increases during the subprime crisis. Compared to the first crisis period, both markets interact more strongly with commodities. Especially crude oil receives high spillovers during and after the second crisis period. While agricultural commodities are generally less affected, there are some spikes in corn and wheat markets.

In summary, evidence points to an overall stronger interaction between financial asset and commodity markets whereby the most pronounced effects can be seen between equity, real estate and crude oil markets. Agricultural range volatility appears to interact stronger with financial assets but not to the same degree as crude oil volatility. If these effects are linked to the use of commodity index funds as financial refuge assets in portfolio strategies then it is natural that energy commodities with much higher index weights are more affected than agricultural commodities. But, nevertheless, all commodity markets appear to be increasingly influenced by shocks to other financial asset markets that have little fundamental connection to commodities.

(III) *Information shocks transmitted by including index funds in financial portfolio strategies can increase price volatility on single agricultural commodity markets*

In the employed HAM, financial portfolio managers, who emerge on the market after index funds have become available, are assumed to trade exclusively via these funds. Their assessment of portfolio attractiveness of commodity index funds is based on individual commodity returns and return or volatility correlations with the other portfolio assets. The individual returns are assessed with a mixed fundamentalist-chartist strategy whereas demand from correlations is modeled with a stochastic demand term that is linked to the state in other financial markets and therefore independent of the demand from commercial traders and speculators. While demand can change each trading period and be long or short, overall position holding of the portfolio managers has to be net long (as it corresponds to index fund replication volume).

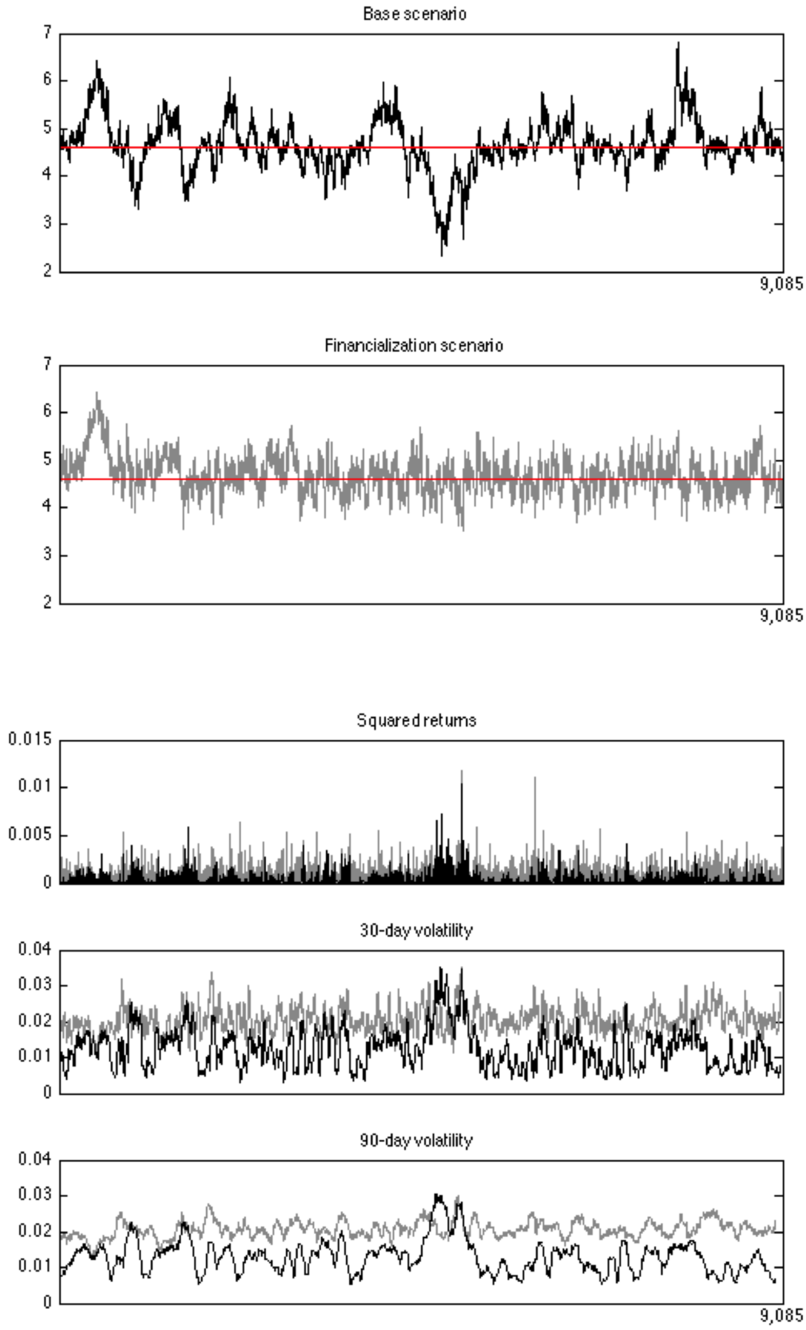
Comparing two estimated parameter sets for the base scenario (without portfolio managers) it becomes clear that the trader group with the highest variance in their stochastic demand most strongly affects short-term price volatility. And, the stronger the response of traders to perceived price misalignments between the current market price and the fundamental value, the shorter are the periods of price deviations away from fundamentals and the less likely is the occurrence of bubbles.

In the financialization scenario, three parameter sets combine different reaction coefficients and stochastic variances for portfolio managers trading volume. Once the additional portfolio managers' volume hits the market, commercial traders and speculators adjust their positions and may for example switch from net long to net short. The resulting price level effect for a scenario with a fast reaction and high stochastic demand variance is shown in the upper two graphs in Figure 1.4. Since portfolio managers also react to deviations of current prices from their fundamental value, the additional volume, although net long, does not inflate price levels but rather contributes to a reduction of price misalignments. But, the price volatility, shown in the lower three graphs in Figure 1.4, reacts to the information shocks presented by the stochastic portfolio managers demand component and volatility is inflated compared to the base scenario. The higher the stochastic variance, the stronger the volatility increase. Thus, in periods of financial turmoil, where information shocks related to asset return or volatility correlations may be of a larger magnitude, commodity price volatility can increase significantly, without any change in market fundamentals.

1.4 Conclusions and outlook

The objective of this thesis was to investigate to what extent the financialization of agricultural commodity markets contributed to the rising price levels and increased price volatility during and after the 2007/2008 food price crisis. Financialization thereby refers to the combination of increased presence of financial investors, mounting trading activity on derivative markets and

Figure 1.4: Price level and volatility effect of index trading



Notes: Price level effects for a period of 9,085 trading days are shown in the upper two graphs, volatility effects in the lower three graphs. Black lines shows base scenario prices and volatilities, grey lines financialization scenario prices and volatilities. The horizontal line in the upper graph is the constant fundamental price.

creation of commodity-linked investment products. Portfolio diversification has been identified as a principal motive for financial commodity investment and commodity index funds are a convenient investment vehicle to execute portfolio strategies with commodities. Index trading activities on the agricultural futures markets, i.e. taking long futures positions and rolling these positions forward (CFTC 2014), are linked to the index replication strategies of these commodity index funds. The higher the portfolio attractiveness of index funds, the larger will likely be the index trading (replication) volume on agricultural commodity markets.

Focusing primarily on price effects from financial portfolio inclusion of agricultural commodities, the research objective of this thesis has been separated into three specific research questions on (I) the robustness of findings from previous empirical studies that use GC tests to assess price effects of commodity index trading, (II) market linkages between traditional financial assets and agricultural commodities as a result of tactical portfolio management, and (III) direct price level and volatility effects on the single commodity markets due to portfolio inclusion of commodity index funds. These research questions have been addressed in three separate articles, choosing suitable methodologies and thereby transferring methodological and theoretical findings from financial market research to the area of agricultural economics.

While the GC tests present the most direct approach to empirically test for an influence from index trading on the price mechanism on agricultural markets, their stand-alone application suffers from serious limitations with regard to the interpretation of their results. Once implications from the informational efficiency of markets with respect to existing or forecast information and consequences from omitted variables are taken into account, it is not possible to interpret either the presence or the *absence* of a Granger-Causal influence from index trading activity to price levels, returns, volatilities or spreads on agricultural commodity markets as evidence for or against a true underlying structural influence. Consequently, alternative approaches are needed.

Some of the issues related to the interpretation of the GC tests are linked to data availability. While the CFTC offers data on “index trader” positions, the trading strategies leading to portfolio inclusion of commodity index funds are unobservable. In contrast, a few-type HAM allows to simulate the interaction between specific stylized trading strategies. Financial portfolio managers are assumed to primarily assess the portfolio attractiveness of commodity index funds based on return or volatility correlations with other asset classes, but may also consider returns of the individual commodities. Expectations on these individual returns could at least partially stem from a fundamentalist trading strategy such that the portfolio managers will also react to price misalignments between the current and the fundamental market price of the agricultural commodity. In that case, and provided that other traders are flexible enough to adjust their total positions to the new long-only trading volume, there is no systematic inflation of price levels as a result of index trading. But, the information shocks that are transmitted to agricultural commodity markets as a result of changing return or volatility correlations and resulting portfolio weight adjustments may indeed increase price volatility in the sense of short-term fluctuations.

The range volatility spillover indices between agricultural, energy and selected financial asset markets do indeed show an increase in volatility linkages during and after the subprime mortgage and global liquidity crisis. Compared to the first crisis period at the beginning of this millennium, where commodity markets were less financialized, the degree of linkage with financial asset markets is higher. The strongest effects are visible between crude oil, U.S. equity and U.S. real estate markets. If commodities are used as refuge assets to preserve portfolio value and liquidity and investors choose commodity indices rather than single commodities, then it is clear that the most pronounced effects would occur in the single commodity markets with the largest index weights. But, even if comparably less pronounced, there is a visibly stronger interaction between agricultural and financial asset markets.

While few-type HAMs provide the opportunity to test for direct price effects of specific stylized trading strategies, they are nevertheless limited in their possibility to consider the full complexity of real world markets. Validation of the model parameters is also a critical issue. The simulation-based estimation technique of the MSM and the subsequent model validation is a first step in linking the simulation model to empirical data. But, as some parameters are still fixed à priori and the nonlinear nature of the objective function hinders identification of a global minimum, more research is needed in this area. On the other hand, the empirical investigation of volatility linkages is more directly related to the real world data generation process. But, while it is informative about any changes in the general degree of market interaction, direct causal attribution of observed effects is not possible.

In summary, the thesis results indicate that, based on existing empirical evidence, it is not possible to make any definite statement on whether the observed correlation between index trading volume and price levels on agricultural commodity markets has an underlying true causal relation. Any criticism of index funds based on such an assertion is likely premature. In fact, the HAM simulation showed that index trading volume, despite it being of large magnitude and always net-long, will not *automatically* increase prices beyond fundamentally justified levels, which contradicts the “Masters hypothesis”. In fact, the strong focus on price levels that dominated the academic and public discussion at the beginning of this research project fell short of capturing the volatility implications from portfolio inclusion of agricultural commodities. There is evidence for a stronger integration of agricultural commodity and financial asset markets with resulting volatility spillover effects. And, portfolio reweightings may transmit information shocks to agricultural commodity markets. In both cases, fundamentally unconnected events can affect the price mechanism on agricultural commodity futures markets. Especially in times of financial crises, the resulting volatility effects may be substantial.

Future research should focus on expanding knowledge on the price level and volatility effects of financial portfolio strategies and thereby extend and refine existing methodologies. Understanding of how to measure price volatility and which measure or model to use in which context should be improved. Often, volatility levels are dependent on temporal aggregation and there is need to better differentiate between short-term (even day-to-day) price fluctuations and the emergence of price spikes or bubbles that will affect historical medium- to long-term volatility. There is also potential for the development of empirical models that could structurally explain price levels and volatilities on agricultural futures markets, and the respective contribution of either financial or fundamental factors. Ultimately, these models need to become more useful for policy analysis, as also recently proposed in White and Pettenuzzo (2014) in the context of macroeconomic modeling. Clearly, in order to assess potential (adverse) consequences of financial derivative trading activity for global food security more research is also needed on the linkages between local spot and the global futures markets, which have not been covered in this thesis. Research should move beyond a mere analysis of price transmission towards a structural understanding of the linkages between the two markets.

Clearly, data availability on trading positions will continue to remain an issue. While there are calls for increased transparency also in the over-the-counter markets (e.g. vial central clearing) and exchanges outside the U.S., it will likely take time before the data quantity and quality is sufficient for further empirical analysis. Also, while traders can be classified according to their primary trading motive, the exact trading strategies will continue to remain secret such that their direct price impact cannot be empirically investigated. Thus, there is further potential for the use of few-type HAMs to explore the effects of trading strategies on futures markets and to include linkages between future and spot markets. The HAMs essentially provide us with a "laboratory market" that could also be used to test specific regulatory policy measures such as previously attempted in Westerhoff (2003); Westerhoff and Dieci (2006); Anufriev and Tuinstra (2013) for financial markets in general.

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Chapter 2

What Does Granger Causality Prove? A Critical Examination of the Interpretation of Granger Causality Results on Price Effects of Index Trading in Agricultural Commodity Markets*—

Abstract

The influence of index trading on price levels, returns, spreads or volatility in agricultural commodity markets is frequently investigated with bivariate Granger Causality (GC) tests. A joint review of existing empirical studies reveals scant and inconsistent evidence of GC from index activity to prices. Some findings of reverse GC from prices to index activity are reported. The literature offers three different interpretations of GC test results: (i) as prima facie causal evidence; (ii) as a test for informational efficiency of the markets; or (iii) as a test for the ability of one variable to improve the forecast of another variable. A critical examination of these interpretations against an extended theoretical background reveals that none allows direct inferences about the existence or absence of an influence from index trading activity on the price mechanism in the market. This severely limits the usefulness of a stand-alone application of GC tests.

JEL classification: C18, Q02, Q13

Key words: Agricultural commodity markets; Granger Causality; index trading; informational efficiency

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2.1 Introduction

Agricultural commodities are increasingly perceived as a financial asset class or as members of a broader commodity asset class and, as such, are included in investment strategies (see e.g. Erb and Campbell (2006); Gorton and Rouwenhorst (2006); Miffre and Rallis (2007)). Preference for agricultural commodity price indices such as the Standard & Poors GSCI (S&P GSCI) or the Dow Jones UBS Commodity index (DJ UBS) rather than investment in single commodities is frequently referred to as "index trading".[1] Index trading can be conducted directly in the futures markets, via commodity swaps or via investment in index funds, which replicate the performance of a specific index or sub-index. Commodity index funds are typically either mutual funds, Exchange Traded Funds (ETF) or other Exchange Traded Products (ETP).[2]

Academic research that investigates the price effects of financially-motivated trading activities in agricultural commodity markets in general, and index trading in particular can be broadly classified into three categories: (i) tests for (speculative) price bubbles; (ii) analysis of financial market integration of agricultural commodities; (iii) investigation of direct price effects from index trading.[3]

Studies of the first type are conducted under the null hypothesis that financial investment may cause prices to temporarily deviate from their fundamental value and create a price bubble. Recent studies that find periodical evidence of rational bubbles in agricultural commodity markets are, for example, Gutierrez (2013) and Liu et al. (2013). Behavioural bubbles, on the other hand, are assumed to occur as a result of boundedly rational heterogeneous trading strategies. Westerhoff and Reitz (2005) and Reitz and Westerhoff (2007) show that the interaction of such trading strategies can create transitory price bubbles on the commodity markets.

Studies of the second type investigate whether financial investment in agricultural commodities may lead to increased interdependence with other asset markets. Silvennoinen and Thorp (2010); Chan et al. (2011); Diebold and Yilmaz (2012) and Huang and Zhong (2013) are recent contributions that identify increased volatility or return interdependence between commodity and other

[1]In the context of this paper, "index trading" and "index investment" can be understood as synonyms.

[2]Following the definitions used in BlackRock (2011), the term ETF refers only to structures similar to an index-type mutual fund. ETPs include all products that share similarities with ETFs but are debt securities.

[3]A fourth type of study that is less focused on financialisation effects and therefore omitted from this review is investigation of convergence between commodity spot and future prices. Examples are Silvério and Szklo (2012); Baldi et al. (2011); Figuerola-Ferretti and Gonzalo (2010) and Yang et al. (2005).

asset markets, especially in times of financial crises, although Büyükşahin et al. (2010) and Gao and Liu (2014) do not fully confirm this finding. Tang and Xiong (2010); Bicchetti and Maystre (2013) and Büyükşahin and Robe (2012) investigate intra-commodity market links and show an increase in market interdependence.

Neither type of study directly controls for the presence and trading motives of index traders or other types of financial investors on the market, which limits their potential for causal attribution. Therefore, this paper focuses on studies of the third type, which currently represent the most direct approach to econometric investigation of the price effects from index trading. The U.S. Commodity Futures Trading Commission (CFTC) initiated publication of special data on index trader positions on 5 January 2007, allowing for direct examination of lead-lag relations between index activity, as classified by the CFTC, and price variables via GC tests in the tradition of Granger (1969).

Irwin and Sanders (2011, 2012a) include a review of relevant empirical studies. Overall, evidence tilts in favour of no Granger-Causal influence from index activity to prices, even though inconclusive results remain.[4] While the authors consider general limitations of the methodology, research still lacks an assessment of the fundamental ability of GC tests to allow conclusions on either the presence or absence of an influence of index trading on price levels, returns, volatility or spreads in agricultural commodity markets. Given the statistical, rather than structural, nature of GC (Pearl 2010, p. 32), such structural or causal inferences demand theoretical support. To fill the gap, this paper provides a synthesis of key GC results from empirical studies and examines their interpretation against an extended theoretical background, taking into account informational efficiency of markets with respect to existing and forecast information.

The structure of the paper is as follows. Section 2 briefly describes the CFTC data on index trading activity and the GC methodology. Section 3 reviews relevant empirical studies and synthesises their results. Section 4 then analyses the potential for structural or causal inference, and section 5 concludes the analysis and discusses future research possibilities.

2.2 Data and Methodology

GC tests require inclusion of measured variables in the underlying information set. Price data for U.S. dollar denominated agricultural commodity futures

[4] Fatthouh et al. (2013) conduct a similar review of findings from different types of studies on the effects of financialisation with a focus limited to the crude oil markets.

contracts can be directly obtained from the exchange, i.e. the Chicago Board of Trade (CBOT), the Chicago Mercantile Exchange (CME) the Kansas City Board of Trade (KCBT) (now all part of the CME group) and the Intercontinental Exchange (ICE), or from third party data providers. Detailed data on index traders' position holdings in these markets are provided in the CFTC reports.

2.2.1 CFTC reports on index trading activity

The CFTC publishes a range of market reports on traders' position holdings on U.S. exchanges: the Commitments of Traders Reports (COT), the Disaggregated Commitments of Trader Reports (DCOT), the supplemental Commodity Index Trader (CIT) Reports and the Index Investment Data (IID) Report.[5]

The COT Report gives a snapshot of traders' long position open interest (LPOI), short position open interest (SPOI) and net open interest (OI) in futures and combined futures and options contracts for selected markets. OI is disaggregated into that from "commercial" traders with business activities linked to physical commodities, "non-commercial" reporting traders and non-reporting traders. The DCOT Reports, published from 1 December 2009, and including historical data, differentiate between four reportable trader categories: "Producer/Merchant/Processor/User", "Swap Dealers" (SWAP), "Managed Money" and "Other Reportables" (CFTC 2012b). Traders of the first category use the futures markets to hedge their commercial risk from exposure to the physical commodity, while SWAP traders are mostly financial institutions that hedge the risk from swaps with their clients. Managed Money traders include registered Commodity Trading Advisors (CTA) or Commodity Pool Operators (CPO)[6] or unregistered actively managed funds, including hedge funds or pension funds (Stoll and Whaley 2010).

The CIT Report on index trading is a supplement to the (D)COT Reports with published backdated historical data on combined futures and options positions until 2006. CIT Report traders are split into "commercial", "non-commercial" and "index traders" (INDEX) and the report shows associated LPOI, SPOI and spreading positions. Twelve agricultural commodity markets are covered: CBOT wheat (W), corn, (C) soybeans (S) and soybean oil (BO), KCBT wheat (KW), CME live cattle (LC), feeder cattle (FC), lean hogs (LH),

[5]Details on these reports are available directly from CFTC (2012a,b,c). Stoll and Whaley (2010) and Sanders et al. (2009) also provide detailed summaries. A specific description and assessment of the IID Report's contents can be found in Irwin and Sanders (2012b).

[6]CFAs give investment advice in commodity futures, which can include exercising the trading and managing the accounts of their customers; CPOs manage funds that are pooled from investors for futures and/or options trading (NFA 2012).

and ICE cocoa (CC), coffee (KC), sugar no. 11 (SB) and cotton (CT). All CFTC (D)COT and CIT reports are published every Friday at 3:30 pm EST and report position holdings at market close on Tuesday of the same week.

The latest addition is the IID Report, constructed with data obtained from a CFTC "Special Call" issued to 43 selected swap dealers and index funds (including asset managers and ETP sponsors) known to conduct index trading. From December 2007 to June 2010, end of quarter data are available. Starting from June 2010 the report shows end-of-month data. It contains the total notional value and equivalent number of futures positions of the entities' index business over the reporting period, either on their own behalf or on behalf of their clients. Positions are split into long, short and net positions and reported for 21 U.S. commodity markets. For markets outside the U.S., only the total notional value is stated. The IID Report is the first to also cover the over-the-counter (OTC) markets (CFTC 2012c).

Compared with the CIT Report, the IID Report covers more markets, includes OTC positions, identifies reporting entities based on knowledge of their actual index trading activity and only includes positions that the traders themselves identified as index trading. While the CIT Report only shows the net positions in the futures markets, the IID Report shows all positions on the long or short side of the market. Due to the required compilation time, the IID is published less frequently than the CIT Report.

2.2.2 Granger Causality tests

The concept of GC was introduced in the seminal paper by Granger (1969). A full discussion of the models and procedures that are now available to test for GC between a set of variables exceeds the scope of this paper. The studies sampled in this paper focus on bivariate linear tests for GC in mean on which this section is centred.[7] The description below largely follows Granger (1980); Hamilton (1994) and Lütkepohl (2007).

According to the general definition of GC, a variable X can be said to cause another variable Y if the probability of correctly forecasting Y_{t+1}, with $t = 1, ..., T$, increases by including information about X_t in addition to other information contained in a specific information set at time t (Ω_t). Underlying this definition of GC are three Axioms (Granger 1980). *Axiom I*: an event can only be the cause of another event if it precedes it in time, a future event can thus never be the cause of an event in the past; *Axiom II*: there should not be any redundancy in the information set; *Axiom III*: all causal relationships remain constant in their direction over time, only the strengths

[7] It is also possible to test for GC in the second moment (variance) (e.g. Cheung and Ng 1996; Hong 2001; Pantelidis and Pittis 2004) or in risk (Hong et al. 2009).

of the relationships or the time lags may change. It is possible that GC runs in both directions, i.e. X_t helps to forecast Y_{t+1} and Y_t helps to forecast X_{t+1}. In this case there is feedback between the two variables X and Y.

More formally, X_t is a cause in mean for Y_{t+1} if:

$$E\left[Y_{t+1}|\Omega_t\right] \neq E\left[Y_{t+1}|\Omega'_t\right],$$

where Ω_t is an information set containing all relevant information available in the world except the information on X. Ω'_t is an extended information set containing also information on X_t. However, in reality the information set will be restricted. Establishing *prima facie* causality instead of full causality allows the assumption that X_t is causing Y_t as long as no disproving information is added to the information set. In addition, if a point forecast rather than the whole distribution of Y_{t+1} is considered, a predictor that would minimise a measure of forecast accuracy such as the mean squared error (MSE) (e.g. (Granger 1980, p. 337); Hamilton (1994, p. 303); Lütkepohl (2007, p. 42)) should include X_t if GC between X_t and Y_{t+1} is present. Assuming the information set J_t to include only information on past and present values of Y and J'_t to also contain X_t, then we can state that X_t is a *prima facie cause in mean* for Y_{t+1} if:

$$MSE\left(E\left[Y_{t+1}|J_t\right]\right) > MSE\left(E\left[Y_{t+1}|J'_t\right]\right),$$

which in the bivariate case would hold for any *h-step* ahead forecast.

In order to implement a statistical test for GC, it is necessary to first estimate the system with a correct specification representing the data generation process, for example as a bivariate Vector Autoregressive (VAR) model of the form:

$$Y_t = c_1 + \sum_{i=1}^{m} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + \epsilon_{1t} \tag{2.1}$$

$$X_t = c_2 + \sum_{i=1}^{m} \gamma_i Y_{t-i} + \sum_{j=1}^{n} \delta_j X_{t-j} + \epsilon_{2t} \tag{2.2}$$

for $t = 1, ..., T$, where m and n denote lag-lengths, c_1 and c_2 are constants, α, β, γ and δ are regression coefficients, and ϵ_{1t} and ϵ_{2t} are white noise processes. The bivariate VAR consists of two autoregressive distributed lag (ADL) models. In the first ADL(m,n), a test of whether X helps to forecast Y can be conducted by placing zero constraints on the β coefficients. Thus, the null hypothesis (H_0) is: $\beta_1 = \beta_2 = \ldots = \beta_n = 0$. Equivalently, in the second ADL (m,n), a test of whether Y helps to forecast X would entail the H_0: $\gamma_1 = \gamma_2 = \ldots = \gamma_m = 0$. Thus, given the H_0, statistical tests are essentially tests for non-causality.

In a bivariate linear VAR with stationary variables, a standard Wald test can be used to test the null hypothesis. For integrated or co-integrated variables, Toda and Yamamoto (1995) developed a modified Wald test for GC. For systems with more than two variables, tests for multi-step causality with stationary or co-integrated variables have been discussed for example in Dufour and Renault (1998); Dufour et al. (2006); Yamamoto and Kurozumi (2006) and Lütkepohl (2007). Baeck and Brock (1992); Hiemstra and Jones (1994) and Diks and Panchenko (2005) are examples for studies developing GC tests in non-linear models.

2.3 Review of Empirical Studies

Selection criteria for the sampled empirical studies are the application of GC tests, a focus on the price effects from index trading on agricultural commodity markets and the inclusion of the time of the 2007/2008 price spike. An overview of relevant empirical studies is presented in Table 2.1.[8]

Most studies focus on return effects of index activity within the futures markets. Only Robles et al. (2009); Gilbert (2010, 2013) and Gilbert and Pfuderer (2014) investigate spot price effects. Robles et al. (2009); Gilbert (2010) and Capelle-Blancard and Coulibaly (2011) assess future price level effects. Aulerich et al. (2010); Irwin and Sanders (2010a,b); Aulerich et al. (2012); Brunetti et al. (2011); Sanders and Irwin (2011b) and Gilbert (2013) cover future price volatility effects and Stoll and Whaley (2010) and Irwin et al. (2011) discuss effects on the spread between nearby and first deferred future contracts.

Public availability of weekly CIT Report data constrains the time period of observation and feasible temporal disaggregation levels. Exceptions are Aulerich et al. (2010); Brunetti et al. (2011); Irwin et al. (2011); Sanders and Irwin (2011a) and Aulerich et al. (2012) who use non-public data on index investor positions for the years 2004-2005 on selected commodity markets. Aulerich et al. (2010, 2012) and Brunetti et al. (2011) obtain non-public daily data.

[8]This remains a rapidly evolving area of research and any omission is not deliberate. Related studies that focus on other commodity markets are Büyükşahin and Harris (2011) and Hamilton and Wu (2013) for the crude oil market and Irwin and Sanders (2012b) for the crude oil and natural gas markets.

Table 2.1: Overview of empirical studies

Study	Commodity coverage	Time period	Data disaggregation	Model	Focus	Bi-directional GC test
Gilbert (2013)	C, S, W, KW, BO	*Model 1*: ADL 06/13/2006-12/27/2011 *Model 2*: GARCH 06/20/2006-12/13/2011 (nearby future) 06/20/2006-12/27/2011 (cash)	Weekly (Tuesday)	ADL (GARCH)	Volatility	No
Gilbert and Pfuderer (2014)	C, S, W, KW, BO, SM, IMF Price Indices*	01/03/2006-12/27/2011	Weekly (Tuesday)	ADL	Return	No
Aulerich et al. (2012)	C, S, W, KW, BO, FC, LC, LH, CC, KC, SB, CT	01/2004-09/2009	Daily	ADL (SUR)	Return, Volatility	Yes
Brunetti et al. (2011)	C	*Model 1*: Returns 01/03/2005-03/19/2009 *Model 2*: Volatility 08/01/2006-03/19/2009	Daily/Intraday	VAR	Return, Volatility	Yes

Continued on next page

Table 2.1 continued

Study	Commodity coverage	Time period	Data disaggregation	Model	Focus	Bi-directional GC test
Capelle-Blancard and Coulibaly (2011)	C, S, W, KW, BO, FC, LC, LH, CC, KC, SB, CT	*Sample 1*: 01/03/2006-12/29/2010 *Sample 2*: 01/2006-09/2008 *Sample 3*: 09/2008-12/2010	Weekly (weekday not specified)	VAR (SUR)	Level	No
Irwin et al. (2011)	C, S, W	01/06/2004-09/07/2010	Weekly (Tuesday)	ADL	Spread	No
Sanders and Irwin (2011b)	C, S, W, KW, BO, FC, LC, LH, CC, KC, SB, CT	06/2006-12/2009	Weekly (Tuesday)	ADL (SUR)	Return, Volatility	No
Sanders and Irwin (2011a)	C, S, W, KW	01/06/2004-09/01/2009	Weekly (Tuesday)	ADL	Return	No
Aulerich et al. (2010)	C, S, W, KW, BO, FC, LC, LH, CC, KC, SB, CT	01/2004-08/01/2010	Daily	ADL	Return, Volatility	No
Gilbert (2010)	IMF Agricultural Food Price Index	03/2006-06/2009	Monthly	ADL/SEM	Level	No

Continued on next page

Table 2.1 continued

Study	Commodity coverage	Time period	Data disaggregation	Model	Focus	Bi-directional GC test
Irwin and Sanders (2010a,b)**	C, S, W, KW, BO, FC, LC, LH, CC, KC, SB, CT	06/13/2006-12/29/2009	Weekly (Tuesday)	ADL	Return, Volatility	No
Stoll and Whaley (2010)	W, C, S, BO, CT, LH, LC, FC, CC, CT, SB	01/2006-07/2009	Weekly (weekday not specified)	ADL	Return	Yes
Gilbert (2009)	C, S, W	01/2006-03/2009	Weekly (weekday not specified)	ADL	Return	Yes
Robles et al. (2009)	C, S, W, RR	01/2006-05/2008	Monthly	ADL	Level	No

Notes: ADL, autoregressive distributed lag; GARCH, generalized autoregressive conditional heteroskedasticity; VAR, vector autoregressive; SUR, seemingly unrelated regression; SEM, simultaneous equation model; W, CBOT wheat; C, corn; S, soybeans; BO, soybean oil; KW, KCBT wheat; LC, CME live cattle; FC, feeder cattle; LH, lean hogs; CC, ICE cocoa; KC, coffee; SB, sugar no. 11; CT, cotton; SM, soybean meal; RR, rough rice; * food, beverages, agricultural raw materials, metals and minerals, non-energy, crude oil; ** GC tests in Irwin and Sanders (2010b) only report a summary of results in Irwin and Sanders (2010a). In this paper, both studies are analyzed jointly.

2.3.1 Model description

Brunetti et al. (2011) and Capelle-Blancard and Coulibaly (2011) estimate a VAR model, the other studies employ bivariate ADL specifications.[9] One VAR or ADL model is estimated for each commodity. A generalised version of a VAR model consisting of two ADL models, as employed in the studies, is given by:

$$Price_t = c_1 + \sum_{i=1}^{m} \alpha_i Price_{t-i} + \sum_{j=1}^{n} \beta_j Activity_{t-j} + \epsilon_{1t} \tag{2.3}$$

$$Activity_t = c_2 + \sum_{i=1}^{m} \gamma_i Price_{t-i} + \sum_{j=1}^{n} \delta_j Activity_{t-j} + \epsilon_{2t} \tag{2.4}$$

for $t = 1, \dots, T$.

The lag lengths m and n are selected with information criteria or Wald tests. Depending on the variable specification chosen, $Price_t$ may represent price levels, returns, spreads, or volatilities and $Activity_t$ represents a proxy measure for index trading activity in the market, discussed in more detail in the next section. The null hypothesis of no GC from $Activity_{t-j}$ to $Price_t$ is H_0: $\beta_1 = \beta_2 = \ldots = \beta_n = 0$. Only Gilbert and Morgan (2010); Stoll and Whaley (2010); Brunetti et al. (2011) and Aulerich et al. (2012) test for reverse GC from $Price_{t-i}$ to $Activity_t$ with H_0: $\gamma_1 = \gamma_2 = \ldots = \gamma_m = 0$.

This model represents a basic specification, which is extended and augmented in some of the studies. For example, Aulerich et al. (2010, 2012) include additional exogenous variables in the form of monthly seasonal dummies. Gilbert (2010) also considers changes in the oil price (as endogenous variable) and the U.S. Dollar exchange rate against a basket of major currencies (as exogenous variable). Some studies use a feasible generalised least squares (FGLS) estimator in a cross-sectional Seemingly Unrelated Regression (SUR) framework instead of separate estimation of the bivariate models with ordinary least squares (OLS). Examples are Sanders and Irwin (2011b) and Aulerich et al. (2012). Another alternative is presented in Capelle-Blancard and Coulibaly (2011) who estimate a VAR with one specific equation for each included market with a SUR approach. They then conduct a panel GC test with bootstrapped critical values.

Aulerich et al. (2010) split the sample period into two sub-periods (2004-2005 and 2006-2008). Capelle-Blancard and Coulibaly (2011) distinguish between a pre-2008 financial crisis period (January 2006 to September 2008) and

[9]Only Gilbert (2013) also uses a GARCH model and includes the *Activity* variable in the volatility equation.

a 2008 financial crisis period (September 2008 to December 2010) after having estimated the model over the whole sample period. Aulerich et al. (2012) also investigate price effects of index activity during roll periods of the contracts.[10] Under the hypothesis that it may be a gradual long-term build-up of index positions that influences prices, Aulerich et al. (2010) and Sanders and Irwin (2011a) also estimate alternative models where position holdings enter as a moving average (MA) term, in analogy to a long-horizon "fads" model developed by Jegadeesh (1991).

2.3.2 Individual variable specifications

There is some variation concerning measurement of the *Price* and *Activity* variables. *Price* variable specifications are summarised in Table 2.2. Most studies use relative returns (R) to investigate price effects. Future price (FP) or spot price (SP) data are non-stationary, which is either solved by taking differences (Robles et al. 2009; Gilbert 2010) or by using bootstrapped critical values in the GC test (Capelle-Blancard and Coulibaly 2011). The price spread in Irwin et al. (2011) is calculated as the price difference between the first deferred ($FP1$) and nearby ($FP0$) futures contracts, expressed as a percentage of the cost of carry of the commodity, while Stoll and Whaley (2010) use the difference in returns for the nearby and first deferred contracts. Almost all studies investigate within future market effects. Exceptions are Robles et al. (2009) who use FAO spot price data, Gilbert (2010) and Gilbert and Pfuderer (2014) who use the IMF (food) price indices, which use both spot and nearby futures prices, depending on the commodity, and Gilbert (2013) who uses cash prices from the exchanges. For volatility effects, studies use the range-based volatility, implied volatility from the options markets, realised volatility computed from intraday returns or conditional volatility from a GARCH model specification.[11]

Specifications for the *Activity* variables are summarised in Table 2.3. The majority use INDEX data from the CIT Report while Irwin and Sanders (2010a,b); Brunetti et al. (2011) and Gilbert (2013) also take SWAP data from the DCOT report. Finally, Brunetti et al. (2011) use non-public CFTC information to specifically categorise some position holdings as "hedge fund" related. The *Activity* variables can be classified into three categories. First, *Activity* proxies measuring the *net flow* of index trader position holdings.

[10] Stoll and Whaley (2010) also test for roll-period effects by regressing the return spread of nearby and first deferred contracts on the number of nearby contracts that are rolled forward in the same period t but do not conduct GC tests in this context.

[11] The return-based volatility measure computed either from squared historical returns or the standard deviation of historical returns is not used in the sampled studies. Irwin and Sanders (2012b) use the return-based proxy to conduct GC tests for effects of index investing in the crude oil and natural gas markets.

These follow the hypothesis that it is the new flow of index trader positions from one time period $t-1$ to another period t that influences prices. Second, proxies representing a *relative magnitude* of position holdings are employed under the hypothesis that it is the relative size of index traders' position in the market that will affect prices. Third, proxies representing the *absolute magnitude* of position holdings are used to test the hypothesis that it is the absolute size of index traders' positions that influences prices.

2.3.3 Synthesis of results

Differences in individual model and variable specifications prevent full comparability of the studies. Instead, this section provides a synthesis of their main results and conclusions, as summarised under the sub-headings. A detailed list of all rejections of the null hypothesis of no GC at a level of significance $\leq 5\%$ is provided in Tables A2.1 and A2.2 in the Annex.

2.3.3.1 Only few significant findings of GC from *Activity* to *Price* variables

Overall, given the large array of conducted tests, there is scant evidence that lagged *Activity* has any Granger-Causal influence on returns, levels, spreads or volatility in agricultural commodity markets, either on a daily, weekly or monthly basis. In most cases, the null hypothesis can only be rejected at a level of significance $\leq 5\%$ for selected commodities, time periods and variable specifications. Some studies fail to find any evidence of GC. For example, in their panel GC test, between index trader net OI and futures prices, Capelle-Blancard and Coulibaly (2011) cannot reject the null of no GC for any of the tested commodities. Brunetti et al. (2011), using daily returns and realised volatility as *Price* variables and SWAP or hedge fund net OI as *Activity* variables also fail to find evidence of GC from *Activity* to *Price*.

2.3.3.2 Most significant findings outside the grains markets

The cases where GC from *Activity* to *Price* variables is detected appear to concentrate on markets other than grains (C, W, KW). Examining short-run return effects in the grains markets, Sanders and Irwin (2011a) cannot reject the null hypothesis of no GC, using net OI of index traders or percent of index trader LPOI relative to total LPOI as *Activity* proxies. Aulerich et al. (2010) find some results on GC in the CBOT wheat market but most in the soybean and soybean oil markets. Using a SUR-based estimation Aulerich et al. (2012) find GC in the KW and livestock markets (FC, LH). One exception within the grains complex is the CBOT corn market where Irwin and Sanders (2010a,b) and Gilbert and Pfuderer (2014) detect comparably robust evidence of lagged *Activity* (either measured as net OI, net OI as percent of total LPOI or LPOI

Table 2.2: *Price* variable specifications

Variables	Source	Description	Study
Return			
R_t	Exchange	$\ln(FP_t/FP_{t-1}) = \ln FP_t - \ln FP_{t-1}$	Gilbert and Pfuderer (2014) Aulerich et al. (2012) Sanders and Irwin (2011a) Sanders and Irwin (2011b) Brunetti et al. (2011) Aulerich et al. (2010) Stoll and Whaley (2010)* Irwin and Sanders (2010a,b) Gilbert (2009)
Level			
$\ln FP_t$	Exchange	Logarithm of futures prices	Capelle-Blancard and Coulibaly (2011)
$\ln SP_t$	FAO	Logarithm of spot prices	Robles et al. (2009)
$\log IMF_t$	IMF	Logarithm of IMF food price index (first difference due to I(1))	Gilbert (2010)
Spread			
$Carry_t$	Exchange	$\frac{FP1_t - FP0_t}{\text{Cost of carry}} \cdot 100$ Price spread between first deferred and nearby contract, expressed as percentage of cost of carry for the commodity (storage + financing cost)	Irwin et al. (2011)
$R1_t - R0_t$	Exchange	Return differential between first deferred and nearby contract	Stoll and Whaley (2010)
Volatility			
Vol_t^{Range}	Exchange	(Annualized) Range-based volatility measure as introduced in Parkinson (1980), based on the difference between daily high and low prices	Gilbert (2013) Sanders and Irwin (2011b) Aulerich et al. (2010)** Irwin and Sanders (2010a,b)
$Vol_t^{Implied}$	barchart.com	Implied volatility from the options market	Aulerich et al. (2012) Sanders and Irwin (2011b) Irwin and Sanders (2010a,b)
$Vol_t^{Realised}$	CFTC	Realised volatility estimated with the two-scales realised volatility estimator introduced in Zhang et al. (2005)	Brunetti et al. (2011)
Vol_t^{GARCH}	Exchange	Conditional volatility from a standard GARCH(1,1) model specification	Gilbert (2013)***

Notes: * The formula for return calculation is not provided in Stoll and Whaley (2010); ** Aulerich et al. (2012) also conduct GC tests using a range-based volatility measure but do not publish the results; *** Gilbert (2013) computes the conditional volatility for nearby futures and cash prices.

Table 2.3: *Activity* variable specifications

Variables	Source	Description	Study
Net flow in position holdings			
$Delta\ LPOI_t$	CIT	$LPOI_t - LPOI_{t-1}$	Stoll and Whaley (2010)
$Delta\ LPOI_t(\%)$	CIT	$\frac{LPOI_t - LPOI_{t-1}}{LPOI_{t-1}} \cdot 100$	Irwin et al. (2011)
$Delta\ Net\ OI_t$	CIT	$Net\ OI_t - Net\ OI_{t-1}$	Gilbert (2013) Aulerich et al. (2012) Irwin et al. (2011) Aulerich et al. (2010)
$Delta\ Net\ OI_t$	DCOT	$Net\ OI_t - Net\ OI_{t-1}$	Gilbert (2013)
Relative magnitude position holdings			
$PercentTotalNetOI_t$	CIT	$\frac{Net\ OI_t^{INDEX}}{\sum Net\ OI_t^{ALL}}$	Aulerich et al. (2010)*
$PercentTotalLPOI_t$	CIT	$\frac{LPOI_t^{INDEX}}{\sum LPOI_t^{ALL}}$	Sanders and Irwin (2011a) Irwin and Sanders (2010a,b)**
$PercentTotalLPOI_t$	DCOT	$\frac{LPOI_t^{SWAP}}{\sum LPOI_t^{ALL}}$	Sanders and Irwin (2011b) Irwin and Sanders (2010a,b)
Absolute magnitude position holdings			
$Index\ of\ Net\ OI_t$	CIT	Index of Net OI of index traders in all agricultural commodities included in CIT Report over period January 2006 to June 2009, base period weights are prices as of 3 January 2006 (Gilbert 2010) or 31 December 2007 (Gilbert 2009)	Gilbert (2010) Gilbert (2009)
$Net\ OI_t$	CIT	$LPOI_t - SPOI_t$	Gilbert and Pfuderer (2014) Sanders and Irwin (2011a) Capelle-Blancard and Coulibaly (2011) Irwin and Sanders (2010a,b) Robles et al. (2009)***
$Net\ OI_t$	DCOT	$LPOI_t - SPOI_t$	Brunetti et al. (2011)**** Irwin and Sanders (2010a,b)
$Net\ OI_t$	Private	$LPOI_t - SPOI_t$	Brunetti et al. (2011)

Notes: * Aulerich et al. (2012) also conduct GC tests using $Percent\ Total\ Net\ OI_t$ as *Activity* measure but do not publish the results; ** Irwin and Sanders (2010a,b) also calculate Working's T-index (Working 1960) as an *Activity* variable. However, since this measure is not specifically related to index investments, results are not reported in this study; *** Robles et al. (2009) also calculate different proxies for financial trading activity. However, since these measures are not specifically related to index investments, results are not reported in this study; **** Brunetti et al. (2011) also conduct GC tests for different *Activity* measures (Futures long positions, Futures short positions, Net Futures and Options positions) but do not report results.

as percent of total LPOI) to Granger-Cause weekly returns. Robles et al. (2009) find net OI to Granger-Cause monthly FAO corn spot price levels only for price level effects and Gilbert (2010) reports GC from the index investment index to the monthly IMF price index.

A more diverse picture emerges for short-run volatility effects. Aulerich et al. (2010) find either daily net OI or percent of OI to have a Granger-Causal influence on range-based volatility for a larger part of the investigated commodity sample, but the only grains market where evidence can be found is CBOT wheat. Similarly, Irwin and Sanders (2010a,b) cannot find their *Activity* variables to Granger-Cause implied or range-based volatility in the grains markets and only detect GC for soybeans, soybean oil, live cattle and some soft commodities (CC, KC). Gilbert (2013) finds that changes in the net OI of index traders Granger-Cause range-based volatility of soybean and soybean oil futures. But for conditional volatility, effects appear more pronounced and also extend to the grains markets. There is evidence for GC from swap dealer position changes to conditional volatility of the CBOT wheat cash and KCBT nearby futures prices and for GC from index trader position changes to conditional volatility in the soybean oil cash and futures prices as well as to the KCBT wheat conditional cash price volatility.

In their long-horizon tests, the studies find some of their *Activity* proxies (calculated as MA terms) to Granger-Cause returns (Aulerich et al. 2010; Sanders and Irwin 2011a) or range-based volatility (Aulerich et al. 2010). However, all evidence is concentrated on the oilseeds, livestock and soft commodities markets, except one finding for KW (return) and W (range-based volatility) in Aulerich et al. (2010). For effects on the spreads Stoll and Whaley (2010) and Irwin et al. (2011) do not find weekly changes in their *Activity* variables to Granger-Cause weekly future price spreads.[12]

2.3.3.3 Inconclusive results with regard to the direction of the *Price* effect

For the cases of rejection of the null of no GC from *Activity* to *Price* variables in the short-run tests, there are no conclusive results on the direction of the effect. Considering return effects, an almost equal amount of estimates show that an increase in *Activity* increases or decreases returns. Similarly, for volatility effects, some results suggest an increasing effect from changes in lagged *Activity* variables to volatility (e.g. Aulerich et al. 2010) while others suggest a decreasing or dampening effect (e.g. Gilbert 2013).

[12] In Irwin et al. (2011), if observations $< 100\%$ carry are eliminated from the sample, the null of no GC is rejected for soybeans at a level of significance of 5% (negative direction).

In the long-horizon tests (Aulerich et al. 2010; Sanders and Irwin 2011a), the case for a positive relationship between *Activity* variables and returns and for a negative relationship between *Activity* and volatility seems to be clearer but not unambiguous. Conversely, during the roll period from the nearby to the first deferred contract, the estimated coefficients in Aulerich et al. (2012) show that an increase in lagged index trader net OI has a decreasing effect on returns and an increasing effect on implied volatility.

2.3.3.4 Roll period effects more pronounced than normal market effects

Investigating roll-period effects, Aulerich et al. (2012) find more evidence of GC from *Activity* variables to returns or implied volatility than during normal contract trading periods. This suggests that index trading activity has a larger price influence during times where contracts are rolled over. One potential explanation is that index traders need to roll their positions from the expiring nearby to the next deferred futures contract in order to continue index replication. Since information about the rolling strategies for the commodity indices and index funds is public knowledge, other traders can anticipate the index investors' trades and attempt to take any potential roll returns by adjusting their own trading positions.

2.3.3.5 Few time-period dependent effects discovered by sample splits

Aulerich et al. (2010) split the sample into early years with strong growth rates of index-related products (2004-2005) and subsequent years (2005-2010) but cannot find significant differences in GC between *Activity* and returns. For their range-based volatility measure, there is indication of a negative direction of influence from the *Activity* variable in the years 2004-2005 (decreasing effect on volatility), while the direction of impact is more often positive in the years 2006-2008 (increasing effect on volatility). Using the panel GC approach, Capelle-Blancard and Coulibaly (2011) cannot find any GC running from their *Activity* proxy to returns in the agricultural future markets, regardless of whether investigation is conducted during periods of financial crises (2008-2010) or other periods (2006-2008).

2.3.3.6 Some evidence for reverse causality

Among the sampled studies only Gilbert (2009); Stoll and Whaley (2010); Brunetti et al. (2011) and Aulerich et al. (2012) report results from bi-directional GC tests. While Brunetti et al. (2011) cannot find any reverse GC for CBOT corn and Stoll and Whaley (2010) only detect GC from lagged returns to the change in index trader net long positions in the KCBT wheat market, Gilbert

(2009) and Aulerich et al. (2012) show GC from returns to their *Activity* proxies for a larger array of commodities. All studies unanimously find that if returns Granger-Cause *Activity* variables, the influence is in a positive direction, i.e. higher returns will lead to higher index trading activity. Aulerich et al. (2012) also find some results on daily implied volatility Granger-Causing daily net OI of index traders in a way that an increase in implied volatility would decrease index trading activity.

In summary, the empirical studies find only selected evidence for GC from *Activity* to *Price* variables, most notably in markets outside the grains complex and during roll-periods. Results remain inconclusive with regard to the direction of *Price* effects. Even though few studies report results from reverse GC tests, there is some evidence that *Price* variables may Granger-Cause *Activity* variables.

2.4 Interpretability and Explanatory Power of GC Test Results

GC tests are sensitive to the proper specification of the time series model and choice of estimators. For example, some studies stress the issue of high volatility of the dependent variable (e.g. Sanders and Irwin 2010, 2011b), which may reduce power of the GC tests to reject the null hypothesis if not accounted for by proper model specification or choice of estimators.[13] However, since the focus of this paper is on a conceptual assessment of GC result interpretability, these issues are not considered in more detail here.

Full causal interpretation of GC tests is impeded by the fact that they only test lead-lag relationships between variables, contemporaneous relationships are not considered (e.g. Granger 1980; Hiemstra and Jones 1994; Lütkepohl 2007, p. 47; Gilbert and Pfuderer 2014). In addition, GC is a statistical concept that relies on testing the H_0 of no causality given a pre-specified and necessarily restricted information set (Pearl 2010, p. 32). Test results are thus sensitive to the composition of the information set and may be disturbed by omitted variables, wrong variable specification, measurement errors, high temporal data aggregation levels or time varying effects over the observation period. The standard linear bivariate GC tests may also fail if the underlying Granger-Causal relationship is non-linear, which is, however, unlikely to be a major concern for the analysed studies. Detailed discussions of these issues are for example provided in Granger (1980); Newbold (1982) and Hoover (2001).

[13]For example, Sanders and Irwin (2011b) use a SUR-based estimation approach to mitigate this effect.

With full causal interpretation of GC tests being out of question, alternatives are needed. Three rather different interpretations of GC tests of index activity on commodity prices are discussed in the literature: (i) as *prima facie* causal evidence on index trading affecting the price mechanism; (ii) as a test for the informational efficiency of agricultural commodity markets; and (iii) as a test of whether index trading activity helps to forecast *Price* variables. In the following, each of these interpretations is assessed in more detail.

2.4.1 Robustness of *prima facie* causality given *Activity* variable specification

The possibility of interpreting the presence of GC as *prima facie* causal evidence has already been introduced in section 3.3.1 of this paper. If GC between *Activity* and *Price* variables is detected, the robustness of the *prima facie* causality hinges on the likelihood of finding a different specification of the information set that could disprove it. General issues related to, for example, temporal aggregations or measurement errors may apply in this context but are well discussed in the existing literature (e.g. Granger 1980; Newbold 1982; Hoover 2001). This section focuses on specific issues arising from specification of the *Activity* variables used in the studies, which depends on the CFTC data.

Activity variables contain two types of information: (i) trading volume in the market at a specific point in time, and (ii) its association with a trader type according to CFTC classification. Levels and changes of *Activity* of INDEX traders are a function of demand from index funds, hedging demand from swap dealers and demand from other traders who replicate an index in the futures markets. However, both the CIT and the IID Reports show that these data are insufficient measures for this demand since the INDEX positions are neither clearly associable with a genuine trading motive nor with a related trading strategy.

While portfolio diversification is a plausible motive for index trading (e.g. Stoll and Whaley 2010; Gilbert and Pfuderer 2014), hedging and speculation on future price movements are also possible motives. The index funds are only instruments to gain exposure to index movements as an alternative to direct investment in the futures markets. Any trading strategy is merely a derived strategy in the form of passive replication of the index price movement. It is the trading strategy leading to an inflow of liquidity into the index funds that is linked to the genuine trading motive of the investor and this cannot be observed from CFTC data.

Similarly, if the replication scheme of the index fund is synthetic, via swap agreements, the swap dealer would hedge the open position in the futures markets and become part of the CFTC INDEX data. The high correlation of DCOT SWAP positions and CIT INDEX positions (LPOI correlation coefficients of, for example, 0.84 for wheat, 0.62 for corn and 0.63 for soybeans) reflects this relationship and provides the justification for Irwin and Sanders (2010a,b) and Brunetti et al. (2011) to use SWAP positions as one proxy for index trading activity. Again, the hedging need is influenced by the liquidity allocated to index funds whose determinants are unobservable.

The consequence of the unobservable trading motives and strategies that determine index fund liquidity inflow is an increased likelihood of omitted variable bias and associated decrease in robustness of the *prima facie* causal evidence. For instance, any trading strategy that considers market fundamentals is likely to mean that both *Activity* and *Price* are determined by the same fundamental factors of supply and demand for the agricultural commodity.

The sampled studies do not discuss this source of omitted variable bias in more detail. Gilbert and Pfuderer (2014) suggest a potential omitted variable leading to GC from *Activity* to *Price* variables in the soybean complex but do not investigate it further. However, for those cases where presence of GC is detected, inclusion of market fundamentals in the information set is a necessary robustness check for GC test results if they are to be interpreted as *prima facie* causal evidence.

2.4.2 Consequences from market efficiency with respect to existing information

A second interpretation of GC between *Activity* and *Price* variables is emphasised by Gilbert and Pfuderer (2014) who point out that in efficient markets an influence from lagged *Activity* to *Price* should not *ex-ante* be expected as all relevant information contained in the *Activity* variables will be impounded in the market price at any given time t. Thus, a test for GC from *Activity* to *Price* variables can be interpreted as a test for informational efficiency of the market. Indeed, GC tests have been applied in this context.[14]

A market is efficient with respect to the information set J_t if prices fully account for this information and trading on it would not lead to economic profits (Jensen 1978). With weak-form efficiency, J_t contains only past and current prices and related information such as trading volume. Under semi-strong efficiency, J_t includes all publicly available information and with strong-form efficiency, J_t includes all existing public and private information (Fama 1970; Figlewski 1978; Timmermann and Granger 2004).

[14] For example, Cornelius (1993) and Mookerjee (1987) apply GC tests to investigate the informational efficiency of stock markets with respect to money supply.

Thus, interpreting GC tests as tests for informational efficiency of the market with respect to *Activity* variables requires specification of the degree of efficiency that is assumed under the null hypothesis. This has to entail an assessment of nature and timing of public availability of both types of information within the *Activity* variables, (i) trading volume, and (ii) associability with a CFTC trader category.

The trading volume component within *Activity* suggests a relationship with tests on price-volume relationships in financial asset markets. While some argue for lead-lag relationships (Lee and Rui 2002), it is frequently asserted that both are simultaneously reacting to an inflow of information, leading to contemporaneous relationships. For example, within commodity markets, Chevallier and Sévi (2012) find contemporaneous intraday relationships between trading volume and realised volatility in the crude oil and natural gas markets.[15] If trading volume were the only informational component of *Activity*, a test of GC between *Activity* and *Price* would be a test for weak-form informational efficiency and one would ex-ante expect that the null hypothesis would not be rejected.

The second informational component within *Activity*, associability of volume with a CFTC trader category, remains private from Tuesday to Friday 3:30 pm in a given week t. Since most weekly studies use Tuesday-to-Tuesday data, their *Activity* variables change character from private to public information within the observation period. Consequently, a test for GC between weekly *Activity* and *Price* variables is a test for semi-strong informational efficiency of the investigated agricultural commodity markets as all information on *Activity* should be impounded in the price once it becomes public. The studies using non-public daily CFTC data (Aulerich et al. 2010, 2012; Brunetti et al. 2011), on the other hand, construct *Activity* variables that contain some private information over the whole measurement period. Their GC tests can indeed be argued to be tests for strong-form market efficiency within the agricultural commodity market.

Ex-ante assessment of whether the null hypothesis of no GC will be rejected has to entail an examination of whether semi-strong or strong-form informational efficiency can be assumed for agricultural commodity markets. Garcia and Leuthold (2004) provide a recent review on the relevant empirical literature, which shows that while in the long-run markets exhibit semi-strong informational efficiency, short-term periods of market inefficiencies may nevertheless exist. This is line with general findings of transitory periods of asset market inefficiencies (Beja and Goldman 1980; Timmermann and Granger

[15] Karpoff (1987) provides an overview of earlier results on contemporaneous price-volume correlations.

2004), caused for example by imperfect institutional market structure (Beja and Goldman 1980), costly information gathering (Grossman 1976), a "psychological and behavioural element" in the form of heterogeneous boundedly rational market participants (Malkiel 2003; Singleton 2011) or illiquidity of the market (Chordia et al. 2008). However, strong-form informational efficiency has been frequently shown to be non-existent (Timmermann and Granger 2004).

While for GC tests with daily data, the ex-ante assumption would thus be to detect presence of GC, for weekly (or monthly) data such detection implies rejection of semi-strong form informational efficiency, which should generate a search for the source for the inefficiency. However, detection of absence of GC may be the mere consequence of semi-strong informational efficiency of the markets and is not evidence *per se* for a lack of influence of index activity on prices. Further analysis would be needed, for example in the form of an investigation of contemporaneous effects via impulse response analysis, as conducted in Brunetti et al. (2011).[16]

2.4.3 Consequences from market efficiency with respect to forecast information

The general definition of GC presented in section 3.3.1 suggests interpretation of GC as a test of whether *Activity* variables help to forecast *Price* variables (see, for example, Hamilton (1994, p. 308)). Thus, rejecting the null hypothesis of no GC means that a forecast of *Price* can be improved by adding lagged *Activity* to the information set. A logical implication of this perspective is that market agents will not only forecast *Price* but also formulate expectations about all other variables potentially helpful in improving this forecast. Thus, the *ex-ante* hypothesis that lagged *Activity* could help to forecast *Price* has to entail the hypothesis that in this case market agents will attempt to forecast *Activity* in periods $t+h$ $(h = 1, 2, \ldots)$.

If the market is informationally efficient with respect to the forecast for $Activity_{t+h}$ (see, e.g. Timmermann and Granger (2004)), this information will be impounded in *Price* variables in period t. The consequences have been stressed in both Hamilton (1994) and Hoover (2001). A test may reveal GC in the "wrong" direction, i.e. from *Price* to *Activity* even though the true relationship is really that *Activity* has a Granger-Causal influence on *Price* (Hamilton 1994, p.307; Hoover 2001, p. 137). This relationship is formally demonstrated for rational expectations type forecasts in Hoover (2001, pp. 153-155). To allow deviation from the rational expectations hypothesis, it is necessary to extend the concept of informational efficiency from efficiency with

[16] Brunetti et al. (2011) find that contemporaneous effects appear to mirror the lead-lag relationships of the GC tests.

regard to existing information (public or private) to efficiency with regard to information from any forecast model (Timmermann and Granger 2004).

Timmermann and Granger (2004) suggest that markets will impound information from forecast models that have become widely used and respected. Inefficiencies would only exist transitorily, e.g. with respect to technically innovative models. Thus, in the following it will be assumed that market agents make a collective forecast of *Activity* based on an array of known forecasting models. Any assumptions about particular model specification would be necessarily partial and thus an arbitrary representation of the true information set.

In any case, it can be assumed that market agents will employ some forecasting models that are common practice. Forecasts for $Activity_{t+h}$ from that part of employed forecasting models will be aggregated in $Price_t$. The *ex-ante* hypothesis would thus be to reject the null hypothesis in a test for GC from $Price_{t-h}$ to $Activity_t$. Some information on $E[Activity_t]$ will be present in $Price_{t-h}$ and naturally improve a forecast of $Activity_t$. GC would indeed run in "reverse" direction from *Price* to *Activity*. The closer the collective forecast is to the information contained in a rational expectations type forecast, the higher the likelihood of observing this effect.

However, there are also implications for tests from GC from $Activity_{t-h}$ to $Price_t$. If some forecast of $Activity_t$ is aggregated in $Price_{t-h}$ and that forecast is based on observed past $Activity_{t-h}$, e.g. by containing autoregressive components, then including lagged *Activity* in addition to lagged *Price* in the information set only adds limited additional information. Assuming that $E[Activity_t]$ could be forecast on publicly available information on $Activity_{t-1}$, suggests that $Activity_{t-1}$ would already be fully aggregated in $Price_{t-1}$, which yields the same result as assumed under semi-strong form informational efficiency: non-rejection of the null hypothesis. However, considering that some information on $Activity_{t-1}$ is private, which is especially true for the daily models, $E[Activity_{t-1}]$ will nevertheless be aggregated in $Price_{t-1}$ in the form of a forecast. The only information added by including actual $Activity_{t-1}$ would be the prediction error, i.e. the unexpected $Activity_{t-1}$. Thus, the size of the prediction error determines the likelihood of rejection of the null.

Consequently, interpretation of GC tests as tests for the ability of *Activity* to forecast *Price* must entail the hypothesis that a collective forecast of $Activity_{t+h}$ may be aggregated in $Price_t$. Therefore, detection of absence of GC from $Activity_{t-h}$ to $Price_t$ again does not permit the conclusion that index activity does not influence the price mechanism. On the contrary, if *Activity* variables are potentially helpful in forecasting *Price* variables, i.e.

do influence prices, then it is even more likely that an investigator will fail to find GC from *Activity* to *Price*, even using daily data. On the other hand, detection of the presence of GC from $Price_{t-h}$ to $Activity_t$ can be interpreted as evidence that $E[Activity_{t+h}]$ is aggregated in $Price_t$ because *Activity* is helpful in forecasting *Price*. This would then not *per se* permit the conclusion that index traders are trend-followers as suggested in Aulerich et al. (2012).

2.5 Conclusion

This paper has reviewed a sample of recent empirical studies that investigate the price level, return, spread or volatility effects of (CFTC) index trading activity on agricultural commodity markets via bivariate linear GC tests. A synthesis of results reveals an overall lack of rejection of the null hypothesis of no GC from *Activity* to *Price* variables at a level of significance $\leq 5\%$. If presence of GC is detected, it is mostly outside the grains markets (W, C, KW) and with varying direction of influence. Even though few studies investigated reverse causality, there is some evidence for GC from *Price* to *Activity* variables.

Since structural or causal interpretation of GC is entirely dependent on its statistical nature and focus on lead-lag relations, three alternative interpretations of positive GC test results are considered here: (i) GC as *prima facie* evidence of a causal relationship between *Activity* and *Price* variables; (ii) GC as a test for market efficiency with respect to information contained in the *Activity* variables; and (iii) GC as a test for the ability of *Activity* variables to improve the forecast of *Price* variables. It has been shown that none of these options allows robust conclusions on either the presence or absence of price effects from index trading activity.

First, extending the information set with determinants of genuine trading motives and strategies, which lead to *Activity* levels and changes, may disprove the *prima facie* causal evidence. Since any trading strategy based on market fundamentals is likely to lead to an omitted variable bias, the likelihood of disproving an earlier GC detection is high. Second, when interpreting GC results as tests for the efficiency of markets with respect to existing information on *Activity*, the *ex-ante* hypothesis for weekly data or higher aggregation levels should be to not reject the null of no GC unless the semi-strong form market efficiency can also be reasonably rejected. Third, interpreting GC in terms of whether *Activity* helps to forecast *Price* variables has to entail the hypothesis that market agents will also forecast *Activity*. If these collective forecasts are aggregated in the market price at any time t and contain a small prediction error, the additional informational content of past *Activity* observations in an autoregressive forecast model for *Price* would be very low and absence of

GC may be suspected *ex-ante*. Impounding of expectations about *Activity* in the market price may even lead to detection of "reverse" GC from *Price* to *Activity* variables.

Thus, the potential for a stand-alone application of bivariate GC tests to resolve the research question is limited. The presence of GC cannot be taken as robust evidence for an influence of index trading on the price mechanism in agricultural commodity markets, but, by the same token, the absence of GC does not qualify as robust evidence against such an influence. A similar conclusion is reached by Hoover (2001, p. 155) on the overall limited usefulness of GC in structural macroeconomic analysis.

Future research urgently requires augmented or complementary approaches. As also pointed out by Fatthouh et al. (2013), understanding of underlying cause-and-effect relationships will necessitate multivariate structural modeling approaches. In this context, structural VAR models are currently (re-)gaining momentum and their potential for the research question should be further explored. Thereby, GC tests for lead-lag relationships will still play a supporting role in investigating exogeneity of variables. However, they should in principle be performed bi-directionally. In addition, analysis of contemporaneous relationships, e.g. with innovation accounting techniques such as impulse response analysis or variance decompositions should complement lead-lag investigations.

Clearly, non-linear effects could also be considered via adequate specifications such as threshold autoregressive models where index activity could be hypothesised to only influence the price mechanism once it exceeds a specific threshold. However, all econometric approaches that directly include index trading activity as a model variable will ultimately suffer from the limitations imposed by the CFTC data. On the other hand, econometric analysis without direct *Activity* variable inclusion faces problems of attributability. An alternative would be to complement econometric approaches with simulation models. Agent-based models would allow for an investigation of interaction of heterogeneous market agents such as index traders and traditional market participants and could for example build on existing models by Westerhoff and Reitz (2005) and Reitz and Westerhoff (2007).

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2.7 Annex

A2.1: Results on *Activity* Granger-Causing *Price*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
Short-term effects						
W	Jun 2006-Dec 2011	$Delta\ Net\ OI_t$	Vol_t^{GARCH} $(cash)$	1%	+	Gilbert (2013)
W	2004-05 (daily)	$Delta\ Net\ OI_t$ (lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
W	2006-08 (daily)	$Delta\ Net\ OI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)
W	2006-08 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
KW	Jun 2006-Dec 2011	$Delta\ Net\ OI_t$	Vol_t^{GARCH} $(nearby)$	5%	–	Gilbert (2013)
KW	Jun 2006-Dec 2011	$Delta\ Net\ OI_t$	Vol_t^{GARCH} $(cash)$	5%	–	Gilbert (2013)
KW	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	R_t (nearby)	5%	–	Aulerich et al. (2012)
C	3 Jan 2006-27 Dec 2011 (weekly)	$Net\ OI_t$ (lag 1)	R_t (nearby)	5%	–	Gilbert and Pfuderer (2014)
C	Jun 2006-Dec 2009	$Net\ OI_t$ (lag 1)	R_t (nearby)	1%	–	Irwin and Sanders (2010a,b)
C	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ (lag 1)	R_t (nearby)	5%	–	Irwin and Sanders (2010a,b)
C	Jan 2006-May 2008 (monthly)	$Net\ OI_t$ (lag not specified)	$\ln SP_t$ (nearby)	5%	+	Robles et al. (2009)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
S	Jun 2006-Dec 2011	$Delta\ Net\ OI_t$ (lag 2)	Vol_t^{Range}	5%	+	Gilbert (2013)
S	14 Jan 2004-7 Sep 2010	$Delta\ Net\ OI_t$	$Carry_t$ (corrected for observations $\leq$ 100% carry)	5%	–	Irwin et al. (2011)
S	2004-2005 (daily)	$Delta\ Net\ OI_t$	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
S	2004-2005 (daily)	$PercentTotalNetOI_t$ (lag not specified)	R_t (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
S	2004-2005 (daily)	$PercentTotalNetOI_t$ (lag not specified)	R_t (first deferred)	5%	+ (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	R_t (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$Delta\ Net\ OI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
S	Jun 2006-Dec 2009	$Net\ OI_t\ SWAP$ (lag 1)	$Vol_t^{Implied}$	1%	–	Sanders and Irwin (2011b)
S	Jun 2006-Dec 2009	$Net\ OI_t\ SWAP$ (lag 1)	Vol_t^{Range}	1%	–	Sanders and Irwin (2011b)
S	Jun 2006-Dec 2009	$Net\ OI_t$ (lag 1)	$Vol_t^{Implied}$	1%	–	Irwin and Sanders (2010a,b)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
S	Jun 2006-Dec 2009	$Net\,OI_t\ SWAP$ (lag 1)	$Vol_t^{Implied}$	1%	–	Irwin and Sanders (2010a,b)
S	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ (lag 1)	$Vol_t^{Implied}$	5%	–	Irwin and Sanders (2010a,b)
S	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ $SWAP$ (lag 1)	$Vol_t^{Implied}$	5%	–	Irwin and Sanders (2010a,b)
S	Jun 2006-Dec 2009	$Net\,OI_t\ SWAP$ (lag 1)	Vol_t^{Range}	5%	–	Irwin and Sanders (2010a,b)
BO	Jun 2006-Dec 2011	$Delta\ Net\,OI_t$ (lag 1)	Vol_t^{Range}	5%	+	Gilbert (2013)
BO	Jun 2006-Dec 2011	$Delta\ Net\,OI_t$	Vol_t^{GARCH} (cash)	5%	–	Gilbert (2013)
BO	Jun 2006-Dec 2011	$Delta\ Net\,OI_t$	Vol_t^{GARCH} (nearby)	1%	–	Gilbert (2013)
BO	3 Jan 2006-27 Dec 2011 (weekly)	$Net\,OI_t$ (lag 3)	R_t (nearby)	5%	+	Gilbert and Pfuderer (2014)
BO	3 Jan 2006-27 Dec 2011 (weekly)	$Net\,OI_t$ for S (lag 3)	R_t (nearby)	5%	+	Gilbert and Pfuderer (2014)
BO	3 Jan 2006-27 Dec 2011 (weekly)	$Net\,OI_t$ for S and BO (lag 3)	R_t (nearby)	5%	+	Gilbert and Pfuderer (2014)
BO	2004-2005 (daily)	$Delta\ Net\,OI_t$ (lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
BO	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	R_t (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
BO	2004-2005 (daily)	$Delta\ Net\ OI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)
BO	2004-2005 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)
BO	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
BO	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ (lag 1)	$Vol_t^{Implied}$	1%	–	Irwin and Sanders (2010a,b)
BO	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ $SWAP$ (lag 1)	$Vol_t^{Implied}$	1%	–	Irwin and Sanders (2010a,b)
FC	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	R_t (nearby)	5%	–	Aulerich et al. (2012)
LC	2006-2008 (daily)	$Delta\ Net\ OI_t$ (lag not specified)	Vol_t^{Range} (nearby)	5%	+ (cumulative)	Aulerich et al. (2010)
LC	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
LC	Jun 2006-Dec 2009	$Net\ OI_t$ (lags 1-3)	$Vol_t^{Implied}$	1%	– (cumulative)	Irwin and Sanders (2010a,b)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
LH	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	R_t (nearby)	1%	–	Aulerich et al. (2012)
LH	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	5%	+ (cumulative)	Aulerich et al. (2010)
CC	2004-2005 (daily)	$Delta\ Net\ OI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	5%	+ (cumulative)	Aulerich et al. (2010)
CC	2004-2005 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
CC	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
CC	Jun 2006-Dec 2009	$Net\ OI_t\ SWAP$ (lag 1)	Vol_t^{Range}	5%	–	Sanders and Irwin (2011b)
CC	Jun 2006-Dec 2009	$Net\ OI_t\ SWAP$ (lag 1)	Vol_t^{Range}	5%	–	Irwin and Sanders (2010a,b)
KC	2004-2005 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
KC	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
KC	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ (lag 1)	$Vol_t^{Implied}$	5%	–	Irwin and Sanders (2010a,b)
KC	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ $SWAP$ (lag 1)	$Vol_t^{Implied}$	1%	–	Irwin and Sanders (2010a,b)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
CT	Jan 2006-Jul 2009	$Delta\ Net\ LPOI_t$ (lags 1-2)	R_t (nearby)	5%	n/a	Stoll and Whaley (2010)
CT	Jun 2006-Dec 2009	$Net\ OI_t$ (lag 1)	R_t (nearby)	1%	+	Irwin and Sanders (2010a,b)
CT	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
CT	2004-2005 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
CT	2006-2008 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
SB	2004-2005 (daily)	$PercentTotalNetOI_t$ (lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
SB	2006-2008 (daily)	$Delta\ Net\ OI_t$ (lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
IMF Index	Mar 2006-Jun 2009 (monthly)	Index of $Net\ OI_t$	$\ln SP_t$	5%	+	Gilbert (2010)
System	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ (lag 1)	$Vol_t^{Implied}$	5%	– (cumulative)	Irwin and Sanders (2010a,b)
System	Jun 2006-Dec 2009	$PercentTotalLPOI_t$ $SWAP$ (lag 1)	$Vol_t^{Implied}$	1%	–	Irwin and Sanders (2010a,b)
System	Jun 2006-Dec 2009	$Net\ OI_t$ (lag 1)	Vol_t^{Range}	5%	–	Irwin and Sanders (2010a,b)
System	Jun 2006-Dec 2009	$Net\ OI_t\ SWAP$ (lag 1)	Vol_t^{Range}	5%	–	Sanders and Irwin (2011b)

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A2.1 *(continued)*

Com-modity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
Long-term effects						
W	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
KW	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
S	6 Jan 2004-1 Sep 2009	$Net\ OI_t$ (MA lag 8)	R_t (nearby)	5%	+ (cumulative)	Sanders and Irwin (2011a)
S	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
S	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	5%	+ (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
S	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
S	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
BO	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
BO	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
BO	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
BO	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
BO	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
BO	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
BO	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
FC	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
FC	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
FC	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
FC	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
LC	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
LC	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
LC	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)
LC	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
LC	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	5%	+ (cumulative)	Aulerich et al. (2010)
LH	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
LH	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (nearby)	5%	+ (cumulative)	Aulerich et al. (2010)
LH	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
LH	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
LH	2006-2006 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	5%	+ (cumulative)	Aulerich et al. (2010)
KC	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
KC	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
KC	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
KC	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
CC	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
CC	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
CC	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
CC	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
CC	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	1%	+ (cumulative)	Aulerich et al. (2010)
CT	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
CT	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	5%	– (cumulative)	Aulerich et al. (2010)
CT	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
CT	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
CT	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
CT	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)
SB	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (nearby)	1%	+ (cumulative)	Aulerich et al. (2010)
SB	2006-2008 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	R_t (first deferred)	5%	+ (cumulative)	Aulerich et al. (2010)
SB	2006-2008 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	R_t (first deferred)	1%	– (cumulative)	Aulerich et al. (2010)

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A2.1 *(continued)*

Commodity	Time period	*Activity* variable (lag)	*Price* variable	Significance level	Direction	Study
SB	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
SB	2004-2005 (daily)	$Delta\ Net\ OI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
SB	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (nearby)	1%	– (cumulative)	Aulerich et al. (2010)
SB	2004-2005 (daily)	$PercentTotalNetOI_t$ (MA lag not specified)	Vol_t^{Range} (first deferred)	5%	– (cumulative)	Aulerich et al. (2010)
Roll period effects						
KW	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 4)	R_t (nearby, first deferred)	1%	– (cumulative)	Aulerich et al. (2012)
KW	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (cumulative lags)	R_t (nearby, first deferred)	5%	– (cumulative)	Aulerich et al. (2012)
FC	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	$Vol_t^{Implied}$	1%	+	Aulerich et al. (2012)
LC	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	R_t (nearby, first deferred)	1%	–	Aulerich et al. (2012)
LH	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	R_t (nearby, first deferred)	1%	–	Aulerich et al. (2012)
CC	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lags 1-5)	R_t (nearby, first deferred)	1%	– (cumulative)	Aulerich et al. (2012)
CC	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	$Vol_t^{Implied}$	1%	+	Aulerich et al. (2012)
CT	Jan 2004-Sep 2009	$Delta\ Net\ OI_t$ (lag 1)	R_t (nearby, first deferred)	1%	–	Aulerich et al. (2012)

A2.2: Results on *Price* Granger-Causing *Activity*

Commodity	Time period	*Price* variable (lag)	*Activity* variable	Significance level	Direction	Study
W	Jan 2004-Sep 2009	R_t (nearby) (lag 1)	$Net\ OI_t$	1%	+	Aulerich et al. (2012)
W	Jan 2006-Mar 2009 (daily)	R_t (lags 1-3)	$Index\ of\ Net\ OI_t$	1%	+ (cumulative)	Gilbert (2009)
W	Jan 2004-Sep 2009	$Vol_t^{Implied}$ (lags 1-2)	$Net\ OI_t$	1%	– (cumulative)	Aulerich et al. (2012)
C	Jan 2004-Sep 2009	R_t (nearby) (lag 1)	$Net\ OI_t$	1%	+	Aulerich et al. (2012)
C	Jan 2006-Mar 2009 (daily)	R_t (lags 1-3)	$Index\ of\ Net\ OI_t$	1%	+ (cumulative)	Gilbert (2009)
C	Jan 2004-Sep 2009	$Vol_t^{Implied}$ (lags 1-5)	$Net\ OI_t$	1%	– (cumulative)	Aulerich et al. (2012)
S	Jan 2006-Mar 2009 (daily)	R_t (lags 1-3)	$Index\ of\ Net\ OI_t$	5%	+ (cumulative)	Gilbert (2009)
S	Jan 2004-Sep 2009	R_t (nearby) (lags 1-2)	$Net\ OI_t$	1%	+ (cumulative)	Aulerich et al. (2012)
KW	Jan 2004-Sep 2009	R_t (nearby) (lag 1)	$Net\ OI_t$	1%	+	Aulerich et al. (2012)
C	Jan 2006-Jul 2009	R_t (nearby) (lags 1-2)	$Net\ OI_t$	5%	n/a	Stoll and Whaley (2010)
BO	Jan 2004-Sep 2009	R_t (nearby) (lag 1)	$Net\ OI_t$	5%	+	Aulerich et al. (2012)

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A2.2 *(continued)*

Commodity	Time period	*Price* variable (lag)	*Activity* variable	Significance level	Direction	Study
LH	Jan 2004-Sep 2009	R_t (nearby) (lag 1)	$Net\,OI_t$	5%	+	Aulerich et al. (2012)
LC	Jan 2004-Sep 2009	R_t (nearby) (lag 1)	$Net\,OI_t$	5%	+ (cumulative)	Aulerich et al. (2012)
CC	Jan 2004-Sep 2009	$Vol_t^{Implied}$ (lags 1-5)	$Net\,OI_t$	1%	– (cumulative)	Aulerich et al. (2012)
CT	Jan 2004-Sep 2009	R_t (nearby) (lag 1)	$Net\,OI_t$	5%	+	Aulerich et al. (2012)
CT	Jan 2004-Sep 2009	$Vol_t^{Implied}$ (lag 1)	$Net\,OI_t$	5%	–	Aulerich et al. (2012)
SB	Jan 2004-Sep 2009	$Vol_t^{Implied}$ (lag 1)	$Net\,OI_t$	1%	–	Aulerich et al. (2012)
System	Jan 2004-Sep 2009	R_t (nearby)	$Net\,OI_t$	1%	+ (cumulative)	Aulerich et al. (2012)
System	Jan 2004-Sep 2009	$Vol_t^{Implied}$	$Net\,OI_t$	1%	– (cumulative)	Aulerich et al. (2012)

Chapter 3

Directional Volatility Spillovers between Agricultural, Crude Oil, Real Estate and other Financial Markets*—

Abstract

The addition of commodities to financial portfolios and resulting weight adjustments may create volatility linkages between commodity and financial markets, especially during financial crises. Also, biofuel mandates are suspected to integrate agricultural and energy markets. We calculate directional pairwise range volatility spillover indices (Diebold and Yilmaz 2012) for corn, wheat, soybeans, crude oil, equity, real estate, U.S. Treasury notes and a U.S. dollar index between 06/1998 and 12/2013. During the recent financial crisis, volatility spillovers from equity and real estate to commodities, particularly crude oil, rise to unprecedented levels. Yet, we find no indication of a parallel increase of volatility linkages between agricultural and crude oil markets.

JEL classification: Q13, C32, G11, G01

Key words: Volatility spillovers; financialization; generalized forecast error variance decomposition; VAR

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3.1 Introduction

Portfolio diversification is a principal motive for financial commodity trading (Fortenbery and Hauser 1990). The fundamentals that drive their supply and demand largely differ from those of other financial assets, suggesting low or negative return correlations. And, like real estate, commodities can serve as an inflation hedge as their prices drive inflation but their holding is not directly associated with inflation-threatened cash flows (Ankrim and Hensel 1993; Huang and Zhong 2013; Bodie and Rosansky 1980; Satyanarayan and Varangis 1996; Anson 1999; Gorton and Rouwenhorst 2006; Daskalaki and Skiadopoulos 2011).

The spread of electronic trading and the creation of commodity index-linked exchange-traded products (ETPs) or mutual funds have made commodities more accessible to financial portfolio managers (Conover et al. 2010; Daskalaki and Skiadopoulos 2011). Between 2002 and 2010, assets under management of commodity ETPs grew from 0.1 billion (bn) to 45.7 bn U.S. dollars (BlackRock 2011). Simultaneously, combined open interest for the Chicago Board of Trade (CBOT) corn, soybean and wheat futures climbed from 0.7 million (m) to 2.7 m contracts (CFTC 2013).

Attractive diversification benefits and a facilitated portfolio inclusion stimulate the use of agricultural commodities in strategic or tactical portfolio management. While the former may maintain a fixed commodity share (e.g. 4-7% according to Greer (2007)), the latter continuously resets portfolio asset weights due to cross-market arbitrage (Büyükşahin et al. 2010) or as a response to shocks or extreme regimes in selected markets (cf. Conover et al. 2010; Jensen et al. 2002). Particularly during financial crises, portfolio managers may shift weights to comparatively less risky and more liquid refuge assets, a phenomenon known as “flight-to-quality” or “flight-to-liquidity” (Beber et al. 2007). Such use of commodities is suggested e.g. by Silvennoinen and Thorp (2013) and Chong and Miffre (2010) who propose a shift out of equity and bond markets and into commodities during crisis periods. Finally, the need to meet margin calls in distressed markets may affect weights of all other portfolio assets, if the latter are sold to obtain liquidity (Büyükşahin et al. 2010).

By any of these channels, tactical portfolio allocation may create or intensify commodity and financial market linkages, especially during crises. It may also affect agricultural and energy linkages as both commodity groups are included in indices such as the Standard and Poor’s (S&P) GSCI or the Dow Jones UBS (DJ UBS) Commodity index, which are replicated by index-linked products and funds. In any case, volatility rather than returns is the more interesting linkage due to its closer relation to information flows (Chiang and Wang 2011; Cheung and Ng 1996). Also, the development of ETP assets suggests a steadily emerging financial interest and motivates the search for a gradual change rather than a sudden structural break in market linkages.

In this paper we analyze time-varying short-term volatility spillovers between (1) commodity and financial markets and (2) agricultural and energy markets with rolling volatility spillover indices as introduced in Diebold and Yilmaz (2012) over the period June 1998 to December 2013. These are based on rolling generalized forecast error variance (FEV) decompositions in a Vector Autoregressive (VAR) model and allow us to calculate gradually changing directional volatility spillovers between any pair of included assets over the entire observation period. Volatility is measured as the daily range, based on the difference between high and low prices (Parkinson 1980).

Our analysis contributes to existing research in several aspects. First, we investigate volatility linkages between agricultural commodities and financial assets, which remain scarcely researched. Second, we include a broad market network rather than conduct a bivariate analysis, thereby specifically taking into account potential substitution between commodity and real estate as a result of the subprime crisis and the aforementioned parallel characteristics between the two asset classes. This also aids the investigation of agricultural-energy linkages as commodity markets are part of a global financial market network and any bivariate relation may thus be affected by the state of third markets. Finally, we do not impose any structural breakpoint and reach beyond the comparison of selected periods (e.g. before and after the financial crisis or before and after the introduction of biofuel mandates) towards the analysis of gradual structural change.

The remainder of the paper is structured as follows. The next section focuses on existing empirical evidence on commodity-financial and agricultural-energy linkages, which is followed by a brief description of the methodology. Subsequently, we present and discuss our model results and compare them to previous research. The final section concludes the analysis.

3.2 Previous empirical results on market linkages

Agricultural-energy market linkages via the use of crops in biofuel production or the use of energy as an agricultural production input are frequently researched. In comparison, research on commodity-financial market linkages is scarce and only recently gaining momentum (Chan et al. 2011).

3.2.1 Agricultural-energy market linkages

We review recent empirical studies that focus on volatility linkages and cover at least part of the time period after the subprime crisis.[1] The studies typically split their data sample either around 2006, due a hypothesized structural change in market linkages after the introduction of biofuel mandates or around 2008, reflecting the potential effect of the financial and food price crises. Most studies use daily data, Gardebroek and Hernandez (2012) and Du et al. (2011) use weekly data.

To investigate volatility dependencies, Nazlioglu et al. (2013) and Harri and Hudson (2009) conduct Granger Causality in variance tests (cf. Cheung and Ng 1996). Nazlioglu et al. (2013) find no volatility linkages between daily energy and agricultural spot prices before 2005. The exception is wheat, which Granger-Causes the variance of crude oil in that period. Likewise, Harri and Hudson (2009) do not detect volatility linkages between daily corn and crude oil futures prices in the period before 2006. After 2006, Nazlioglu et al. (2013) find volatility spillovers from crude oil to corn and bidirectional spillovers between crude oil and soybeans and crude oil and wheat. Harri and Hudson (2009) only discover Granger Causality in mean, but not in variance, from crude oil to corn.

Du et al. (2011) use bivariate weekly stochastic volatility models for corn, wheat and crude oil futures returns over the period 1998-2009. They detect increasing volatility transmission from crude oil to both corn and wheat as well as within the corn-wheat couple in the later subsample 2006-2009.

Several studies employ multivariate GARCH models. Gardebroek and Hernandez (2012) estimate both BEKK and DCC trivariate GARCH models for weekly U.S. corn, crude oil and ethanol spot prices over the period 1997-2011. There are some short-run volatility spillovers from corn to ethanol but no significant volatility spillovers in the other direction. Structural break tests and subsequent sample splits show that after 2008 volatility persistence is stronger in all markets. Trujillo-Barrera et al. (2011) estimate BECKK GARCH models with daily futures returns for U.S. crude oil, ethanol and corn for the period 2006-2011. Similar to Gardebroek and Hernandez (2012) they find that volatility linkages between corn and ethanol increase after 2007 with significant volatility spillovers from corn to ethanol but only modest spillovers from ethanol to corn. But they do find strong volatility spillovers from crude oil to both corn and ethanol markets. Ji and Fan (2012) and Chang and Su (2010) employ bivariate E-GARCH models. Chang and Su (2010) use daily returns for crude oil, corn and soybean futures over the period 2000-2008. Before 2004, there are no significant volatility spillovers from crude oil

[1] This remains a vibrant field of research and any potential omission is not deliberate.

to either corn or soybeans, which changes in the 2004-2008 period. Ji and Fan (2012) use daily returns of crude oil futures and several Commodity Research Bureau (CRB) indices over the period from 2006 until 2010 and introduce the U.S. Dollar exchange rate as an exogenous shock. They find that volatility spillovers from crude oil to the CRB crop index decrease after the subprime crisis.

3.2.2 (Agricultural) commodity-financial market linkages

We review recent empirical studies that cover at least part of the time period of the subprime crisis and also consider corn, soybeans, wheat or a relevant commodity index in their sample. Most studies centre on relations between selected U.S. commodities and equity markets. Other financial asset classes, especially real estate, are underrepresented. In the past, the emphasis was on return linkages but volatility dependencies are moving into focus.

Volatility relations are again mostly examined with help of multivariate GARCH models. Gao and Liu (2014) use bivariate regime switching GARCH models for pairings between the S&P 500 and selected commodity indices over the weeks 1979-2010. Volatility linkages between the S&P 500 and both the grains and energy indices only slightly increase in the few short periods when the assets share a high volatility regime. But, regime switches for the energy index appear more closely related to equity volatility than those of the grains index. Mensi et al. (2013) estimate bivariate VAR-GARCH models for pairings of the S&P 500 with daily wheat, beverage, gold, crude oil, and Brent oil price indices over the period 2000-2011. Past volatility and unexpected volatility shocks to the S&P 500 have significant effects on oil, gold and beverage markets but not on wheat. For commodity-foreign exchange relations, Ji and Fan (2012) find that volatility spillovers from the U.S. Dollar index to the CRB crop index were weaker after than before the subprime crisis while Harri and Hudson (2009) observe Granger Causality in mean but not in variance from the U.S. Dollar exchange rate to corn futures prices in the period before and after 2006.

Diebold and Yilmaz (2012) use their volatility spillover indices to investigate volatility linkages between the DJ UBS Commodity index and the S&P 500, U.S. Treasuries and a U.S. Dollar index over the period 1999-2010. They find a significant increase in linkages between the DJ UBS Commodity index and the other markets after the beginning of the subprime crisis. Volatility spillovers from the S&P 500 to the commodity index occur throughout the crisis while the commodity index spills volatility to U.S. Treasury and the U.S. Dollar index during the middle and end of the last decade.

Multivariate GARCH models are also used to investigate commodity--financial return linkages. Using a bivariate DCC GARCH model for the period

1991-2008, Büyükşahin et al. (2010) find negative weekly conditional return correlations between the S&P GSCI, its energy sub-index or the DJ UBS Commodity index and equities to peak during 2003-2004 and to a lesser extent also at the beginning of the subprime crisis. Correlations between the S&P 500 and the S&P GSCI agricultural index returns appear unaffected by the crisis. Creti et al. (2013) use bivariate DCC GARCH models for pairings between the daily S&P 500 returns and a sample of 25 commodity spot returns and the CRB index over the period 2001-2011. While they find that dynamic correlations decrease during the subprime crisis for most of the sampled commodities, return correlations between crude oil and the S&P 500 increase in times of increasing and decrease in times of decreasing stock prices. In contrast, Silvennoinen and Thorp (2013), who use a bivariate DSTCC GARCH model[2] with weekly data between 1990-2009, show that conditional weekly return correlations between both corn and soybeans and equities increased in 2002-2003 while correlations between wheat and crude oil and equities peaked in mid 2008. Commodity-bond relations remain relatively constant. Similarly, results from the DCC GARCH model in Huang and Zhong (2013) for the days between 1999-2010 and the months between 1979-2010 show that conditional correlations of the S&P GSCI with U.S. bonds do not considerably increase in the subprime crisis period. Yet, conditional rolling return correlations between the S&P GSCI and equities increase from negative to strongly positive. In addition, mean-variance spanning tests reveal that the S&P GSCI, REITs and U.S. inflation-linked securities each offer unique portfolio diversification benefits, suggesting relatively weak market linkages. Finally, Bicchetti and Maystre (2013) examine rolling window bivariate intraday return correlations over the period 1996-2011 between corn, wheat, soybeans and crude oil and equities. The authors find an increase in correlations between all sampled commodity and equity returns after September 2008, which only in the case of crude oil decline again in 2011.

Thus, there is some indication of increased agricultural-energy and commodity-financial volatility or return linkages around 2006-2008. But, in the former case, results are rather mixed. In the latter case, the strongest effects appear to exist between U.S. equities and crude oil. In both cases the time-dependent dynamics and the direction of influence remain unclear. The wide majority of studies focus on multivariate GARCH models and therefore have to restrict the investigation to a bivariate or at maximum trivariate model.

[2]Dynamic Smooth Transitional Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity model.

3.3 Description of the methodology and data

Volatility spillover indices as introduced by Diebold and Yilmaz (2009, 2012) allow us to include a larger sample of asset markets while permitting a time-dependent analysis of gradually changing volatility relations. Their computation requires externally calculating a volatility proxy variable, which is then used in the rolling VAR model estimation.

Given that there is no universally accepted best volatility measure (Engle and Gallo 2006), a choice has to be made based on informational content, interpretability and statistical properties. We expect financial linkages between markets to mostly affect short-term volatility relations. Therefore, we use the range volatility proxy that is illustrated in Parkinson (1980), which has also been shown to have superior statistical properties over the classical volatility proxy, calculated as the variance of daily returns, which may be associated with large, non-Gaussian measurement errors (cf. Parkinson 1980; Alizadeh et al. 2002; Chiang and Wang 2011). The range is calculated as:

$$Range_{it} = 0.361 \left[\ln \left(\frac{high_{it}}{low_{it}} \right) \right]^2 , \tag{3.1}$$

where *high* is the highest and *low* the lowest price observed on a trading day t.

3.3.1 Data

We use a sample of CBOT corn, soybeans and (soft red winter) wheat futures, New York Metal Exchange (NYMEX) WTI crude oil futures, the S&P 500 U.S. equity index, the Dow Jones Equity all REIT index, CBOT 10-year U.S. Treasury Note futures, and the Intercontinental Exchange (ICE) Futures U.S. Dollar index. The REITs index consists of all U.S. publicly traded companies within the Dow Jones stocks indices that are classified and taxed as equity REITs. The U.S. Dollar Index is a geometrically-averaged index of exchange rates of the Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona and Swiss Franc against the U.S. Dollar.[3] Price and volume data is obtained from Bloomberg for trading days between 3 June 1998 and 31 December 2013.[4] Missing observations are linearly interpolated.[5] All futures prices are historical first generic price series and expiring active futures contracts are rolled to the next deferred contract after the last trading day of front month.[6]

[3]Weights are as follows: Euro: 57.7%, Yen: 13.6%, British Pound: 11.9%, Canadian Dollar: 9.1%, Swedish Krona: 4.2%, Swiss Franc: 3.6%.

[4]Data for the REIT index is not available prior to that period.

[5]Interpolation implemented with the MATLAB linear interpolation function.

[6]This corresponds to Bloomberg's "relative to expiration" rolling procedure.

3.3.2 Generalized forecast error variance decompositions

The FEV decompositions split the FEV of the range of each asset i included in a VAR model into shares stemming from own shocks and shares stemming from shocks to the range of another asset j. A VAR model with lag length p (VAR(p)) that consists of range observations for all assets is written as $y_t = A_0 + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t$, where y_t is a $Nx1$ vector of range volatilities and N corresponds to the number of assets in the system. A_i is a fixed coefficient NxN matrix (including intercept terms), and u_t is a $Nx1$ vector of white noise innovations, such that $E(u_t) = 0, E(u_t u_t') = \Sigma$ and $E(u_t u_{t-s}) = 0$. The equivalent VAR(1) in matrix notation is given as $Y_t = c + AY_{t-1} + U_t$, where

$$Y_t = \underset{N\cdot p\times 1}{\begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}};\ c = \underset{N\cdot p\times 1}{\begin{bmatrix} c \\ 0 \\ \vdots \\ 0 \end{bmatrix}};\ A = \underset{N\cdot p\times N\cdot p}{\begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_N & 0 & \dots & 0 & 0 \\ 0 & I_N & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_N & 0 \end{bmatrix}};\ U_t = \underset{N\cdot p\times 1}{\begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}}$$

The Moving Average (MA) representation of this process is $y_t = \mu + \sum_{h=0}^{\infty} \Phi_h u_{t-h}$ with $\Phi_h = JA^h J'$ and $J = [I_N : 0 : \dots : 0]$, which is a $NxN \cdot p$ selection matrix (Lütkepohl 2007, pp. 15 ff.). The coefficient matrices Φ_h contain the impact multipliers of the system. Their element $\phi_{ij,h}$ describes the response of the i^{th} asset range volatility to a shock in the j^{th} asset range volatility, h periods ago. $\Phi_j(h)$ is the corresponding impulse response function.

The elements in u_t are correlated and estimation of the coefficient matrix Φ_h requires external coefficient restrictions. One possibility is to orthogonalize the shocks, e.g. via a Cholesky decomposition of the covariance matrix (Σ) such that the orthogonalized impulse response function traces the system's response to a *specific ceteris paribus shock* in the range of asset j over time. But this makes impulse responses sensitive to VAR model variable ordering (Enders 2010, p. 309). As we investigate volatility interactions within a system of different asset markets such an order is difficult to impose and inhibits the danger of adding an unwanted subjective element to the estimation.

Generalized impulse responses are an alternative restriction method developed in Koop et al. (1996) and extended in Pesaran and Shin (1998). The generalized impulse response function is computed as $\Phi_j^g(h) = \sigma_{jj}^{-\frac{1}{2}} \Phi_h \Sigma e_j$, where σ_{jj} is the variance of the error term in the equation for the j^{th} range volatility and e_j is a $Nx1$ selection vector containing 1 as its j^{th} element and 0 otherwise (Pesaran and Shin 1998). These impulse responses are responses of the range of asset i to a shock in the range of asset j, taking into account the contemporaneous correlations contained in Σ (Pesaran and Pesaran 1997, p. 428). The impulse response function thus traces the system's response to a *typical composite shock* emanating from the range in asset j (Pesaran and Shin 1998). The responses are independent of variable ordering and therefore more suitable for the analysis of our asset market system. Pesaran and Shin (1998) calculate generalized FEVs (θ_{ij}^{g}) as:

$$\theta_{ij}^{g}(h) = \frac{\sigma_{jj}^{-1}\sum_{l=0}^{h-1}(e_i'\Phi_l\Sigma e_j)^2}{\sum_{l=0}^{h-1}(e_i'\Phi_l\Sigma\Phi_l' e_i)},\ i,j = 1,2,\ldots,N, \tag{3.2}$$

where the subscript l denotes the respective forecast period.[7] The correlated shocks lead to a non-diagonal Σ and elements in the rows of the θ_{ij}^{g} matrix will not sum up to 1.

3.3.3 Volatility spillover indices

Time-varying volatility spillover indices require rolling estimation of the VAR model. A regression window of size w and T observations for the range volatilities will give a total of $T - w + 1$ estimates for the θ_{ij}^{g} matrices. For a system of N assets, the elements off the main diagonal in the θ_{ij}^{g} matrices show the contributions of shocks to the range of assets $j = 1,\ldots,N$ to the *h-step* ahead FEV for the range of assets $i = 1,\ldots,N$ with $i \neq j$ and the diagonal elements denote the contributions of own shocks. Analogously to the definitions provided by Diebold and Yilmaz (2012), a spillover is defined as the share of the contributions of shocks to the range of assets $j = 1,\ldots,N$ in relation to the total FEV of the range of assets i with $i \neq j$. This constitutes the basis for the spillover index calculations.

First, the θ_{ij}^{g} matrices are normalized with the respective row sums such that the entries in each row sum up to 1.[8] Consequently, the total FEV across the range for all assets in the system is equal to N. The definitions and formulas to calculate the individual spillover indices according to Diebold and Yilmaz (2012) are presented in Table 3.1.

3.4 Empirical results

First, we calculate the assets' range volatilities and use them in the rolling VAR estimation from which we compute the volatility spillover indices. Finally, we discuss the results and relate the findings to the current literature.

[7] The typing error in Pesaran and Shin (1998, pp. 20 ff.) where σ_{ii} is used instead of σ_{jj}, as pointed out in Diebold and Yilmaz (2011, p. 6) has been corrected.

[8] As suggested in Diebold and Yilmaz (2012), it would also be possible to normalize with the column sums.

Table 3.1: Volatility Spillover Indices

Total spillover index (TOTAL)	
Sum of spillovers to the range across all asset classes in relation to the total FEV in the system.	$TOTAL(h) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \theta_{ij}^{g}(h)}{N} \cdot 100$
Directional spillover index *from* all other assets (FROM)	
Spillovers received by the range of asset i *from* the range of all other assets $j = 1, \ldots, N$, $j \neq i$, in relation to the total FEV in the system.	$FROM_i(h) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \theta_{ij}^{g}(h)}{N} \cdot 100$
Directional spillover index *to* all other assets (TO)	
Spillovers transmitted by the range of asset i *to* all other assets $j = 1, \ldots, N$, $j \neq i$, in relation to the total FEV in the system.	$TO_i(h) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \theta_{ji}^{g}(h)}{N} \cdot 100$
Net spillover index (NET)	
Spillovers transmitted by the range of asset i to the range of all other assets $j = 1, \ldots, N$, $j \neq i$, less spillovers received from the range of all other assets $j = 1, \ldots, N$, $j \neq i$, in relation to the total FEV in the system.	$NET_i(h) = TO_i(h) - FROM_i(h)$
Net pairwise spillover index (PAIR)	
Spillovers transmitted by the range of asset i to the range of one specific asset j, $j \neq i$, less spillovers received from the range of this asset j, in relation to the total FEV in the system.	$PAIR_{ij}(h) = \left(\frac{\theta_{ji}^{g}(h) - \theta_{ij}^{g}(h)}{N} \right) \cdot 100$

3.4.1 Development of volatilities, prices and trading volumes

Figure 3.1 shows annualized range volatilities as well as daily closing prices and trading volume for all assets. Starting in 2005, commodity market volume gradually increased. Crude oil volume almost tripled from an average of 80 thousand contracts between June 1998 and October 2006 to an average of 270 thousand contracts between October 2006 and December 2012. Over the period 2007/08 price levels and range volatilities soared in all commodity markets. Before that, oil prices were high in August 2004 and smaller price spikes for corn, soybeans and wheat occurred in March and April 2004. Range volatility for corn and soybeans was highest in September 2004, wheat volatility in March 2002 and crude oil volatility in September 2001 during the wars in Afghanistan and Iraq.

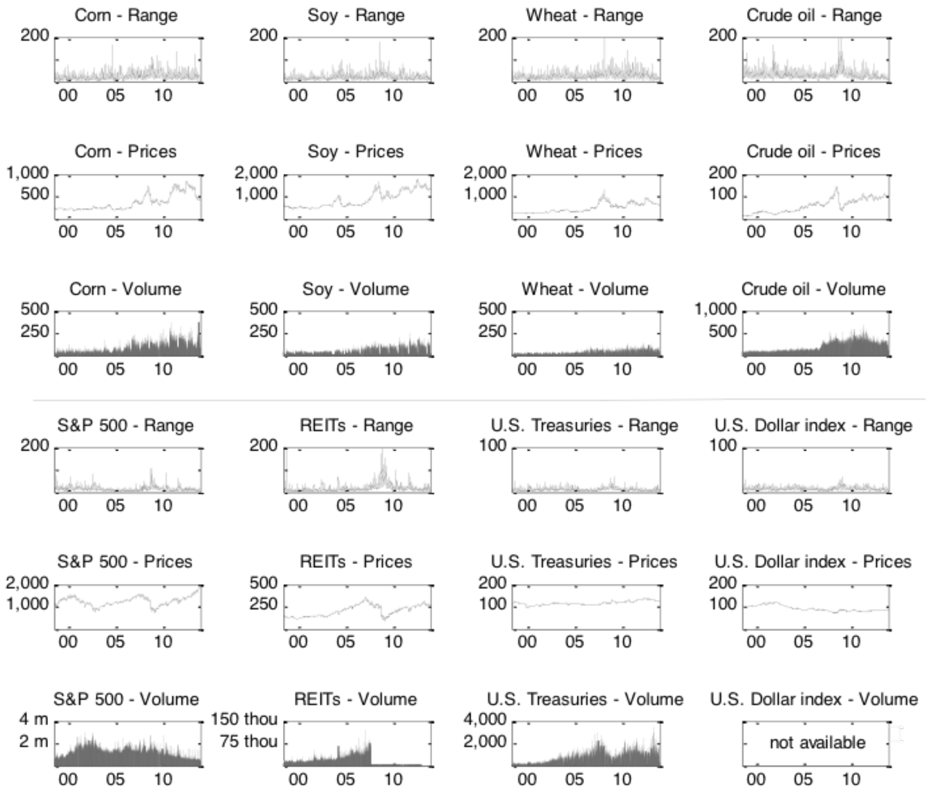
S&P 500 trading volume was highest between 2000-02 after the index price had peaked in March 2000. Prices dropped with the burst of the U.S. dot.com bubble and by October 2002 the index level had almost halved. The subprime crisis resulted in a second price floor in March 2009 but trading volume moved horizontally. Range volatility was high during and after the dot.com bubble and peaked in November 2008. In contrast, REIT index volume crashed during the subprime crisis and decreased from 32.2 million contracts to a mere 32.1 thousand contracts in August 2008. Prices reached bottom in March 2009 after a peak in February 2007. Range volatility soared to an all time high in December 2008. Compared to equity and real estate, U.S. Treasuries and the U.S. Dollar index exhibit little price fluctuations and only few peaks. Range volatilities are on average less than half of those of the other assets. Yet, volatilities in both markets sharply increase in March 2009. U.S. Treasuries volume peaked in July 2007 before plummeting in 2008.

3.4.2 Rolling VAR estimation and spillover index calculation

Lütkepohl and Xu (2012) show that taking logs can in many cases substantially improve forecast precision. We thus estimate the rolling VAR model with logged range volatilities (summary statistics are provided in Table A3.1 in the Annex) and include a total of 3,930 observations for each of the 8 assets and a window length of 252 trading days. Augmented Dickey Fuller (ADF) tests show the logged ranges to be stationary. Details are shown in Table A3.2 in the Annex.

To obtain a parsimonious model, the lag lengths are selected with the Schwartz Bayesian Criterion (SBC), which is a consistent criterion with good large sample properties (Lütkepohl 2007). For the full sample, the SBC selects a VAR(5), which is also used in each of the 252-day regression windows. The generalized FEV matrices are calculated for a forecast horizon of 10 days. The

Figure 3.1: Annualized range volatilities, closing prices and trading volume



Notes: Upper graphs show annualized range volatilities, calculated as $(Range_{it} \cdot 252)^{\frac{1}{2}} \cdot 100$, middle graphs closing prices in U.S. Dollars, and lower graphs trading volume in thousand contracts.

choice depends on the underlying assumption regarding the time horizon of asset market linkages and 10 days is a common horizon used in financial Value at Risk calculations (Diebold and Yilmaz 2011). A total of 3,679 observations are obtained for each index and the first observation corresponds to the end of the first regression window (2 June 1999).

We perform a range of robustness checks, such as using a different futures rolling procedure (on first notice day), including the CBOT S&P 500 futures instead of index prices, using a window size of 126 instead of 252 days, using different lag lengths and forecast horizons. None of the changes significantly affected the patterns of volatility spillovers. The biggest effect came from a change in window size. Results from the robustness checks are presented in Figure A3.3 in the Annex.

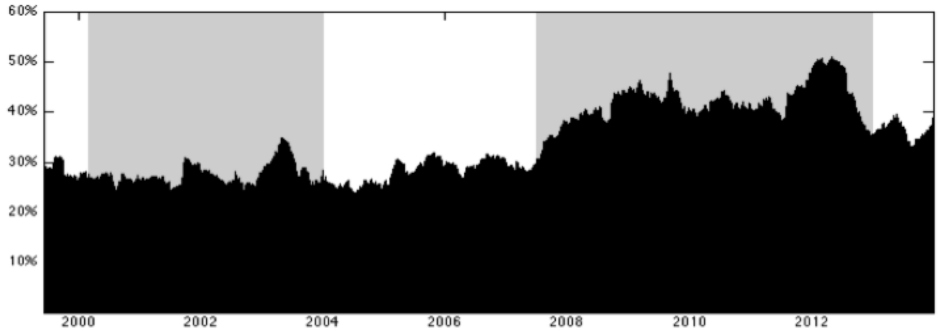
3.4.3 Volatility spillover indices

Figure 3.2 shows the total volatility spillover index between 2 June 1999 and 31 December 2013. The grey-shaded areas mark the two main crisis periods of the last decade. The "first/early crisis period" between March 2000 and December 2003 is characterized by the burst of the dot.com bubble, the NASDAQ crash and the overall downturn in equity markets. The real economy in the U.S. and the EU experienced low Gross Domestic Product (GDP) growth rates and the events of September 11 and the wars in Afghanistan and Iraq led to political unrest. Agricultural commodity markets were influenced by the continued EU effort to reduce buffer stocks as well as China's World Trade Organization (WTO) accession in December 2001 with growing U.S. soybean exports.

The "second/later crisis period" between July 2007 and December 2012 started with the early events of the subprime crisis and transformed into a global liquidity crisis and later sovereign bond and state debt crisis. The U.S. Federal Reserve Bank decreased interest rates 12 times successively during the period between August 2007 and December 2008 and the real economy in the U.S. and EU was hit with low or negative GDP growth rates. Agricultural commodity markets experienced further growing soybean imports from China and the introduction of biofuel mandates in the EU and U.S. At the beginning of the period, stock-to-use ratios for corn and wheat were at low levels of around 13% and 18%, respectively, while the ratio for soybeans was at a peak of 21% (USDA ERS 2012). Commodity ETP assets under management strongly increased from 6.3 bn U.S. dollars in 2007 to 45.7 bn U.S. dollars in 2010 (BlackRock 2011).

The level of volatility spillovers is much higher in the later compared to the early crisis period. While there are two spikes of 31% in September 2001 and 35% in April 2003, the average total spillover between 1 March 2000 and

Figure 3.2: Total volatility spillover index



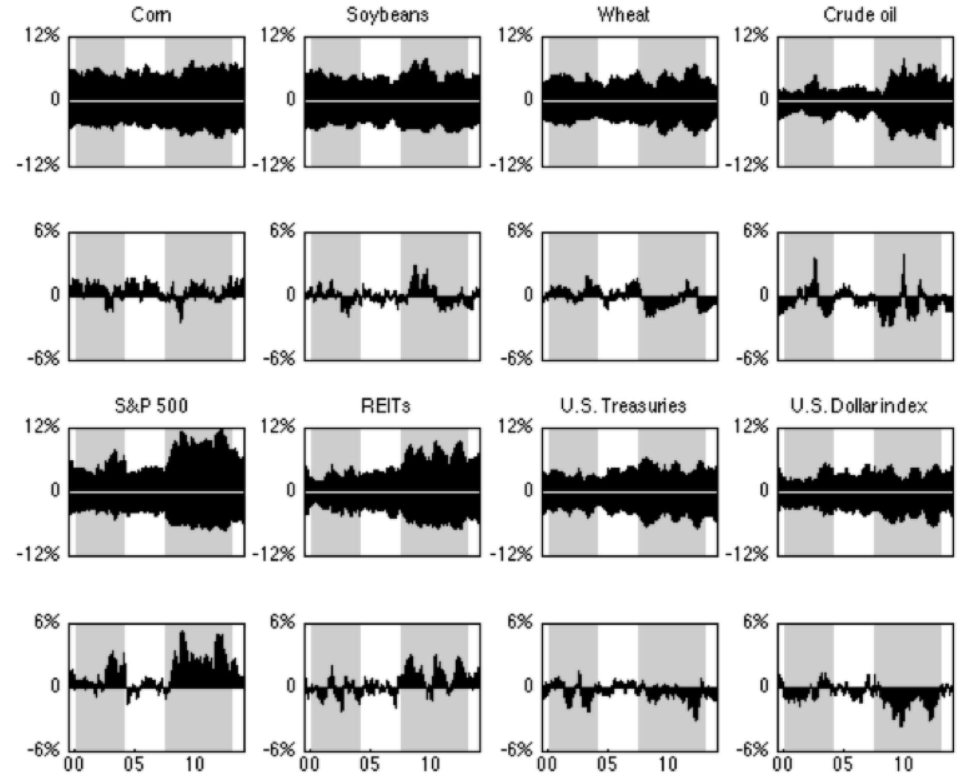
31 December 2003 was 26% compared to an average of 42% between 1 July 2007 and 31 December 2012. The peak of the index is at 51% on 3 May 2012.

In the following, positive values for the spillover indices indicate spillovers *from* the asset, and negative values spillovers *to* the asset. Directional spillovers and the resulting net spillover indices are depicted in Figure 3.3. The upper graphs in each pair show the spillovers from and to this asset compared to all other assets in the system. The lower graph is the resulting net volatility spillover index where a positive (negative) value indicates that the asset is a net volatility transmitter (receiver).

During the first crisis neither of the commodity markets shows a distinct pattern and the indices move almost horizontally into the tranquil interim period. Only crude oil and to some extent wheat futures have spiking directional volatility spillovers. Net spillovers from crude oil peak at 3.4% in August 2002 and net spillovers from wheat at 1.8% in May 2003. In contrast, during the second crisis, volatility spillovers to and from the commodity markets are on a higher level and the net spillover patterns differ from the previous periods. The most pronounced effects are again observable for crude oil, which is a net volatility receiver during most of the crisis period. Notable spillovers also occur in wheat and soybean markets. Soybean net volatility transmission to other assets reaches up to 2.9% in September 2008. Wheat markets are net volatility receivers with a peak of 1.9% in June 2008. Only corn market volatility spillovers appear relatively unaffected by the crisis and only show a slight increase in level.

Among the financial asset markets, the S&P 500 is the largest net volatility transmitter in the system with visible increases in the first (up to 3.4% in February 2003) and very pronounced peaks in the second crisis period (up to 5.3% in November 2008). In difference, both U.S. Treasuries and the U.S. Dollar index are volatility receivers during both crisis periods. Again, the

Figure 3.3: Directional and net spillover indices



effect is more pronounced in the second crisis where net spillovers to the U.S. Treasuries reach up to 3.2% in March 2012 and spillovers to the U.S. Dollar index up to 3.7% in October 2009. The REITs market shows the biggest change in volatility interaction between the two crisis periods. While during the early crisis the market is alternating between the position of net volatility transmitter and receiver, it almost unexceptionally transmits volatility of up to 3% during the later crisis.

The pairwise spillover indices allow the most detailed investigation of structural changes in volatility interaction between agricultural and energy commodities as well as between commodity and financial asset markets.[9] Figure 3.4 first shows the pairwise indices for the agricultural commodities. Over most of the observation period, corn is transmitting volatility to the soybean market at a general magnitude of between 3% and 6%. There is no marked difference between the early crisis and the interim tranquil period. But, during the second crisis the volatility spillover relation is reversed. Between 2008 and 2010, soybean markets are transmitting volatility to corn markets of up to 7.5% in September 2008. Paralleling this development, the volatility spillover relation between soybeans and wheat also changes. Starting in 2008, soybeans are net transmitters of volatility to wheat with a peak of 6% in June 2009. Wheat is mostly a net volatility receiver from corn at a magnitude of up to 4.7% in September 2002 and 6.5% in January 2010. There are exceptions towards the end of the first crisis, before the beginning of the later crisis and most importantly between 2010 and 2012 where wheat spillovers to corn reach up to 5.3% in February 2011.

Figure 3.5 shows the indices for the agricultural-crude oil pairings. Corn is transmitting volatility to crude oil during most of the tranquil period, before the early crisis and during the later crisis of up to 5% in March 2000 and 5.3% in July 2009, respectively. Between November 2001 and January 2003, during the first crisis, and after February 2011, during the second crisis, this relation is reversed and crude oil transmits volatility to corn with spillovers reaching up to 6.1% in September 2002 (first crisis) and 2.6% in May 2011 (second crisis). The soybean-crude oil volatility linkages almost perfectly mirror this development. Soybeans mostly transmit volatility to crude oil and receive volatility of up to 5.2% in July 2002 during the early crisis and up to 4.5% in May 2011 during the later crisis period. While wheat is also mostly transmitting volatility to rather than receiving volatility from crude oil, the magnitude of interaction between the markets' volatility is generally lower than in the case of corn and soybeans. But there is one notable spillover spike of up to 12% in June 2003. And during the tranquil period we observe some stronger spillovers from wheat to crude oil of up to 5.4% in June 2006.

[9] Pairwise indices for financial asset markets cannot be discussed in detail in the scope of

Figure 3.4: Pairwise spillover indices: agricultural commodities

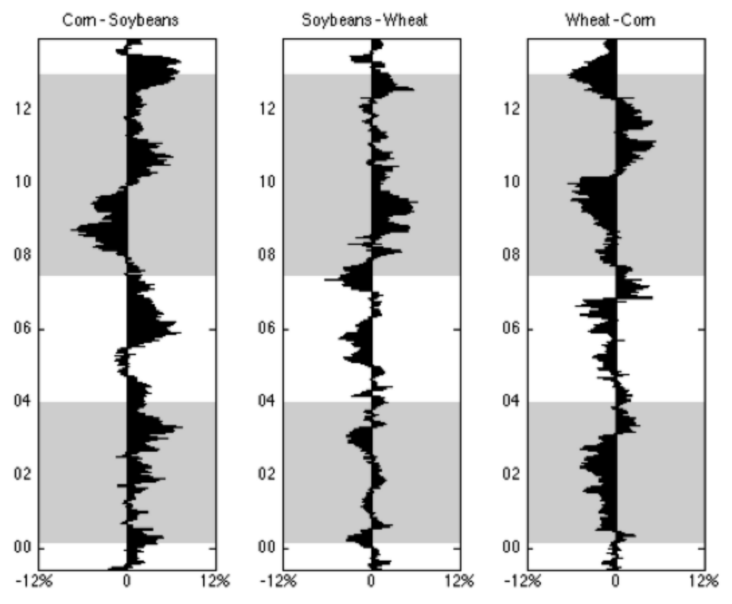


Figure 3.5: Pairwise spillover indices: agricultural-crude oil

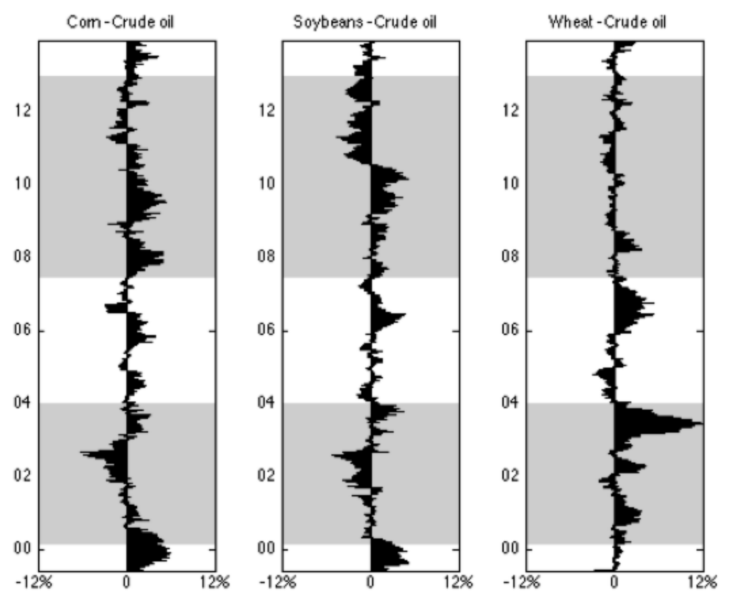


Figure 3.6 shows the pairwise indices for the commodities and the financial asset markets. During the early crisis, spillovers from the S&P 500 reach predominantly corn and wheat markets, with a high of 6.4% in February 2003 for corn and 4.3% in November 2002 for wheat. Soybeans, in contrast, are mostly net transmitters of volatility to the S&P 500 during that period. While crude oil receives some spillovers, the market also transmits volatility to the S&P 500 during November 2001 and October 2002 with a strong magnitude of up to 10.6% in August 2002. But, during and after the later crisis, there is a notable change in this volatility spillover relation, both in direction and in magnitude. Crude oil almost unexceptionally receives volatility from the S&P 500 with a peak at 10.8% in December 2010. A less pronounced but nevertheless visible change occurs in corn and wheat markets where net S&P 500 spillovers increase in frequency around the time of the subprime crisis with peaks of 5.3% in October 2008 for corn and of 6.7% in April 2008 for wheat. Soybeans show no change in the magnitude of spillover relations but in difference to the early 2000s crisis are mostly net volatility receivers from the S&P 500.

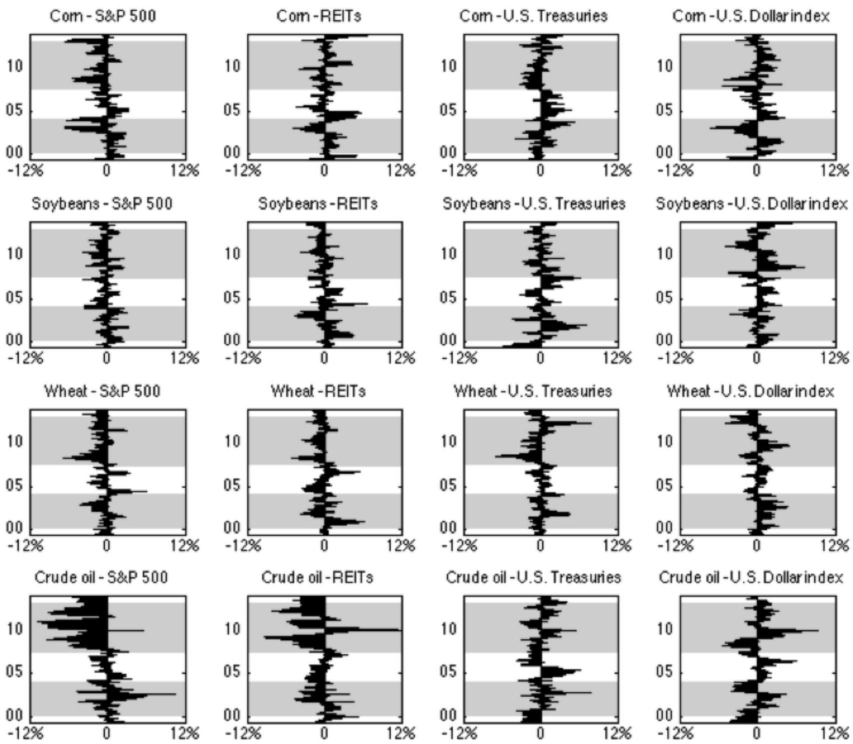
While the REITs market is a net volatility transmitter to all commodities during some periods of the early crisis, this tendency continues for most commodities (except soybeans) into the tranquil interim period. During the crisis, spillovers rise to 4.7% in January 2003 for corn, to 3.8% in October 2001 for wheat, to 4.7% in January 2003 for soybeans and to 4.5% in January 2002 for crude oil. For the agricultural commodities, there is no marked difference in spillover patterns during the later crisis. But, paralleling the developments in the volatility relation with the S&P 500, crude oil starts to receive markedly higher REITs net spillovers of up to 9.3% in February 2009. There is only a short period of reversed transmission between July 2009 and April 2010.

Net spillover between commodities and U.S. Treasuries occur bidirectionally both during the early crisis and during the tranquil period. But there are some exceptions. Around December 2001, there is a period of spillovers of up to 7.2% from soybeans to Treasuries. In the later crisis, corn and wheat markets are almost exclusively net U.S. Treasury volatility receivers of up to 3.2% in March 2008 (corn) and 7% in July 2008 (wheat) while for soybeans and crude oil the patterns are less distinct.

Towards the end of the first crisis, the U.S. Dollar index transmits volatility to the corn, soybean and crude oil markets of up to 7.1% in February 2003 (corn), 4.3% in March 2003 (soybeans) and 4% in December 2002 (crude oil) respectively, while during almost the entire crisis period wheat is a net

this paper but are included in Figure A3.4 in the Annex.

Figure 3.6: Pairwise spillover indices: commodity-financial



volatility transmitter to the index with a peak of 4.6% in August 2002. During the second crisis, in contrast, soybeans and crude oil markets along with wheat transmit net volatility of up to 7.2% in August 2008 (soybeans), 4.9% in September 2009 (wheat), and 9.4% in December 2009 (crude oil) to the U.S. Dollar index while for corn net volatility transmission is lower and directionally less clear.

3.4.4 Discussion of results

The analysis of the above volatility spillover indices does not permit any direct causal attribution of single spillovers. Nevertheless, it is interesting to examine the results in light of the political and economic developments on the markets and in relation to existing empirical findings on volatility linkages.

The total volatility spillover index shows a distinct increase in range volatility interdependence between the markets during the later crisis period. While at the height of the subprime crisis the level of individual range volatilities was also high, the total spillover index peak was only in May 2012 when individual markets' volatility levels had decreased again. In contrast, during the early crisis, there were only two smaller volatility spillover spikes despite high volatility levels in some markets. Thus, during the subprime crisis individual volatilities moved increasingly in sync with significant parallel jumps. On the other hand, the period of increased volatility interdependence stretched beyond the period of individual volatility jumps, pointing to a generally higher degree of market interaction.

Directional and net volatility spillover indices show the S&P 500 to be the strongest volatility transmitter among the assets during the times of financial crises. Thus, the drivers behind the S&P 500 range volatility will likely influence range volatility in other markets. The magnitude of spillovers to and from the other financial asset markets is much lower. While there is also a REITs component within the S&P 500, the stand-alone REITs spillover indices better illustrate the volatility linkages during the subprime crisis where REITs are strong net volatility transmitters and maintain this position until the end of the observation period. U.S. Treasuries, in contrast, are classical refuge assets, towards which liquidity is shifted in times of general economic recessions and individual market crises (e.g. equity or real estate). This effect is visible from the spillover indices where U.S. Treasuries are net volatility receivers during both crisis periods. Unsurprisingly net spillovers are especially high during the sovereign bond crisis at the end of the late crisis period. The U.S. economy experienced an economic recession during both crisis periods, which affects demand for U.S. Dollars. But the U.S. Dollar is also the most important currency for international monetary reserves. While the U.S. Dollar index is a net volatility receiver during both crisis periods, the level of spillovers increases in the second period, at a time when both the need to adjust monetary reserves and to allocate liquidity to comparably "save" U.S. Treasuries was high.

3.4.4.1 Agricultural-energy linkages

Corn appears to be the strongest volatility transmitter among the agricultural commodities with significant spillovers to both wheat and soybeans. This is plausible as on the one hand the U.S. are the world's largest producer of corn and a significant acreage area is allocated to the crop, and on the other hand, corn futures have much higher trading volumes on the CBOT than soybean or wheat futures. Thereby, information could rather disseminate from corn markets to other affected futures markets than in the opposite direction. While seemingly unaffected by the early crisis, the corn-soybean relation reverses between 2008 and 2010. At that time, soybeans also transmit volatility to wheat. This effect could be related to the surging Chinese soybean demand, which shocked the soybean market and through substitution effects also affected corn and wheat.

The pairwise agricultural-energy spillover indices show that the magnitude of spillovers between both corn and soybeans and crude oil is higher than for wheat. The fact that the level of spillovers does not considerably change after 2006 would speak against a clear attribution of this effect to the biofuel production. In fact, the spillover indices do not yield any convincing evidence of an increase in spillovers from the energy to relevant commodity markets as a consequence of biofuel mandates. While there were some spillovers from crude oil to both corn and soybeans in the early crisis, between 2006 and 2010 both markets transmit volatility to crude oil rather than receive it. Only soybeans experience a clear reversal in that relation after 2010.

These results are most in line with the findings from Gardebroek and Hernandez (2012) who, based on weekly conditional volatility over the period 1997-2011 do not discover evidence of energy volatility spilling over to corn price volatility. And while Ji and Fan (2012) do find significant linkages in the conditional daily volatility between crude oil and the crop index (includes corn, wheat, soybeans, soft commodities, livestock, cotton), they also find a decrease in spillovers during the time of the subprime crisis. On the other hand, the results contradict the findings from e.g. Nazlioglu et al. (2013); Du et al. (2011); Chang and Su (2010), who, based on their respective models and volatility measures all show volatility spillovers between crude oil and corn, wheat or soybeans to increase after 2006. But Nazlioglu et al. (2013) also find bidirectional spillovers between crude oil and soybeans and crude oil and wheat after 2006, which is again closer to the results obtained from the spillover indices.

The extraordinary volatility spillover spike from wheat to crude oil of up to 12% in June 2003 would merit closer (causal) investigation. There could be some connection to the end of the United Nations (UN) Iraq oil-for-food program in 2003, which was used by the Iraqi government to secure wheat supplies in exchange for crude oil. It is interesting that Nazlioglu et al. (2013) also find Granger Causality in variance from wheat to crude oil before 2005, which in later periods disappears.

Thus, there is little indication for short-term daily range volatility linkages in the corn, soybean and wheat markets to be affected by biofuel policies. The contradictions with some findings from the GARCH-type models could stem from their sample splits and the restricted sample of two or three markets. The volatility spillovers are calculated for a more comprehensive system of asset markets where some of the apparent bivariate volatility spillovers may be absorbed by other markets. Also, structural breaks are not exogenously imposed. Instead, more gradual structural changes are permitted.

3.4.4.2 Commodity-financial linkages

The linkages between commodity and financial markets vary strongly depending on the commodity and financial asset class involved. In the early crisis, S&P 500 volatility spillovers to commodities were few and of low magnitude. There were in contrast some spillovers from crude oil *to* the S&P 500, which could from a fundamental side be explained with the wars in Afghanistan and Iraq. We thus confirm and strengthen the results from Diebold and Yilmaz (2012) on a DJ UBS Commodity index-S&P 500 range volatility spillover during that time, which the authors also assume to be linked to the Iraqi war. During and after the later crisis, however, all commodity markets are net S&P 500 spillover receivers. This again parallels and extends the findings in Diebold and Yilmaz (2012) for the DJ UBS Commodity index. Our individual commodity market results allow to further disaggregate the spillovers and to show that most reach the crude oil market. Yet, corn and wheat also receive some transitory spiking net spillovers. All commodities, but especially crude oil, have strong fundamental and financial linkages with U.S. equities as inputs in production and are common components of all important commodity indices, where crude oil has generally higher weights than corn, soybeans or wheat. The observed increase in short-term range volatility linkages during a time where both commodity index-linked products spread and commodity trading volume increased, provide evidence in favour of the hypothesis that the financial linkage factor became more important in the second crisis period.

Our results strengthen the existing results on volatility linkages between the S&P 500 and commodities. The results from Mensi et al. (2013) who showed that volatility shocks to the S&P 500 can significantly affect the oil market are confirmed also for range volatility spillovers. Gao and Liu (2014) find that correlations between energy and grains indices and the S&P 500 increase in volatile periods, which is also in line with the above results. But, in their model neither U.S. energy nor grains indices appear to frequently share common volatility regimes with the S&P 500 from which the authors conclude that commodities remain attractive portfolio diversifiers. Yet, the spillover indices show stronger volatility relations, especially between the S&P 500 and crude oil, which may in fact decrease diversification benefits. In addition, our spillover results complement the evidence on increased dynamic conditional return correlations between commodities and the S&P 500 during and after 2008 (e.g. Huang and Zhong 2013; Bicchetti and Maystre 2013; Büyükşahin et al. 2010). The observed increase in oil-S&P 500 return correlations in times of increasing stock prices in Creti et al. (2013) cannot be confirmed for daily range volatility spillovers, which rather increase in times of decreasing stock prices.

The fundamental connection between REITs and commodity markets is much weaker than between commodities and the S&P 500. Nevertheless, spillovers from REITs to crude oil are high in the early 2000s and surge in the late 2000s crisis, which provides additional evidence in favour of the financial linkage hypothesis. But the agricultural commodities appear less affected. Volatility spillovers between commodities and U.S. REITs are barely analyzed in the literature. Somewhat related to our results, Huang and Zhong (2013) show that commodities and REITs (along with inflation-protected securities) each offer unique diversification benefits that tend to disappear in times of financial crisis.

In difference to the S&P 500 and REITs, the magnitude of range volatility spillovers between commodities and U.S. Treasuries generally appears unaffected by either of the crisis periods. This confirms results from Huang and Zhong (2013) who also find that conditional correlations between the S&P GSCI and U.S. Treasuries did not significantly increase during the subprime crisis. The identified net spillovers from the DJ UBS Commodity index to U.S. Treasuries in Diebold and Yilmaz (2012) can again be disaggregated in our model and appear to mostly stem from crude oil and soybeans as both wheat and corn markets are net receivers of U.S. Treasury volatility during that period.

The U.S. Dollar index receives net volatility spillovers from wheat, soybeans and crude oil during both crisis periods. But, spillovers during the late 2000s crisis increase in magnitude. There could be a relation to the increase in Chinese imports of soybeans and crude oil and the associated U.S. dollar demand. Another explanation is foreign activity on U.S. commodity futures markets. The corn-U.S. Dollar index relation is less clear and during the second crisis period corn transmits less volatility to the U.S. Dollar index than the other commodities. Linkages could have decreased following the drop in U.S. corn exports as corn was increasingly used for domestic biofuel production. The results in Diebold and Yilmaz (2012) on the DJ UBS Commodity index-U.S. dollar index spillovers are substantiated for most individual commodities and do not appear to be driven mainly by crude oil. The results in Ji and Fan (2012) on weaker volatility spillovers from a U.S. Dollar index to the CRB crop index after the subprime crisis only match the respective volatility spillover index for corn but not that for soybeans or wheat.

3.5 Conclusions

This paper has investigated directional time-varying range volatility spillovers using a new method developed in Diebold and Yilmaz (2012, 2009). The focus was on short-term volatility interaction effects within a system composed of agricultural, crude oil and selected financial asset markets over the period 3

June 1998-31 December 2013. We have put special emphasis on comparing the two periods of financial and economic crises whereby the later crisis period is also characterized by an increased use of commodities in financial investment.

During and after the subprime crisis, individual range volatilities moved increasingly in sync with significant parallel jumps. Also, the total volatility spillover index shows stronger volatility interdependence. This suggests an overall higher degree of market interaction. The S&P 500 is the strongest net volatility transmitter in the system and spillovers peak during crisis periods. REITs net volatility transmission starts to rise only with the beginning of the subprime crisis.

The pairwise agricultural-energy volatility spillover indices do not provide significant evidence for an increase in spillovers from the energy to relevant commodity markets as a consequence of biofuel mandates. While this confirms some of the findings of e.g. Gardebroek and Hernandez (2012), it stands in contrast to results of other related studies. This could result from the full sample rolling approach of the index as opposed to exogenously introduced structural breaks and the extension of the system to financial assets that can absorb some of the volatility spillovers. Yet, our results do not permit the conclusion that biofuel mandates did not have any effect on the volatility (or return) relation between crude oil and biofuel crops. Due to the focus on short-term range volatility we do not capture any longer-term structural changes arising from e.g. a reallocation of land towards biofuel crops as a consequence of a high or volatile oil price.

The pairwise commodity-financial volatility spillover indices show that commodity-U.S. Treasury volatility interaction appears relatively unaffected by the crisis periods but spillovers from commodities to the U.S. Dollar index increase (except in the case of corn). Yet, the most profound shift in volatility interaction occurs between the S&P 500, U.S. REITs and commodity markets. Crude oil receives high net spillovers from both financial asset markets during and after the later crisis period. Agricultural commodities are less affected although there are some spillover spikes in corn and wheat markets during the later crisis.

The volatility spillover patterns to and from commodities observed in the later crisis period are not to the same extent visible during the early crisis. While direct causal attribution is not possible, these results do provide evidence in favour of the hypothesis of increased financial linkages between the markets. There are two important implications. First, short-term commodity market volatility may increasingly be affected by shocks to financial asset markets that have no direct fundamental connection to commodity markets. Second, if commodities find an increased use as portfolio diversifiers and refuge assets, their diversification benefits may be impeded, especially in times of crisis.

Thus, future research should be directed towards investigating the underlying structural relations behind the volatility linkages. And, as also suggested by Diebold and Yilmaz (2012), a theoretical and empirical comparison of the spillover indices with multivariate GARCH models would be useful. We feel that focus should be put on the relation between short-term conditional volatility and range volatility. A starting point could be the range volatility based GARCH models such as the E-GARCH model in Brandt and Jones (2006) and the conditional autoregressive range model in Chiang and Wang (2011). In any case, the volatility spillover indices are a useful addition to the thitherto GARCH-centred analysis on volatility relations. They should be further exploited to investigate alternative asset systems.

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3.7 Annex

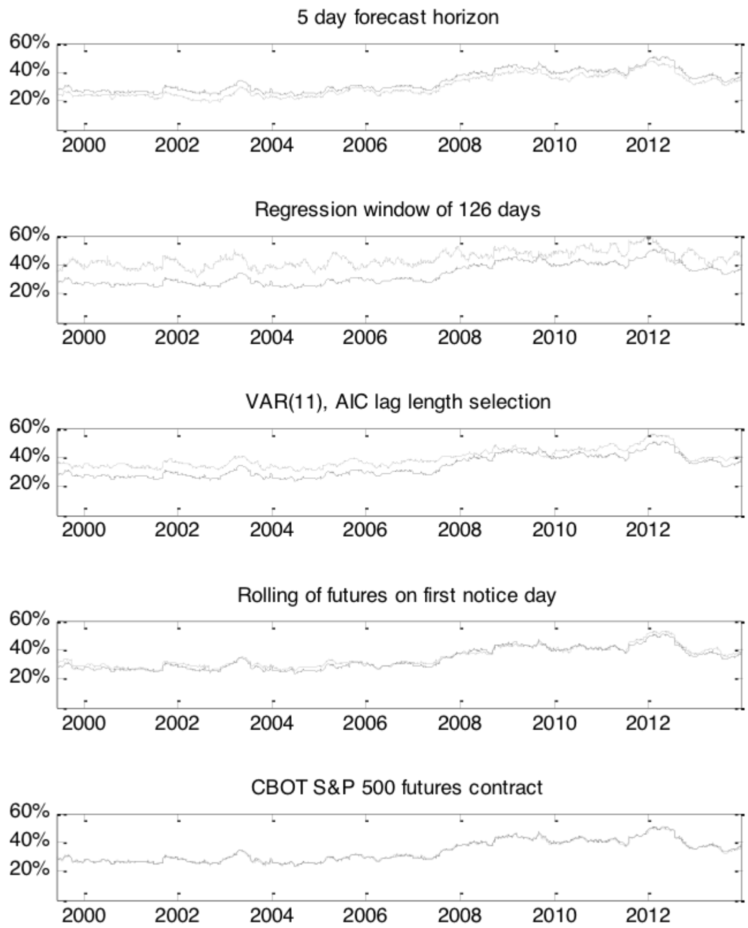
A3.1: Summary statistics for logged range volatilities

	Corn	Soybeans	Wheat	Crude oil
Mean	-8.7	-8.9	-8.4	-8.0
Median	-8.7	-9.0	-8.4	-8.1
Minimum	-13.1	-12.3	-12.2	-13.4
Maximum	-4.5	-4.4	-4.0	-4.0
Std. deviation	1.1	1.0	1.0	0.9
Skewness	0.0	0.4	0.2	0.4
Kurtosis	2.9	3.3	3.4	4.0
	S&P 500	REITs	Treasuries	Dollar index
Mean	-9.7	-9.8	-11.5	-10.8
Median	-9.8	-9.9	-11.5	-10.8
Minimum	-13.0	-13.5	-15.1	-17.6
Maximum	-5.5	-4.0	-7.6	-7.6
Std. deviation	1.2	1.6	1.0	0.9
Skewness	0.2	0.5	0.1	-0.5
Kurtosis	3.1	3.2	3.1	6.3

A3.2: Results from ADF tests for stationarity

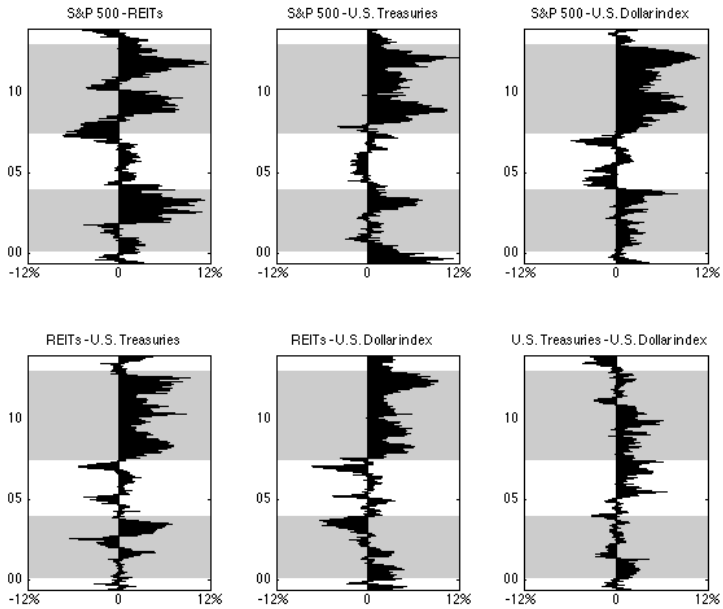
Model: $\Delta y_t = a_0 + \gamma y_{t-1} + \sum \beta y_{t-i} + \epsilon_t$		
y	i	p-value
Corn	8	0.00
Soybeans	10	0.00
Wheat	11	0.00
Crude oil	13	0.00
S&P 500	9	0.00
REITs	10	0.00
U.S. Treasuries	9	0.00
U.S. Dollar index	12	0.00

A3.3: Results from robustness checks



Notes: The grey lines mark the adjusted spillover indices according to the specifications given above the figure, which deviate from the standard specification (black line). The Akaike Information Criterion (AIC) selects a lag length of 11.

A3.4: Pairwise spillover indices: financial



Chapter 4

Price dynamics and financialization effects in corn futures markets with heterogeneous traders*—

Abstract

Presumed portfolio benefits of commodities and the availability of index fund-type investment products increase attractiveness of commodity markets for financial traders. But resulting "index trading" strategies are suspected to inflate commodity prices above their fundamental value. We use a Heterogeneous Agent Model for the corn futures market, which can depict price dynamics from the interaction of fundamentalist commercial traders and chartist speculators, and estimate its parameters with the Method of Simulated Moments. In a scenario-based approach, we introduce index funds and simulate price effects from their inclusion in financial portfolio strategies. Results show that the additional long-only trading volume on the market does not inflate price levels but increases return volatility.

JEL classification: D84, G15, G17, Q02

Key words: Heterogeneous agents; Agent-based modeling; Commodity index trading; Financialization of commodity markets

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4.1 Introduction

Alleged benefits of commodities in financial portfolio strategies (cf. Ankrim and Hensel 1993; Anson 1999; Gorton and Rouwenhorst 2006) have sparked interest in financial commodity investment and promoted the creation of commodity index funds.[1] In the period 2005-2010, assets under management of exchange traded commodity index funds increased from 1.2 to 45.7 billion U.S. Dollars (BlackRock 2011). These funds facilitate market entry for investors who are interested in the return of a diversified commodity portfolio, but are hesitant to trade single futures contracts. Nevertheless, the index funds need to replicate the index return, e.g. by engaging in "index trading" activities in the single futures markets, which corresponds to taking long (buy-side) positions and rolling these positions forward (cp. CFTC 2014a). This has consequences for trading volume on agricultural futures markets. In the case of Chicago Board of Trade (CBOT) corn futures, volume in the active contract more than doubled from 31 thousand contracts in the period 2000-2005 to 73 thousand contracts between 2005-2010 (Bloomberg data). And, U.S. Commodity Futures Trading Commission (CFTC) reports show that long position open interest in CBOT corn futures and options associated with index trading was at an average of 25% of total open interest over the period 2006-2013.

The influence of the commodity index trading volume on price levels and volatilities in agricultural commodity markets have been vividly discussed since the 2007/08 food price crisis, without reaching a definite consensus. According to the prominent "Masters hypothesis"[2], index trading drives commodity price bubbles by creating a constant artificial demand on the futures markets that is disconnected from market fundamentals (cf. Irwin and Sanders 2012; Will et al. 2012). Others reject this hypothesis, stating that an increase in long positions would only affect price levels if it were suspected to convey new information, due to the theoretical possibility to create an infinite amount of futures contracts at a given price (e.g. Irwin et al. 2009). Empirical studies have not succeeded in resolving this theoretical debate. The analysis of direct price level, return or volatility effects from a change in index trading volume on futures markets with help of Granger Causality tests (e.g. Robles et al. 2009; Gilbert 2010; Stoll and Whaley 2010; Sanders and Irwin 2011a,b; Gilbert and Pfuderer 2014) has led to inconclusive results, and further difficulties arise in their interpretation as evidence of presence or absence of a price influence (Grosche 2014). On the other hand, the analysis of indirect effects such as changing return or volatility interdependencies between commodity and traditional asset markets (e.g. Diebold and Yilmaz 2012; Ji and Fan 2012;

[1] We will in the following use the term "index funds" for all financial products that replicate a commodity index.

[2] Authors frequently use this term to refer to the statements of the U.S. hedge fund manager Michael W. Masters in front of Congressional hearings or the CFTC.

Silvennoinen and Thorp 2013; Mensi et al. 2013; Gao and Liu 2014; Grosche and Heckelei 2014) or tests for rational bubbles (e.g. Gutierrez 2013; Liu et al. 2013; Etienne et al. 2014) do not allow a direct causal attribution of these effects to specific trading strategies.

We take an alternative approach and investigate price effects from index trading within a heterogeneous agent model (HAM) that simulates price dynamics emerging from the interaction of a few stylized heterogeneous trader types. These models have previously been applied to financial markets (see e.g. Hommes (2006) for a survey) but there has hitherto been scant application to agricultural commodity markets (exceptions are Westerhoff and Reitz (2005); He and Westerhoff (2005); Reitz and Westerhoff (2007); Redrado et al. (2009)) and only Redrado et al. (2009) specifically consider price effects from financialization. In our model, we first simulate a base scenario where index funds are unavailable. In a later "financialization" scenario, financial portfolio managers include commodities in their portfolio but only via index fund shares. Parameters for the base scenario are empirically estimated with the Method of Simulated Moments (MSM) (Lee and Ingram 1991; Duffie and Singleton 1993). Its use in HAM parameter estimation has recently been developed in e.g. Winker et al. (2007); Franke (2009); Franke and Westerhoff (2011, 2012). We complement these applications with refinements in parameter validation. The focus is on CBOT corn futures due to the importance of corn in global agricultural production and its comparatively large futures market. Corn has the highest trading volume on the CBOT and the largest S&P Goldman Sachs Commodity Index (S&P GSCI) percentage dollar weight among the agricultural commodities.

In the remainder of the paper we first provide some background on commodity index funds and on the general setup of few-type HAMs. Second, we describe our Commodity HAM and the procedure we use for estimation and validation of the model parameters. We then proceed with a discussion of results and the final section concludes the analysis.

4.2 Background

A discussion of strategies and replication schemes of commodity index funds provides the necessary background to model the portfolio managers' trading activities. And, a brief overview of the general setup and previous applications of few-type financial market HAMs serves as the conceptual basis for our Commodity HAM.

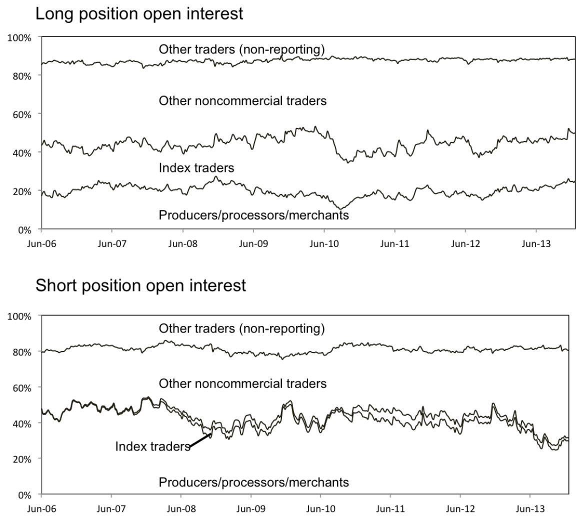
4.2.1 Commodity index funds and index trading

Index funds are in essence investment products that replicate the performance of a specific underlying index. Its investors gain exposure to the index return by buying a share in the fund and thus do not have to trade single futures contracts. The index fund itself then replicates the index either directly by taking adequate long positions in the futures markets or synthetically by engaging in an index return swap with a swap dealer. In the latter case, the swap dealer could then choose to hedge the open position by taking long positions in the futures market. Both direct or synthetic replication can thus ultimately lead to an increase in index trading positions in the single futures markets. The magnitude of these position holdings can be assessed with the CFTC weekly Commodity Index Trader report, which is a supplement to the (Disaggregated) Commitment of Traders report. The "index trader" category groups all positions associated with index trading strategies. Figure 4.1 shows the development of long and short position open interest for index traders and other trader types in the CBOT corn futures and options markets over the period 13 June 2006-31 December 2013. Thereby, "producers/processors/merchants" refers to those traders that deal with the physical commodity and hedge their positions on the futures markets. The "other noncommercial trader category" includes hedge funds or Commodity Trading Advisors and Commodity Pool Operators who trade on behalf of their clients (CFTC 2014b). Unsurprisingly, "index traders" hold a sizable share in long position open interest while their short position open interest share is negligible.

While the overall share of index trader open interest is at a relatively constant 25% level, changes in their position holdings will occur on a daily basis. Reweightings of the underlying index only play a minor role here.[3] The daily fluctuations primarily stem from changes in the desired replication volume. Such changes are the result of investors buying or selling shares in the index fund. The more liquidity flows into the fund, the larger the return cash flow that has to be paid out to the investors and the larger the ultimate long position on the futures market used for return replication. Thus, even though the index fund itself has a passive strategy and only replicates the index, a higher (lower) attractiveness of commodities as financial investments will nevertheless increase (decrease) the size of the total index trader long position.

[3] E.g. substantial S&P GSCI reweightings only occur annually with smaller monthly reviews (S&P Dow Jones Indices 2014)

Figure 4.1: CBOT corn futures and options trader type volume shares



Source: CFTC

4.2.2 Few-type heterogeneous agent models for financial markets

In the past, few-type HAMs have frequently been applied to investigate price dynamics in financial markets. In difference to their many-type counterparts they do not attempt to explicitly model the multitude of possible real world trading strategies but rather focus on selected stylized trading rules. Existing HAMs differ with respect to their market focus. Some models concentrate on exchange rates and/or equities (e.g. Bauer et al. 2009; Manzan and Westerhoff 2005; Franke and Westerhoff 2011, 2012). For commodity markets, Westerhoff and Reitz (2005) and Reitz and Westerhoff (2007) focus on corn and on cotton, lead, rice, sugar, soybeans and zinc respectively. He and Westerhoff (2005) build a HAM for a general commodity market, Redrado et al. (2009) for a mixed commodity index and Ellen and Zwinkels (2010) for the oil market. Finally, Alfarano et al. (2005) develop a model applicable to a broader range of asset markets and base their empirical estimation on gold and selected German stock (index) price series. The interaction of different markets is modeled e.g. in Westerhoff (2012) for a Keynesian goods and a stock market, in Chiarella et al. (2005) and Chiarella et al. (2007) for multiple risky and one risk free asset and in Dieci and Westerhoff (2010) for two international stock markets linked via a foreign exchange market. HAMs have also been used for policy analysis. For example, Anufriev and Tuinstra (2013) model the effect of short-selling constraints, Westerhoff (2003) investigate the effectiveness of price limits and resulting trading breaks, He and Westerhoff (2005) analyze the effects of a minimum and maximum price and Westerhoff and Dieci (2006) investigate transaction taxes.

In a few-type HAM, price dynamics arise from the interaction of selected stylized heterogeneous trading strategies. Commonly, these strategies are either of a fundamentalist or a chartist nature and their development goes back to e.g. Zeeman (1974), Beja and Goldman (1980) and Frankel and Froot (1990). While fundamentalists expect that market prices will revert back to their fundamental equilibrium value, chartists believe that prices follow a trend that can be extrapolated. Formally, a basic expression of the fundamentalist (V_t^F) and chartist trading volume (V_t^C) is given by:

$$V_t^F = \gamma_F(P_F - P_t), \tag{4.1}$$

$$V_t^C = \gamma_C(P_t - P_{t-1}), \tag{4.2}$$

where P_t is the *log* of the market price in period t, P_F is the logged constant fundamental price of the asset andγ_F and γ_C are positive reaction coefficients, measuring how responsive a trader type is to the observed price movement.

Markets can be in disequilibrium and prices are determined from either excess supply or demand on the market. A positive trading volume equals demand and a negative volume supply. A simple price-impact function is defined by:

$$P_{t+1} = P_t + (\phi_t^F V_t^F + \phi_t^C V_t^C), \tag{4.3}$$

Where $\phi_t^F + \phi_t^C = 1$ are the relative weights of the respective fundamentalist or chartist trader groups on the market. These weights are often assumed to be time-dependent and to vary according to a switching mechanism. The exact design of this switching mechanism is model-specific, depending on the underlying assumptions and the desired degree of complexity.

The complexity of the price dynamics that emerge from the traders' interaction over time affect calibration and estimation of the model parameters. While some models may in part allow analytical derivations (e.g. Chiarella 1992; Lux 1997; Chiarella et al. 2002) or permit direct estimation of their parameters (e.g. Alfarano et al. 2005; Westerhoff and Reitz 2005; Reitz and Westerhoff 2007; Redrado et al. 2009), more complex model setups require a simulation-based solution approach. Thereby, parameters are sometimes set "by hand" (e.g. Westerhoff 2003; Manzan and Westerhoff 2005) and their simulated return properties *ex-post* compared to empirical returns. Recently, progress has been made in the area of simulation-based estimation with the MSM where a part of the model parameters is estimated by *simultaneously* setting parameter values and considering differences between simulated and empirical returns. Building on Gilli and Winker (2003), Winker et al. (2007)

demonstrate how to set up an objective function, Franke (2009) extends the work by more explicitly considering the quality of moment-matching, and recently, Franke and Westerhoff (2011, 2012) demonstrate the use of measures of model fit in evaluating the quality of model parameters and comparing models.

4.3 Commodity market HAM

Our Commodity HAM is from a market perspective most closely related to the corn model in Westerhoff and Reitz (2005). But while their direct parameter estimation approach necessitated a relatively simple model setup, estimation with the MSM permits more complex dynamics. For our base scenario HAM we follow the "structural stochastic volatility" (SSV) approach developed in Franke and Westerhoff (2011, 2012). Our base scenario models the time period before 2006, i.e. before the strong growth of commodity index funds. Its setup closely follows the "DCA-TPM" model introduced in Franke and Westerhoff (2012) but in formulating the basic commodity trading strategies we draw some connection to the CFTC trader categories. The financialization scenario then simulates the market entry of a portfolio manager who uses commodities as portfolio diversifiers but does not trade directly on the futures markets but only via index funds.

4.3.1 The base scenario

The "producers/processors/merchants" from the CFTC reports can be interpreted as "commercial traders" (CO) who have some idea about the fundamental value of the commodity (from their primary business operations) and will use this knowledge to trade accordingly. Their trading volume (V_t^{CO}) is generated by a fundamentalist strategy, such that:

$$V_t^{CO} = \gamma_{CO}(P_F - P_t) + \epsilon_t^{CO},\ \epsilon_t^{CO} \sim N(0, \sigma_{CO}^2). \tag{4.4}$$

The first term in the volume equation represents the deterministic volume that stems from deviations between the fundamental price and the current market price. The reaction coefficient γ_{CO} determines how strong the commercial traders' volume reacts to such perceived deviations. The second term is a stochastic volume. In our Commodity HAM this component could capture random shocks due to the traders' different estimates of the fundamental value.

The "other noncommercial traders" are assumed to be trading on price data rather than on fundamentals. They follow trends and can thus be interpreted as "speculators" (S). Their trading volume (V_t^S) is represented by a chartist strategy:

$$V_t^S = \gamma_S(P_t - P_{t-1}) + \epsilon_t^S,\ \epsilon_t^S \sim N(0, \sigma_S^2). \tag{4.5}$$

Again, the first term in the volume equation represents the deterministic volume, which depends on daily price changes and the reaction coefficient γ_S determines how strongly the speculators react to price trends. The second term adds a stochastic volume, which accounts for additional variation in the trading rules (cf. Westerhoff 2003). The commercial traders' and speculators' stochastic volumes are fully independent.

Both trader types trade directly on the commodity futures market.[4] The total contract trading volume is composed of fundamentalist volume (V_t^F) from the commercial traders and chartist volume (V_t^C) from the speculators, such that:

$$\begin{aligned} V_t^F &= \phi_t^F V_t^{CO}, \\ V_t^C &= \phi_t^C V_t^S, \end{aligned} \tag{4.6}$$

where ϕ_t^F and ϕ_t^C are the market weights of the respective trading strategies. The price-impact function is given by:

$$P_{t+1} = P_t + \gamma_{MM}\left(V_t^F + V_t^C\right). \tag{4.7}$$

The coefficient γ_{MM} is a positive reaction coefficient from a "market maker" who somewhat balances supply and demand by releasing inventory (contracts) in case of excess demand and taking inventory (contracts) in case of excess supply to avoid extreme spikes (cf. Westerhoff 2003; Franke and Westerhoff 2012).

We allow the market weights ϕ_t^F and ϕ_t^C to vary based on relative strategy attractiveness. For our commercial trader-speculator setting, we can imagine that a higher attractiveness of a fundamentalist strategy induces more commercial traders to enter the market and speculators to leave, and vice versa. In determining relative strategy attractiveness, we follow the "DCA-TPM" model approach in Franke and Westerhoff (2012) and compute an attractiveness index of a fundamentalist strategy (α_t) as:

$$\alpha_t = \alpha_p + \alpha_h(\phi_t^F - \phi_t^C) + \alpha_m(P_t - P_F)^2,\ \alpha_h, \alpha_m > 0. \tag{4.8}$$

The first summand is the predisposition parameter (α_p), which measures whether traders have an à priori strategy preference, whereby a positive (negative) value indicates preference for fundamentalism (chartism). The second summand accounts for the tendency of the traders to follow the herd, i.e. join a

[4]Even though trading volume corresponds to contract holdings, we will not consider any rolling effects over the time period but assume that trading out of the active and into the first deferred contract can be achieved without any transaction costs, which is equivalent to holding an artificial active contract over the full simulation period.

group that is already dominating the market. Thus, if $\phi_t^F > \phi_t^C$, the attractiveness of fundamentalism increases and the parameter α_h defines the strength of the increase. The last summand accounts for a potential fear of bubbles. The stronger the misalignment between the current and the fundamental price, the higher the attractiveness of fundamentalism. Speculators would leave the market in expectation of a bubble. The parameter α_m measures how strongly price misalignment affects attractiveness of fundamentalism.

The functional relation between the market weights and the attractiveness index is modeled with a "Discrete Choice Approach" (DCA) (Brock and Hommes 1998), where the attractiveness index directly affects the level of market shares:[5]

$$\begin{aligned} \phi_t^F &= \frac{1}{1+exp(-\beta\alpha_{t-1})}, \\ \phi_t^C &= 1-\phi_t^F, \end{aligned} \tag{4.9}$$

where β is the "intensity of choice" parameter that could be used to scale the level of the attractiveness index in the above equation (Franke and Westerhoff 2012).

Inserting the above equations into equation (4.7), leads to:

$$\begin{aligned} &P_{t+1} = P_t + \gamma_{MM}(\phi_t^F(\gamma_{CO}(P_F-P_t)+\epsilon_t^{CO}) + \phi_t^C(\gamma_S(P_t-P_{t-1})+\epsilon_t^S)), \\ \Leftrightarrow &P_{t+1} = P_t + \gamma_{MM}(\phi_t^F(\gamma_{CO}(P_F-P_t)) + \phi_t^C(\gamma_S(P_t-P_{t-1})) + \epsilon_t^P, \\ &\epsilon_t^P \sim N(0,\sigma_{P,t}^2), \\ &\sigma_{P,t}^2 = (\phi_t^F)^2\sigma_{CO}^2 + (\phi_t^C)^2\sigma_S^2. \end{aligned} \tag{4.10}$$

Thus, the variance of the stochastic trading volumes and the trader weights affect the *time-dependent* variance of the stochastic price component, which is key to the SSV model approach (Franke and Westerhoff 2011, 2012).

4.3.2 The financialization scenario

We assume that the portfolio managers' decision on the level of investment in commodity index funds will depend on both idiosyncratic returns of the single commodities in the index and on commodity index return or volatility correlations with other portfolio assets. Trading volume associated with single

[5] An alternative is the Transition Probability Approach (TPA) where the effect on the *rates of change* of the trader-type population shares is modeled. As demonstrated in Franke and Westerhoff (2012), if α_t is composed of the same elements (α_p, α_h, α_m), there will be no major difference in results between DCA and TPA and we choose DCA due to its comparative popularity in the literature.

commodity returns stems from an underlying weighted fundamentalist-chartist strategy, similar to the portfolio manager in Redrado et al. (2009), while trading volume as a result of portfolio correlations is modeled as a stochastic component. Total portfolio managers' trading volume (V_t^{PM}) is expressed as:

$$V_t^{PM} = \gamma_{PM}[\tilde{\phi}_t^F(P_F - P_t) + \tilde{\phi}_t^C(P_t - P_{t-1})] + \epsilon_t^{PM},\ \epsilon_t^{PM} \sim N(0, \sigma_{PM}^2) \quad (4.11)$$

where the first two summands show the deterministic volume and $\tilde{\phi}_t^F$ and $\tilde{\phi}_t^C$ represent the relative fundamentalist and chartists volume weights and γ_{PM} determines the reaction strength to price deviations. ϵ_t^{PM} is the stochastic volume and assumed to be independent of either the stochastic commercial traders' and speculators' volumes.

Since portfolio managers' trading volume ultimately reaches the futures market via index fund replication volume, the total position has to be net long. Therefore, in any period t contract demand is equivalent to the volume derived from equation (4.11). But, contract supply cannot exceed the total long position that has been built up until period t. Formally, this restricted volume ($\tilde{V}_t^{PM}$) is expressed as:

$$\tilde{V}_t^{PM} = \begin{cases} max\left[V_t^{PM}, -\sum_{i=1}^{t-1} V_i^{PM} \cdot (1-\chi)\right] & \text{, if } V_t^{PM} < 0 \\ V_t^{PM} & \text{, otherwise.} \end{cases} \quad (4.12)$$

As a total position holding of zero would strictly mean that index funds go out of business, the parameter χ is introduced as a percentage minimum position holding leading to a moving lower bound for $\tilde{V}_t^{PM}$.

The combined deterministic trading volume of all three trader types is still only associated with either a fundamentalist or a chartist strategy, whereby total fundamentalist and chartist volumes are calculated as:

$$\begin{aligned} V_t^F &= \phi_t^F V_t^{CO} + \tilde{\phi}_t^F \tilde{V}_t^{PM}, \\ V_t^C &= \phi_t^C V_t^S + \tilde{\phi}_t^C \tilde{V}_t^{PM}. \end{aligned} \quad (4.13)$$

This assumes that the fundamentalist/chartist shares in $\tilde{V}_t^{PM}$ are the same as in V_t^{PM} and that size of $\tilde{\phi}_t^F$ and $\tilde{\phi}_t^C$, i.e. the weight of the fundamentalist and chartist components in the portfolio managers' volume, are also determined with a DCA approach from the attractiveness index α_t. But, the herding component within α_t now needs to take into account the additional portfolio managers' fundamentalist and chartist volume, which is why we now use absolute fundamentalist (ψ_t^F) and chartist (ψ_t^C) volume shares, calculated as:

$$\begin{aligned} \psi_t^F &= \frac{\phi_t^F |V_t^{CO}| + \tilde{\phi}_t^F |\tilde{V}_t^{PM}|}{(\phi_t^F |V_t^{CO}| + \phi_t^C |V_t^S| + |\tilde{V}_t^{PM}|)}, \\ \psi_t^C &= \frac{\phi_t^C |V_t^S| + \tilde{\phi}_t^C |\tilde{V}_t^{PM}|}{(\phi_t^F |V_t^{CO}| + \phi_t^C |V_t^S| + |\tilde{V}_t^{PM}|)}, \end{aligned} \quad (4.14)$$

such that α_t becomes:

$$\alpha_t = \alpha_p, +\alpha_h(\psi_t^F - \psi_t^C) + \alpha_m(P_t - P_F)^2, \tag{4.15}$$

Inserting the above trading volumes in the price impact function leads to:

$$\begin{aligned}
&P_{t+1} = P_t + \gamma_{MM}(\phi_t^F(\gamma_{CO}(P_F - P_t)) + \phi_t^C(\gamma_S(P_t - P_{t-1})) + \epsilon_t^P + \tilde{V}_t^{PM}, \\
&\sigma_{P,t}^2 = (\phi_t^F)^2\sigma_{CO}^2 + (\phi_t^C)^2\sigma_S^2 + \tilde{\sigma}_{PM}^2,
\end{aligned} \tag{4.16}$$

where the tilde in $\tilde{\sigma}_{PM}^2$ indicates that the variance will be affected by the short-selling constraint as it truncates the distribution.

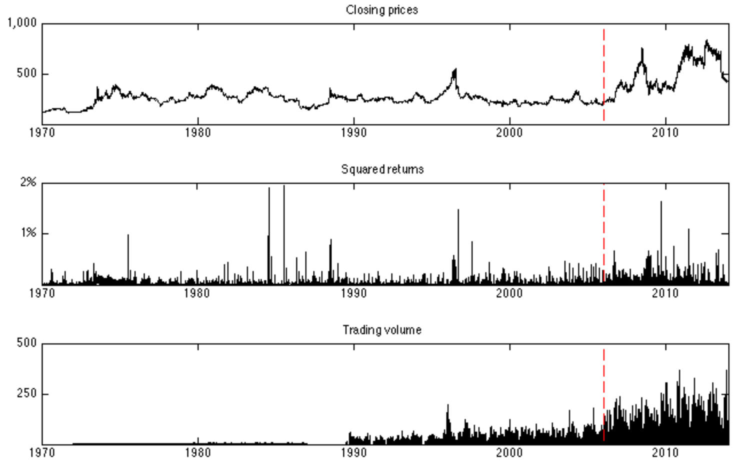
4.4 Base scenario parameter estimation

With the MSM, model parameters are chosen such that moments calculated from simulated returns come close to their empirical counterparts from daily relative returns of CBOT corn. We use price data for the trading days 01/05/1970-12/31/2013 from which we split off the base scenario sample ending on 12/31/2005 with a total number of 9,085 observations. This base period is used for later parameter estimation. Prices are Bloomberg's first generic contract prices where expiring active futures contracts are rolled to the next deferred contract on the last trading day of the active contract ("relative to expiration" rolling procedure). We calculate relative returns (R_t) as $R_t = lnP_t - lnP_{t-1},$, where P_t and P_{t-1} are the closing prices. Squared returns (R_t^2) are used to approximate short-term price volatility. Figure 4.2 shows the development of closing prices in U.S. Dollars, squared returns and trading volume (in thousand contracts) until 12/31/2013. The vertical dashed line indicates the end of the base period. The price level and short-term volatility markedly increase in the period after 2006 while trading volume surges.

4.4.1 Selection and calculation of moments

We first select and calculate the moments before we set up the objective function and continue with its minimization and parameter validation. Moments are chosen to capture important stylized facts of the corn futures prices. Commonly, financial market HAMs aim to replicate the overall volatility level in the price data, the non-autocorrelation property of returns, fat tails in the return frequency distribution, volatility clustering, and long memory effects (cf. Franke and Westerhoff 2011, 2012). While overall volatility is market specific, most of the stylized facts of other financial markets will also be found in commodity returns (Westerhoff and Reitz 2005). Our selection of moments follows suggestions in Franke and Westerhoff (2012) and Winker and Jeleskovic (2007) and calculated empirical moments for both the baseline and the full observation period are presented in Table 4.1.

Figure 4.2: Price, volatility and volume development



Source: Bloomberg

The overall volatility level is captured by calculating the absolute value returns, which show a similar behavior to squared returns (Franke 2009) and can also be used to calculate the autocorrelation function, as illustrated below.

$$\bar{A}_t = \frac{1}{N}\sum_{t=1}^{N} A_t,\ A_t = |R_t| \tag{4.17}$$

The first order autocorrelation coefficient of relative returns is close to zero (non-autocorrelation property of returns) while the autocorrelations of absolute returns should be slowly decaying over the time horizon to demonstrate the long memory effect in the return data. As pointed out by Franke and Westerhoff (2012), this property is also related to volatility clustering. Autocorrelations of lag k are computed from the sample autocovariances (ACV) as:

$$ACV_k = 1/T \sum_{t=k+1}^{T} (Q_t - \bar{Q}_t)(Q_{t-k} - \bar{Q}_t), \tag{4.18}$$

with $Q_t = R_t, A_t$. The sample autocorrelation for either relative (ρ_k^r) or absolute returns (ρ_k^a) is then computed as: ACV_k/ACV_0. For relative returns we only calculate ρ_1^r and rely on the finding in Franke and Westerhoff (2012) that autocorrelations at larger lags will vanish once ρ_1^r is close to 0. For absolute returns, we match the profile of the decaying autocorrelation function (ACF) by computing $\rho_1^{ac}, \rho_5^{ac}, \rho_{10}^{ac}, \rho_{25}^{ac}, \rho_{50}^{ac}, \rho_{100}^{ac}$. The exponent ac denotes that these are "centered" autocorrelation coefficients of absolute returns. The ACF of R_t

may have an autocorrelation coefficient at one of our selected lags that contradicts the typical behavior (e.g. in our corn sample, ρ_5^a is larger than the ρ_1^a). Since we would not expect our simulated returns to match these properties, we follow Franke and Westerhoff (2012) and smooth this effect by calculating the mean of the autocorrelation coefficients at the selected lag and the two lags surrounding it (or one lag in case of ρ_1^{ac}).

The fatness of the tail of the frequency distribution of returns is commonly measured with the Hill-estimator (ξ) and its corresponding tail index ($tail = 1/\xi$) (Hill 1975). The smaller its value, the fatter the tail of the distribution. Also, moments above the value of the tail index are no longer defined. To compute the tail index for (R_t), the returns are first ordered and we write the order statistics from the return sample $R_1, R_2, ..., R_T$ as $R_1^T \geq R_2^T \geq ... \geq R_T^T$. The right tail index is computed as:[6]

$$\begin{aligned} \xi &= \frac{1}{k} \sum_{i=1}^{k} lnR_i^T - lnR_k^T \\ tail &= 1/\xi. \end{aligned} \tag{4.19}$$

The Hill estimator is sensitive to the choice of k. Standard choices are either 5% or 10% of the total observations. We follow Winker and Jeleskovic (2007) and use the mean of the tail indices for $k = 0.05 \cdot N$ and $k = 0.1 \cdot N$. Thus, $tail = 1/2(tail_5 + tail_{10})$.

The moment vector $m = [\bar{A}_t \, \rho_1^r \, tail \, \rho_1^{ac} \, \rho_5^{ac} \, \rho_{10}^{ac} \, \rho_{25}^{ac} \, \rho_{50}^{ac} \, \rho_{100}^{ac}]'$ collects the single moments. In Table 4.1, we have included the respective moments for CBOT soybeans and the S&P 500 U.S. equity index next to those for CBOT corn. As indicated by the level of $\bar{A}_t$, commodity volatility is higher than that of U.S. equities and is higher for the full compared to the base period. The other stylized facts are similar across markets and time periods.

4.4.2 Objective function

The objective function used to choose the model's parameter values is based on a loss function (J) that considers the squared difference between empirical (m^{emp}) and simulated moments (m^{sim}):

$$J = (m^{sim}(\theta) - m^{emp})' W (m^{sim}(\theta) - m^{emp}), \tag{4.20}$$

where the vector (θ) collects all model parameters. The optimal parameter vector (θ^*) will minimize J. W is a weighting matrix of the deviations between empirical and simulated moments that considers their estimated variance (Winker and Jeleskovic 2007). We follow Winker et al. (2007) and Franke

[6] For our model it is only necessary to include a one-sided tail index as the simulated models will produce symmetric positive and negative extreme returns (c.f. Franke and Westerhoff 2012).

Table 4.1: Empirical moments

	Baseline			Full period		
	Corn	Soy	S&P 500	Corn	Soy	S&P 500
$\bar{A}_t$	0.0102	0.0114	0.0077	0.0112	0.0116	0.0080
ρ_1^r	0.0503	0.0568	-0.0381	0.0431	0.0515	-0.0580
tail	2.5209	2.8034	2.7516	2.6944	2.9013	2.5272
ρ_1^{ac}	0.2239	0.2933	0.1807	0.2248	0.2660	0.2545
ρ_5^{ac}	0.2168	0.2755	0.1969	0.2150	0.2506	0.2705
ρ_{10}^{ac}	0.1995	0.2512	0.1685	0.1978	0.2309	0.2424
ρ_{25}^{ac}	0.1421	0.2163	0.1342	0.1585	0.1948	0.1770
ρ_{50}^{ac}	0.0834	0.1495	0.1338	0.1091	0.1365	0.1417
ρ_{100}^{ac}	0.0356	0.0846	0.0835	0.0617	0.0790	0.0979

Notes: Soybean prices are available from 05/20/1970 and S&P 500 prices from 04/21/1981.

and Westerhoff (2011, 2012) and use a block bootstrap (due to the long-memory property of the data) to estimate the sample covariance matrix of the moments (Σ), which also holds advantages for later model validation.

First, we block-bootstrap the baseline returns by dividing the R_t series into blocks of appropriate length. Franke and Westerhoff (2012) propose blocks of 250 days for short-memory moments and 750 days for long-memory moments. We choose to test 250, 500 and 750 day blocks for each moment and then select the bootstrap window length that leads to the smallest deviation between the mean of the bootstrapped moments and the empirical moments, which builds on the window selection procedure in Franke and Westerhoff (2011). Based on these results we select a 250 day window for $\bar{A}_t$, a 500 day window for ρ_1^r, *tail*, ρ_1^{ac} , ρ_5^{ac} , ρ_{50}^{ac}, ρ_{100}^{ac} and a 750 day window for ρ_{10}^{ac}, ρ_{25}^{ac}. In dividing the baseline R_t series by the block size, any residual observations are cut off at the beginning of the series, leading to 9,000 bootstrapped outcomes of R_t and 36, 18 and 12 blocks for 250, 500 and 750 day windows, respectively. Random block draws with replacement (number of draws = number of blocks) are used to construct a new series of R_t from which the bootstrapped moment vector m^b is calculated. This procedure is repeated for $B = 10,000$ bootstrap samples to obtain $m_1^b, ..., m_B^b$, from which we calculate the vector of moment means $\bar{m}^b$

and estimate Σ and W as:

$$\begin{aligned}\Sigma &= \frac{1}{B}\sum_{b=1}^{B}\left(m^b - \bar{m}^b\right)\left(m^b - \bar{m}^b\right)', \\ W &= \Sigma^{-1}\end{aligned} \tag{4.21}$$

4.4.3 Parameter estimation

Some parameters are fixed à priori and summarized in the upper part of Table 4.2. We follow Franke and Westerhoff (2012) and set the reaction coefficient of the market maker to $\gamma_{MM} = 0.01$ and the intensity of choice to $\beta = 1$ since both parameters are essentially "scaling parameters" for the price impact and the attractiveness index. The middle part of Table 4.2 shows the parameters to be estimated. The optimal parameter vector θ^*, is derived by minimizing J subject to a specific simulation period (S) and specific random number seeds ($\nu_t^{CO,S}$) that are underlying the calculation of the stochastic volumes ($\epsilon_t^{CO}, \epsilon_t^{S}$). S is chosen as $10 \cdot N$ (Franke and Westerhoff 2012).[7] Prior to the estimation, the random number seed $\nu_t^{CO,S}$ is drawn from a $N(0,1)$ distribution and the stochastic volumes are calculated as $\epsilon_t^{CO,S} = \nu_t^{CO,S}\sigma_{CO,S}$ (Franke 2009). Thus, we can ensure that any variation in the J-value is exclusively attributable to changes in the parameter vector θ and not to the random number seed. Also, we select starting values for the price P_t ($P_1 = ln99.75$, $P_2 = ln100.25$) and the attractiveness index α_t ($\alpha_1 = 5$). The minimization problem is set up as:

$$\min_{\theta} J = (m^{sim}(\theta, S, \nu_t^{CO,S}) - m^{emp})'W(m^{sim}(\theta, S, \nu_t^{CO,S}) - m^{emp}) \tag{4.22}$$

The optimization implies considerable challenges including that m^{sim} cannot be expressed analytically as a function of model parameters and data (as in more standard estimation approaches), but requires the full simulation with the HAM and subsequent calculation of moments in each optimization step. The nature of the objective function also leads to multiple local minima (e.g. Gilli and Winker 2003; Franke and Westerhoff 2011). Frequently, a Nelder-Mead Simplex search algorithm (cf. Lagarias et al. 1998) is used to locate suitable minima. The error arising from failing to find the global minimum is considered relatively small and authors suggest to not put too much strain on its determination (Franke and Westerhoff 2011, pp.72-74). Our focus during the optimization is thus to find a set of parameter values that constitute a local minimum and lead to a good match between m^{sim} and m^{emp}. We also choose a direct search approach but combine the Nelder-Mead and a Pattern Search algorithm (cf. Torczon 1997) where we can directly consider the parameter bounds shown in column 3 of Table 4.2.

[7] 10% of the observations at the beginning of the simulation are discarded to ensure that no transient effects occur (cf. Franke and Westerhoff 2011, 2012).

Table 4.2: Parameter values

Fixed parameters		Value			
γ_{MM}	Reaction coefficient of market maker	0.01			
β	Intensity of choice coefficient	1			
P_F	Fundamental value of the commodity	$ln100$			
Estimated parameters		**Bound**	**Model 1**	**Model 2**	**Model 3**
γ_{CO}	Reaction coefficient of commercial traders	> 0	0.327	0.702	0.659
γ_S	Reaction coefficient of speculators	> 0	8.823	52.589	25.062
σ^2_{CO}	Variance of commercial traders' stochastic volume	> 0	19.904	69.459	76.074
σ^2_S	Variance of speculators' stochastic volume	> 0	247.88	2.745	15.770
α_p	à priori preferences		-0.174	-0.279	-2.093
α_h	Reaction to herding	> 0	2.176	1.746	3.884
α_m	Reaction to price misalignment	> 0	0.834	9.390	12.372
J-value	Value of the objective function		1.978	3.120	2.540

Table 4.3: Boundaries for sample of starting values

Parameter	Lower bound	Upper bound
γ_{CO}	1	10
γ_S	1	20
σ^2_{CO}	1	25
σ^2_S	1	25
α_p	-5	5
α_h	1	10
α_m	1	10

First, we draw 15 random starting values for each of the estimable parameters from a uniform distribution within the bounds shown in Table 4.3. We then start the *patternsearch* solver in MATLAB and run the optimization for each of the 15 vectors of starting values. The solver allows to start the optimization with the built-in Nelder-Mead algorithm. Once we find a local minimum we use these parameter values as starting points for the subsequent pattern search with a large initial mesh (100), an expansion value of 8 and a contraction value of 0.5 and a full poll. For the 3 parameter combinations that lead to the lowest local minimum, we restart the procedure with an even larger initial mesh (10,000), an expansion value of 8, a contraction value of 0.5 and a full poll. We repeat this previous step and decrease the tolerances with respect to the mesh size, the improvement of the objective function and the distance between points chosen during the optimization until there is neither a significant reduction in the J-value nor a significant change in the parameter size.

The last columns in Table 4.2 show the three estimated parameters sets that led to the local minima with the smallest J-values. In model 1, speculators' stochastic volume is associated with the larger variance. In models 2 and 3, the opposite is true. Also, in models 2 and 3, speculators have higher reaction coefficients than in model 1 and there is a strong reaction to perceived price misalignments. The calculated J-value shown in the last row of Table 4.2 is contingent on the random seeds $\nu_t^{CO,S}$ used during the optimization and provides insufficient information to select the best parameter set. We will therefore choose two alternative approaches to assess the quality of the model parameters.

4.4.4 Evaluation of the model fit

The evaluation of the model fit is first based on how well the combined m^{sim} obtained with the parameter sets match the combined m^{emp}, which is accounted for by the J-value. Second, it checks how well each *single* moment is replicated. We compare m^{sim} and m^{emp} via their distributions. Thereby, we use the 10,000 moment vectors (m^b) from the block-bootstrapped estimation of W to calculate a bootstrapped distribution for the loss functions $J^b = (m^b - m^{emp})'W(m^b - m^{emp})$, for $b = 1, ..., 10,000$ and for each single moment within m^b. We interpret the distribution of J^b and the moments within m^b as an approximation of the true distribution of J and each empirical moment that would arise if the actual data generation process (DGP) behind the empirically observed return series were to be repeated 10,000 times to create 10,000 different return series (Franke and Westerhoff 2012). The comparison of the simulated and empirical (bootstrapped) J values and moments first uses the "p-values" from Franke and Westerhoff (2012), which we label "percentage coverage" [8] and second, calculates the relative entropy, i.e. Kullback-Leibler (KL) divergence, for the respective distributions.

4.4.4.1 Percentage coverages

We calculate a total and a moment-specific percentage coverage. If we use the distribution of J^b as an approximation of the true J distribution, then any simulation run using the optimal parameter vector θ^* cannot be rejected as not being consistent with the actual DGP if the obtained value of J^{sim} falls within the 95% quantile of the distribution of J^b and thus below a critical value ($J^b_{0.95}$) (Franke and Westerhoff 2012). The total percentage coverage calculates the percentage out of 10,000 simulation runs using θ^* and a simulation period T=9,000[9] that lead to $J^{sim} < J^b_{0.95}$. We use the "p-value" from the "DCA-HPM" model in Franke and Westerhoff (2012) of 32.6% as a benchmark, as suggested by the authors. Results for the θ^* parameter sets from the three different base scenario models are shown in Table 4.4. Models 1 and 2 both exceed the chosen benchmark value of 32.6%.

While it permits an overall assessment of the model fit, the total percentage coverage does not measure how well the *single* moments are replicated. We calculate moment-specific percentage coverages by comparing the marginal moment distributions, which may have different left and right bounds. Thus we calculate both a critical 95th and 5th percentile moment value ($m^b_{0.95}, m^b_{0.05}$). The moment-specific percentage coverage calculates the percentage out of 10,000 simulation runs using θ^* and a simulation period T=9,000 that leads to $m^b_{0.05,i} < m^{sim}_i < m^b_{0.95,i}$. We summarize the results in Table 4.5 where the best fit (value closest to 90%) is indicated in bold font. Model 1 is best at

[8] We use this alternative term to illustrate that we actually calculate a percentage of observations that fit within a predetermined value bound rather than perform a formal statistical test.

[9] This corresponds to the length of the bootstrap return sample used to calculate m^b and ensures that the return series underlying the calculation of m^{sim} and m^b have the same length.

Table 4.4: Critical value, percentage coverages and benchmark value

$J^b_{0.95}$	Model 1	Model 2	Model 3	Benchmark
19.68	39.23	**42.74**	28.51	32.6

Table 4.5: Percentage coverages for single moments

	Empirical estimate	Critical values		Calculated p-values		
	m^{emp}	$m^b_{0.95}$	$m^b_{0.05}$	Model 1	Model 2	Model 3
$\bar{A}_t$	0.0102	0.0111	0.0095	76.27	**77.67**	74.81
ρ^r_1	0.0503	0.0696	0.0283	**72.01**	68.23	66.14
tail	2.5209	2.9897	2.3242	**90.70**	85.45	97.93
ρ^{ac}_1	0.2239	0.2839	0.1440	97.84	**97.33**	98.67
ρ^{ac}_5	0.2168	0.2693	0.1443	98.20	98.12	**97.52**
ρ^{ac}_{10}	0.1995	0.2603	0.1130	99.46	99.48	**98.81**
ρ^{ac}_{25}	0.1421	0.1934	0.0665	98.35	94.61	**91.53**
ρ^{ac}_{50}	0.0834	0.1207	0.0286	**86.22**	75.06	68.72
ρ^{ac}_{100}	0.0356	0.0658	-0.0170	**95.69**	68.98	63.41

matching the fatness of the tail, the zero autocorrelation property of the raw returns (ρ^r_1) and the long memory property of the data approximated with the autocorrelations of the absolute returns[10] while model 2 is best at replicating the overall volatility level ($\bar{A}_t$). Before we decide on a parameter set, we first use the KL divergence to compare the distance between the sampling distributions of the simulated and bootstrapped J and moment values.

4.4.4.2 Relative entropy

Compared to the percentage coverage, which only considers how many of the simulated values fit between the pre-defined bounds, the KL divergence can better account for differences in the distributional shape, e.g. with respect to skewness or kurtosis. It is calculated as:

$$\begin{aligned} d_{KL,J} &= \sum_{i=1}^{d} P_i(J) \ln \frac{P_i(J)}{Q_i(J)}, \\ d_{KL,m} &= \sum_{i=1}^{d} P_i(m) \ln \frac{P_i(m)}{Q_i(m)}, \end{aligned} \tag{4.23}$$

[10] The differences to model 2 and 3 coverages for $\rho^{ac}_1, \rho^{ac}_5, \rho^{ac}_{10}$ are generally small but the coverage of $\rho^{ac}_{50}, \rho^{ac}_{100}$ is best.

Table 4.6: KL divergence for moment and loss function distributions

	Model 1	Model 2	Model 3
J^{sim}	0.291	**0.105**	0.114
$\bar{A}_t$	0.546	**0.011**	0.053
ρ_1^r	0.177	**0.071**	0.223
tail	**0.687**	1.169	1.152
ρ_1^{ac}	0.251	0.189	**0.164**
ρ_5^{ac}	0.356	0.216	**0.193**
ρ_{10}^{ac}	0.299	**0.147**	0.234
ρ_{25}^{ac}	0.265	0.226	**0.166**
ρ_{50}^{ac}	0.257	0.197	**0.118**
ρ_{100}^{ac}	0.150	0.076	**0.056**

where $P(J), P(m)$ are the probability density functions of the 10,000 bootstrapped J-values and moments and $Q(J), Q(m)$ are the probability density functions of 10,000 simulated J-values and moments using the optimal parameter vector θ^* and a simulation period T, as described above. $d = 100$ is the number of bins in the histograms underlying the two probability distributions. In the case of two identical distributions, $d_{KL} = 0$, thus, the lower the calculated value, the lower the distance between the bootstrapped and simulated distributions. The results are shown in Table 4.6 where again the best distributional fit is indicated with bold font. The overall distance is lowest for model 2. For the single moments, model 1 best replicates the distribution of the fatness of the tail. Model 2 distances are lowest for $\bar{A}_t, \rho_1^r, \rho_{10}^{ac}$ and thus the model performs best at replicating the volatility level and the zero autocorrelation property of the raw returns. Finally, model 3 shows the lowest distance for ρ^{ac} at all remaining lags and is thus best at matching the decaying ACF and the long memory effects in the return data. Nevertheless, distances for model 2 are in most cases not drastically different from model 3.

In summary, model 2 had the best overall percentage coverage and the lowest distributional distance between J^b and J^{sim}. Its single moment matching is comparable to model 3, which is why we choose model 2 as our main base scenario parameter set. Nevertheless, we found that the parameter values in model 1 were quite different concerning the reaction to price misalignments, the speculators' reaction coefficients and variances of the traders' stochastic volumes. Since its total percentage coverage still exceeds the benchmark of 32.6 and the individual moment matching is quite good, especially for the tail index, we will use model 1 as a comparative base scenario model. This may provide additional insights about the drivers behind price dynamics and allows for some sensitivity analysis regarding the main results.

4.5 Scenario comparison

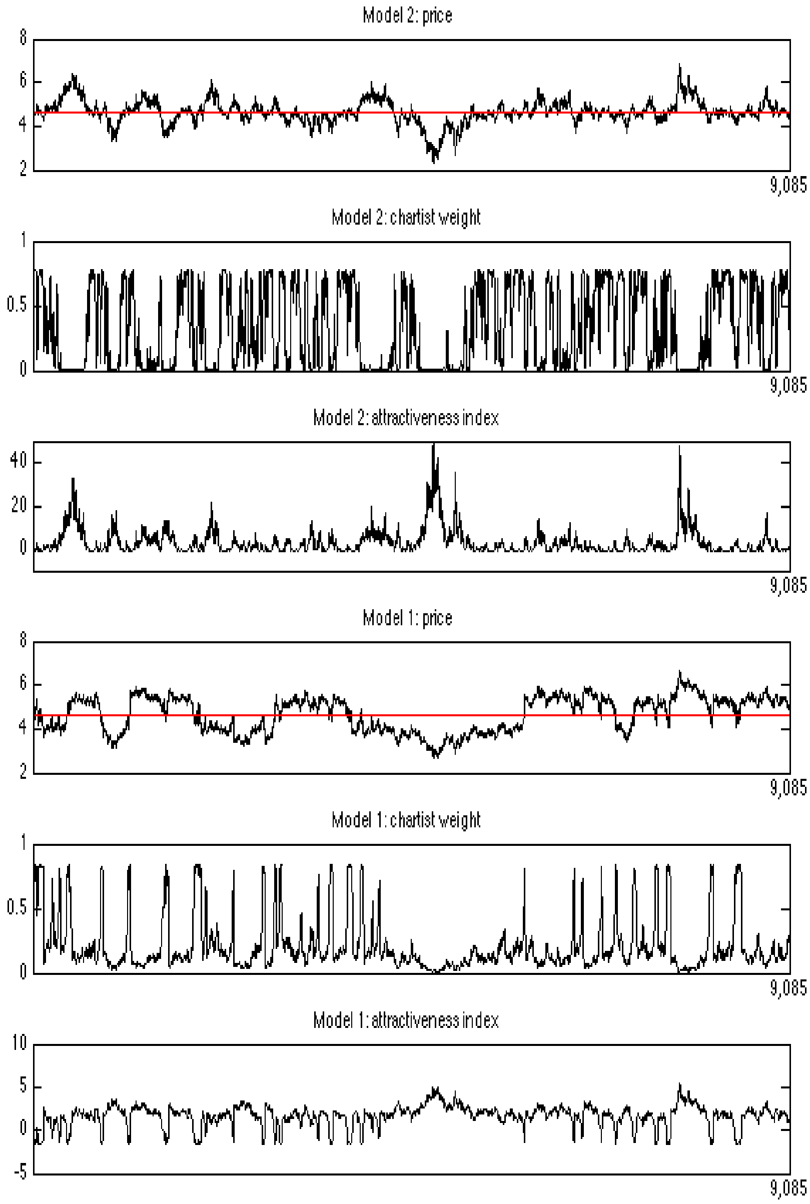
We simulate first the base scenario over a period of 9,085 trading days, equivalent to the number of observations in the base period data sample, with the model 2 and 1 parameters from Table 4.2. For both parameter sets we use identical random number seeds ($\nu_t^{CO,S}$) such that any result differences are solely attributable to the parameter values. In the later financialization scenario, we fix the parameter values à priori in order to better understand sensitivities in the price dynamics with respect to parameter changes.

4.5.1 Base scenario results

A graphical summary of base scenario results for model 2 and model 1 is provided in Figure 4.3. In both models traders have a very small à priori preference for a chartist strategy. And, the reaction to herding incentives of the traders is of a similar magnitude ($\alpha_{h,2} = 1.746$ versus $\alpha_{h,1} = 2.176$). But, the response of traders to a price misalignment between the current and the fundamental price is much stronger in model 2 ($\alpha_{m,2} = 9.39$) than in model 1 ($\alpha_{m,1} = 0.834$). Deviations from the fundamental price (horizontal line) increase the attractiveness of fundamentalism and decrease chartists' market weight. Due to the size of α_m, the maximum level of α_t in model 2 is higher than in model 1. Also, the stronger reaction to price misalignment paired with a high reaction coefficient of speculators ($\gamma_{S,2} = 52.589$ versus $\gamma_{S,1} = 8.823$) in model 2 leads to higher fluctuations in the chartist weight (variance of 0.1 for model 2 and 0.05 for model 1) and deviations from the fundamental price are less persistent than in model 1. The mean price level is almost identical for both parameter sets with $\bar{P}_1 = 4.67$ and $\bar{P}_2 = 4.65$.

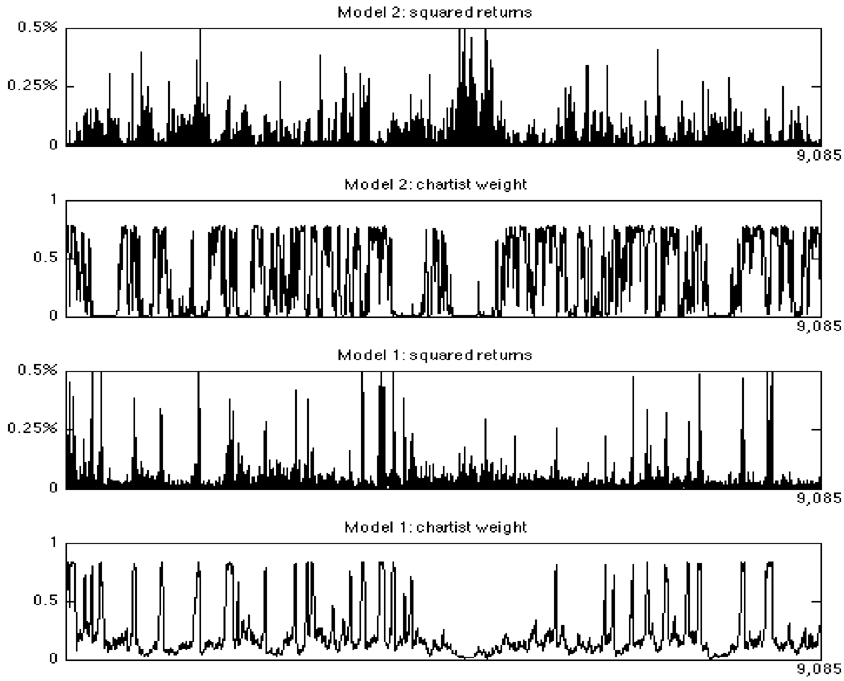
The price volatility effect, measured with R_t^2, is presented in Figure 4.4. In model 1 an increase in the chartist (speculator) weight and thus a higher chartist trading volume with a large variance in the stochastic component, leads to an increase in the level of R_t^2. In model 2 a higher fundamentalist (commercial trader) weight and thus larger fundamentalist trading volume (including the stochastic volume with its high variance) is associated with a high level of R_t^2. Thus, the trader group with the highest variance in the stochastic trading volume will carry the largest information shocks to the market and increase the short-term volatility. From a theoretical perspective, none of the two scenarios seems implausible. The forecast of the fundamental price of corn is associated with uncertainty, which could justify a fundamentalist-chartist variance relation as in model 2. On the other hand, the trading strategies within the group of speculators may be much more diverse than within the group of commercial traders, which could motivate the model 1 variance relation.

Figure 4.3: Base results overview



Notes: Horizontal (red) line in price charts represents the constant fundamental price, black lines represent base scenario results for model 1 and 2 parameter sets.

Figure 4.4: Base results volatility effect



Notes: Black lines represent base scenario results for model 1 and 2 parameter sets.

Table 4.7: Financialization scenarios

	Scenarios		
Parameter	(1) "High impact"	(2) "Low impact"	(3) "Fast reaction"
γ_{PM}	5	0.5	10
σ^2_{PM}	50	5	5
χ	0.2	0.2	0.2

4.5.2 Financialization scenario results

The parameters for the financialization scenario that are set *in addition* to the base scenario parameters are summarized in Table 4.7. The fixed parameters, starting values and random number seeds are the same as in the base scenario and we use an identical simulation period length. We can think of it as a period of another 9,085 days that starts after the introduction of index funds and emergence of portfolio managers on the market. Base scenario reaction coefficients, variances of stochastic volumes and the coefficients in the attractiveness index are assumed to be unaffected by the market entry of portfolio managers.

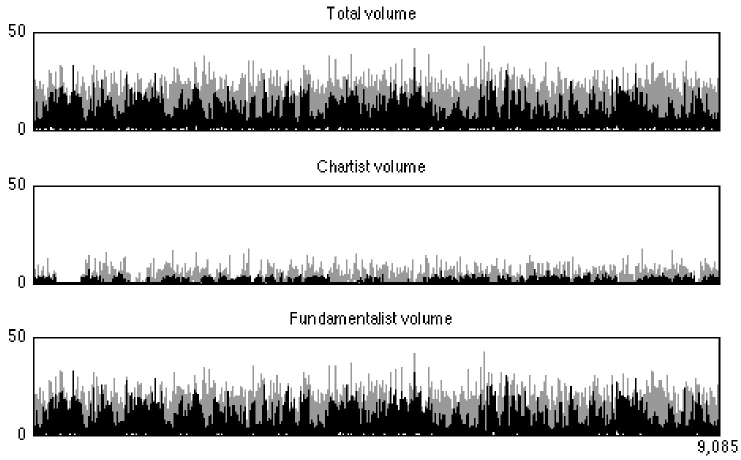
We define three parameter scenarios. Scenario 1 models a "high impact" situation with a relatively strong reaction coefficient for the portfolio managers and high variance in their stochastic volume. Scenario 2 is the "low impact" scenario where both the reaction coefficient and the variance of the stochastic volume are significantly reduced. Scenario 3 shows a situation of a "fast reaction" where portfolio managers' stochastic volume is still associated with a low variance but the reaction coefficient is twice as high as in scenario 1. Minimum position holdings (χ) are always set to 20% of the current total long position. We first show financialization scenario 1 results for a base scenario with model 2 parameters. There are only few differences for model 1 parameters and we only mention those that are significant or provide additional insights. The full set of results for the model 1 parameters is presented in Figures A4.1-A4.7 in the Annex. In the following figures, black bars and lines will represent the base scenario and grey lines the financialization scenario.

4.5.2.1 Volume effect

The creation of index funds and the market entry of portfolio managers increases overall trading volume (V_t) on the market, paralleling the empirically observed volume increase for CBOT corn futures (see Figure 4.2). The absolute position size associable with fundamentalist and chartist trading strategies is calculated as:

$$|V_t^{F,C}| = \phi_t^{F,C} |V_t^{CO,S}|, \tag{4.24}$$

Figure 4.5: Volume effect (Model 2, Scenario 1)



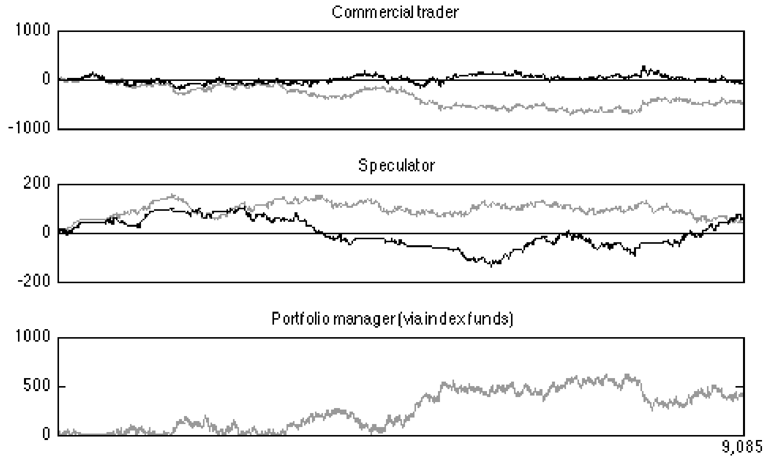
Notes: Black bars represent base scenario results with model 2 parameters, grey bars financialization scenario 1 results.

$$|V_t| = |V_t^F| + |V_t^C|, \tag{4.25}$$

and shown in Figure 4.5. In the base scenario, the mean overall trading volume is 5.1 while in the financialization scenario it is 11.4. In the base scenario, the higher variance in the stochastic commercial trading volume contributes to a higher fundamentalist trading volume while the new portfolio managers' fundamentalist and chartist volume is associated with the same stochastic variance ($\sigma^2_{PM} = 50$).

The total trading position for each trader group sums up the position holdings in each period t over the full simulation period. A positive (negative) total position holding equals a total net long (short) position. The total position development is shown in Figure 4.6. In the base scenario, both commercial traders and speculators either take a net long or a net short position, which can change over the course of the simulation period, depending on the price dynamics. The new portfolio managers' volume is restricted to a net long position that can at maximum be reduced up to a percentage level determined by χ. In the first few periods, the short-selling constraint is frequently binding but is later without effect. In the financialization scenario, the commercial traders' position switches to net short while speculators are predominantly net long. In model 1, both commercial traders and speculators' positions are mostly net short. In any case, the additional net long position of the portfolio managers leads to a change of net positions of the other trader groups. This is possible because the existing traders are as a group not limited in their pos-

Figure 4.6: Position holdings (Model 2, Scenario 1)



Notes: Black lines represent base scenario results with model 2 parameters, grey lines financialization scenario 1 results.

sibilities to either take net short or long positions and switch between them as desired.

4.5.2.2 Price effect

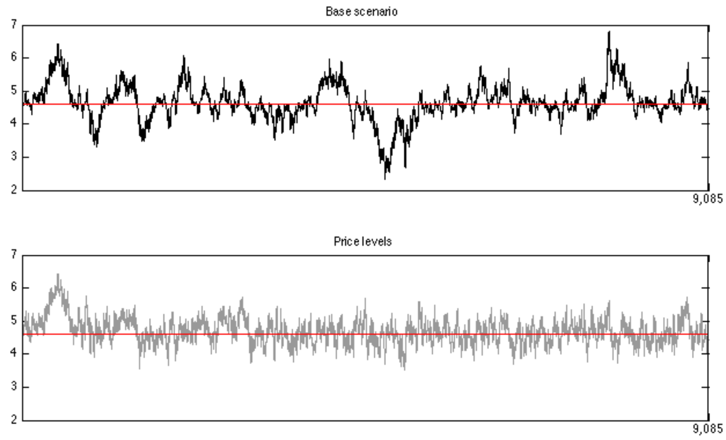
The price dynamics from the base and financialization scenario are shown in Figure 4.7. The additional portfolio manager volume does not inflate the price level but rather has the opposite effect. Apart from the first few periods when portfolio managers' trading volume is very low (and the short-selling constraint is binding), the price dynamics fluctuate closer around the fundamental value and there is less tendency for prices to misalign compared to the base scenario. For model 1 parameters, we obtain the same general results but due to the lower value of the price misalignment coefficient α_m, prices can deviate further away from the fundamental value.

To investigate the volatility effect we use squared returns and the 30-day ($Vol(30)$) and 90-day ($Vol(90)$) return-based volatility, which are calculated as:

$$Vol(m) = \sqrt{\frac{1}{m-1}\sum_{n=1}^{m}(R_{t-n} - \bar{R}(m))^2},\ m = 30, 90. \tag{4.26}$$

The stochastic portfolio managers' volume in Scenario 1 is associated with a variance of $\sigma^2_{PM} = 50$. The SSV model setup implies that the variance inflates the time-dependent variance of the market price (see equation (4.16)). We

Figure 4.7: Price level effect (Model 2, Scenario 1)



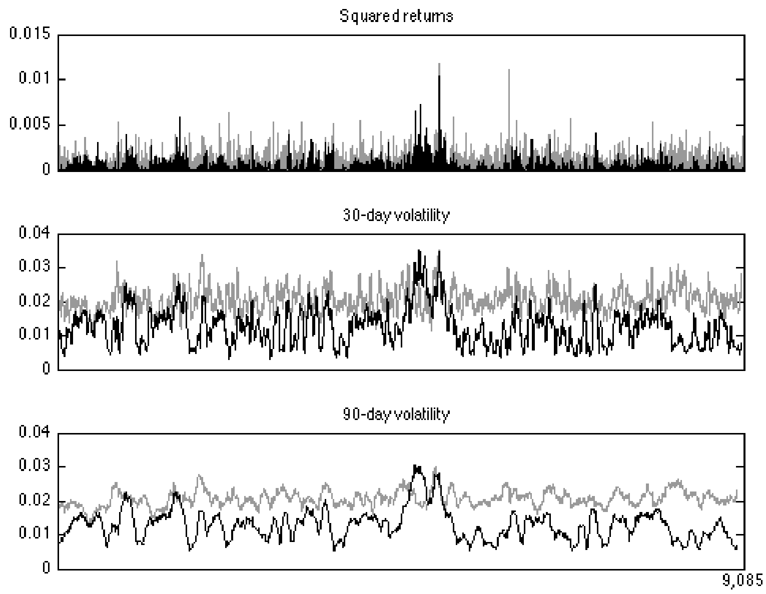
Notes: Horizontal (red) line in price charts represents the constant fundamental price, black lines represent base scenario results with model 2 parameters, grey lines financialization scenario 1 results.

have interpreted the stochastic volume as representing portfolio allocations due to correlations with other assets and as unrelated to stochastic volume from the other traders. If the variance of this volume is high then it significantly increases volatility levels in commodity markets by transmitting new information shocks. With model 1 parameters, the volatility increase is even stronger due to the above mentioned larger magnitude of price deviations away from fundamentals.

4.5.2.3 Effects of parameter changes

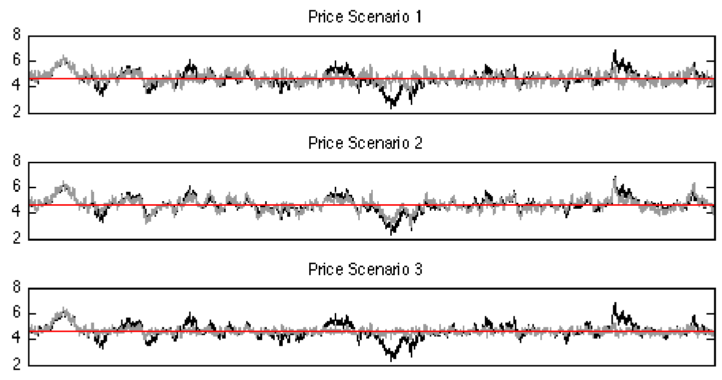
Figure 4.9 shows the price dynamics for the three different financialization scenarios. Comparing the outcome of the "high impact" scenario with the "low impact" and "fast reaction" scenarios, it becomes clear that the observed overall lower price levels and lower likelihood of a price misalignment (or bubble) in the financialization scenario are a result of the size of the portfolio managers' reaction coefficient. Not only the commercial traders and speculators respond to price misalignment by entering or leaving the market but also the portfolio managers by readjusting the weights of their trading strategies. A high reaction coefficient entails a fast reaction to any perceived price misalignments and a market price that will fluctuate closer to the fundamental value. Unsurprisingly, for the model 1 parameter set, where the reaction to price misalignment is much lower, the effect is also visible but much less pronounced.

Figure 4.8: Volatility effect (Model 2, Scenario 1)



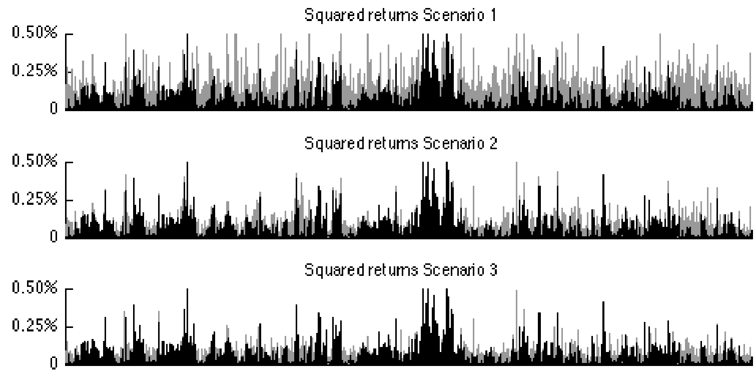
Notes: Black lines represent base scenario results with model 2 parameters, grey lines financialization scenario 1 results.

Figure 4.9: Price levels under different financialization scenarios



Notes: Horizontal (red) line represents the constant fundamental price, black lines represent base scenario results with model 2 parameters, grey lines financialization results for different scenarios.

Figure 4.10: Volatility levels under different financialization scenarios



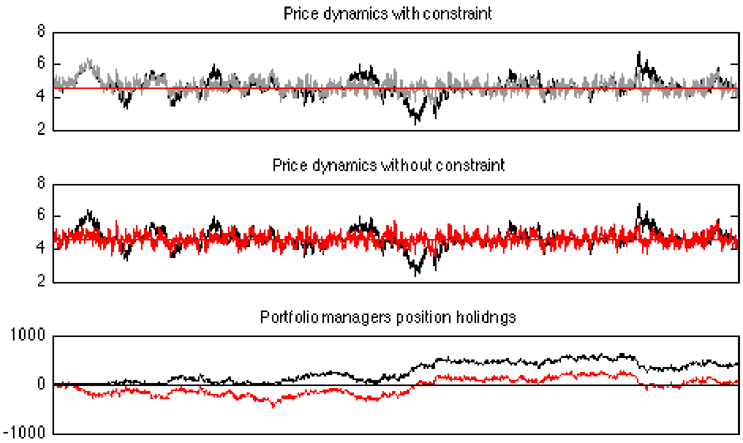
Notes: Black lines represent base scenario results with model 2 parameters, grey lines financialization results for different scenarios.

Figure 4.10 shows the short-term volatility effect. The strongest increase in overall price volatility is brought about by the "high impact" and the lowest increase by the "fast reaction" scenario. In the base scenario, the mean of R_t^2 is 0.019% while in Scenario 1 it is 0.043%, in Scenario 2 0.026% and in Scenario 3 it is only 0.020% and thus relatively close to the base scenario mean. It is clear that a higher variance in stochastic portfolio managers' volume entails a stronger increase in overall price volatility. Thus, in times of market crises that affect asset correlations, the volatility increase on the commodity market could be more pronounced than in tranquil periods. For a given level of stochastic variance, a higher reaction coefficient for the deterministic volume will decrease the volatility level and dampen spikes.

4.5.2.4 Removal of the short-selling constraint

Finally we investigate the effect of a removed short-selling constraint within Scenario 1. The unrestricted trading volume of portfolio managers is determined according to equation (4.11). The results are shown in Figure 4.11. In the first few periods of a binding constraint its removal leads to a net short position of the portfolio managers (third graph). While the short-selling constrained new trading volume did not lead to an inflation of prices above the base scenario levels, price levels are even lower once it is removed, which can be seen from the two price graphs in Figure 4.11.

Figure 4.11: Effects without short-selling constraint



Notes: Black lines represent base scenario results with model 2 parameters, grey lines financialization scenario 1 results, red lines are financialization scenario 1 results without implementation of the short-selling constraint.

4.6 Conclusions

To investigate price effects on agricultural commodity markets from portfolio inclusion of index funds, we employ a few-type HAM with a SSV approach (Franke and Westerhoff 2012) that depicts the price dynamics in the corn futures market populated by fundamentalist commercial traders and chartist speculators. We thereby extend the hitherto econometrics centered analysis on financialization effects with a simulation model approach that allows to directly consider price level and volatility effects of specific trading strategies. Our base scenario parameters are estimated from daily corn futures returns over the period 01/05/1970-12/31/2005 with the MSM. The selected moments capture the overall volatility level, zero autocorrelation of returns, long-memory effects and fat-tailed return distributions. Parameters are validated based on their performance in joint and single moment matching. We thereby extend previous approaches by looking at the whole moment distribution. In our financialization scenario, we model the situation after the year 2005. The increased availability of commodity index funds facilitates market entry of financial portfolio managers who use commodities as portfolio diversifiers and purchase index fund shares rather than single futures contracts. Thereby, portfolio managers' demand depends on individual commodity returns, evaluated with a mixed fundamentalist-chartist strategy, and on return or volatility correlations with other portfolio assets, modeled as a stochastic demand component.

In the base scenario, we compare results from two parameter sets and demonstrate that the trader group with the highest variance in the stochastic volume carries the largest information shocks to the market and thus directly increases volatility levels. The price level, on the other hand, is most strongly affected by how fast traders respond to changes in the factors that affect their deterministic volume and by the traders' reaction to price misalignment on the market. Thereby, higher reaction coefficients decrease the persistence of price deviations and move prices closer to their fundamental value.

In the financialization scenario, portfolio managers' trading via index funds creates new long-only trading volume from the funds' index replication activities. But, price levels are not inflated but rather fluctuate more closely around the fundamental value when the deterministic demand of portfolio managers reacts to price misalignments and herding tendencies. Given these model assumptions, the Masters hypothesis of index funds replication volume creating price bubbles on the market cannot be confirmed. A removal of the short-selling constraint would even further reduce the occurrence of price deviations. In contrast, the volatility effect is more pronounced. The information shocks created by the stochastic portfolio managers' volume that are assumed to be linked to correlations with other asset markets directly increase volatility levels. The higher the variance of these demand or supply shocks, e.g. in times of financial crises, the larger the volatility increase. The transmission of information shocks affecting volatility is most closely related to the argument in Irwin et al. (2009) where new volume would affect prices if it transports new information to the market. In our model, index fund replication volume may thus increase price volatility but decreases price levels.

Future research could, on the one hand, focus on modifying the model design and addressing some current limitations. Liquidity constraints for the group of commercial traders and speculators or specific position requirements due to hedging of primary business activities could influence the price level effect. Time-varying correlations between commodities and other financial assets could be modeled more explicitly within a multiple market setup and also consider crisis effects. And, spot and futures markets could be linked via the fundamental value of the commodity. Finally, the model could be used for the analysis of regulatory proposals such as transaction taxes or price limits. One the other hand, model estimation and validation also hold potential for future research, e.g. by considering different random number seeds already during the minimization rather than in an ex-post validation and extending the current methods used for parameter validation.

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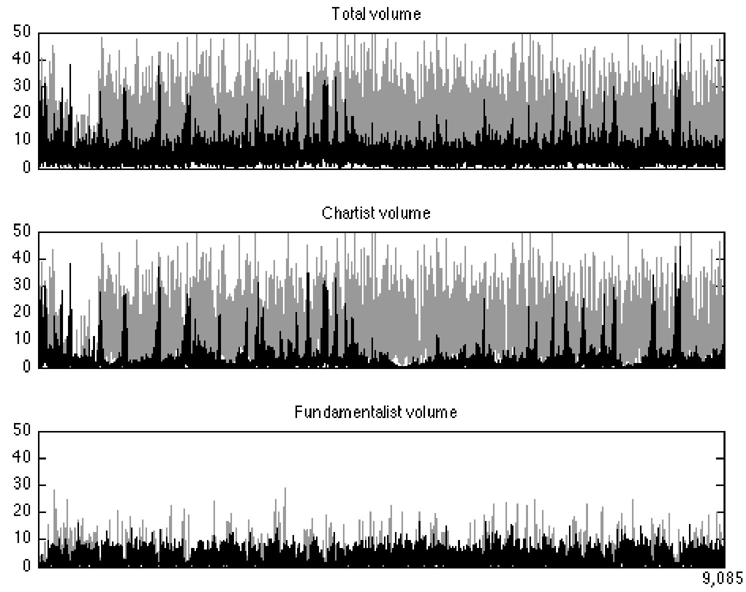
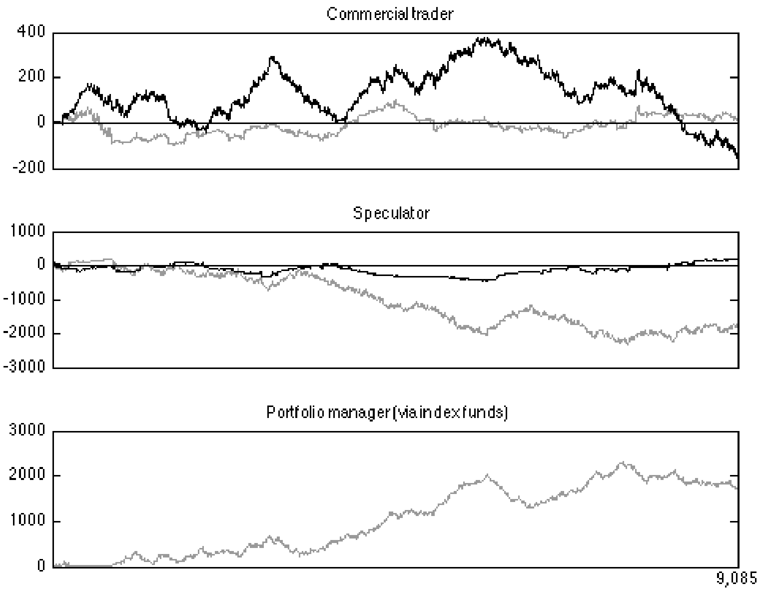
4.8 Annex

A4.1: Volume effect (Model 1, Scenario 1)



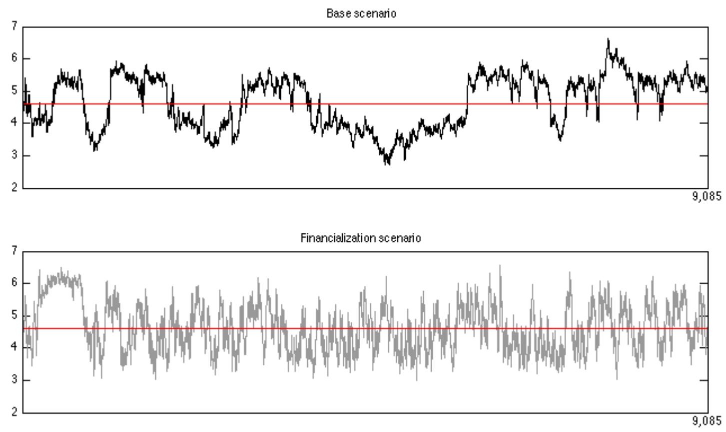
Notes: Black bars represent base scenario results with model 1 parameters, grey bars financialization scenario 1 results.

A4.2: Position holdings (Model 1, Scenario 1)



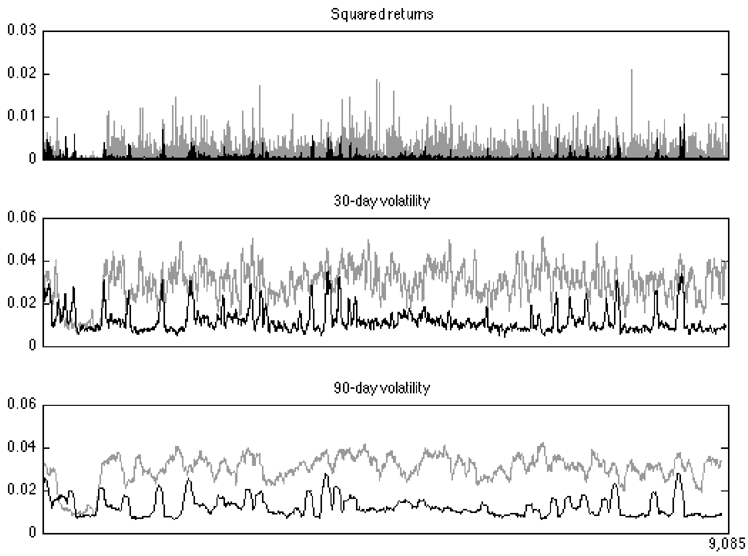
Notes: Black lines represent base scenario results with model 1 parameters, grey lines financialization scenario 1 results.

A4.3: Price level effect (Model 1, Scenario 1)



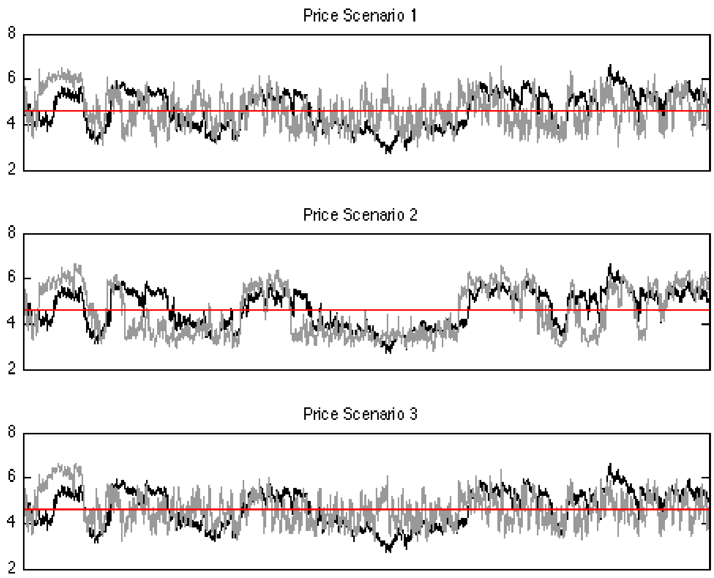
Notes: Horizontal (red) line in price charts represents the constant fundamental price, black lines represent base scenario results with model 1 parameters, grey lines financialization scenario 1 results.

A4.4: Volatility effect (Model 1, Scenario 1)



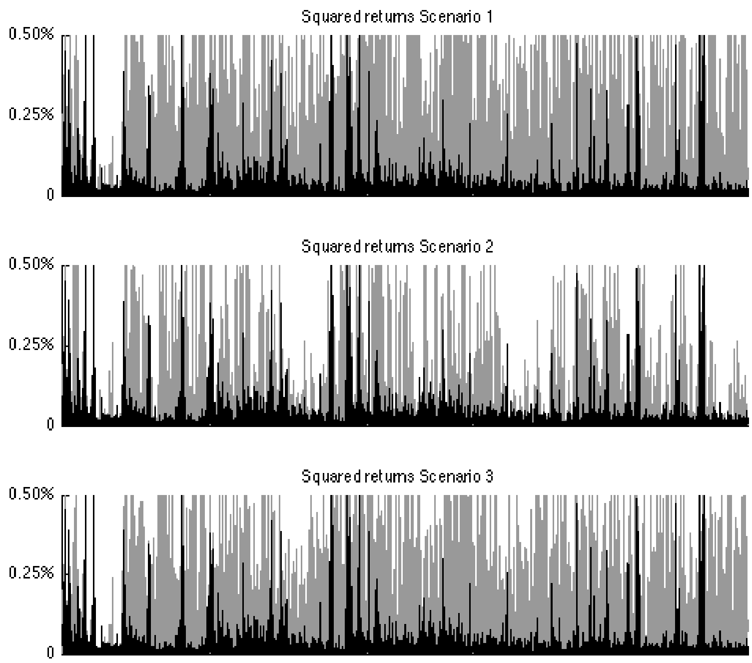
Notes: Black lines represent base scenario results with model 1 parameters, grey lines financialization scenario 1 results.

A4.5: Price levels under different financialization scenarios



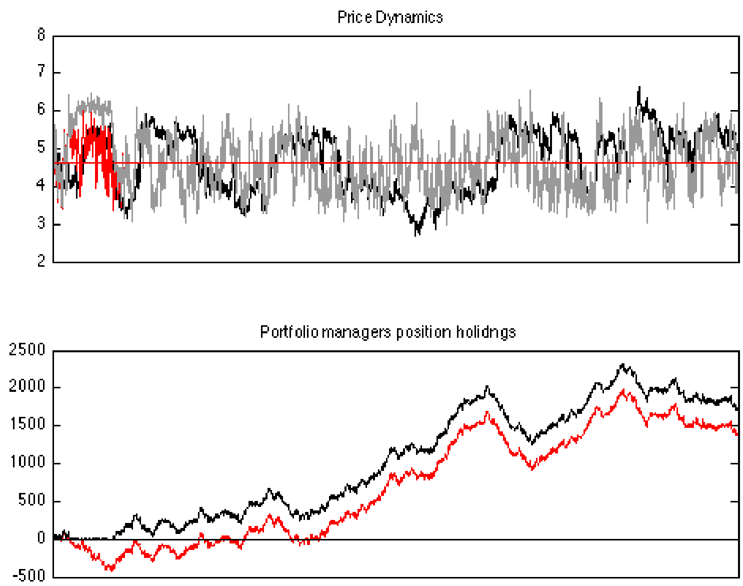
Notes: Horizontal (red) line represents the constant fundamental price, black lines represent base scenario results with model 1 parameters, grey lines financialization results for different scenarios.

A4.6: Volatility levels under different financialization scenarios



Notes: Black lines represent base scenario results with model 1 parameters, grey lines financialization results for different scenarios.

A4.7: Effects without short-selling constraint



Notes: Black lines represent base scenario results with model 1 parameters, grey lines financialization scenario 1 results, red lines are financialization scenario 1 results without implementation of the short-selling constraint.