Four Essays on Commodity Price Dynamics and Risk

Fire essay om råvarepriser og risiko

Philosophiae Doctor (PhD) Thesis

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Summary

This thesis consists of four empirical studies of commodity markets, with emphasis on agricultural commodities and energy. Employing a variety of time series techniques, I analyze market behavior, price dynamics and risk.

The first essay deals with long-run development, interrelationships and possible structural breaks in the production and pricing of the three major grains, i.e. corn, wheat and soybeans. This is an explorative study, where we look at grain prices and production in a historical (long-term) perspective. Focusing on major political and other events, I analyze long-run price equilibrium, and short-term adjustments of deviations from this equilibrium 1961-2016. My main conclusion is that grain markets generally adjusts smoothly and continuously. This implies that producers and consumers adjust to dramatic events quickly and effectively, perhaps reducing the need for seemingly required regulations imposed by politicians. The first essay also acts as an introduction to the subsequent essays that take a much more short-term perspective oncommodity markets, and the fundamental factors influencing commodity markets.

The second essay is a contribution to the debate on whether speculation is destabilizing commodity markets. Many have argued that commodity prices have been disconnected from their fundamental values. Instead, it is claimed, prices are driven by psychological factors and financial sentiments with similar impacts across commodities that are only remotely (physically) connected. Adopting a framework known from event studies I examine whether oil price shocks, defined as a large price change from one day to the next, are immediately (or rapidly) transmitted to the grain markets. I argue that studying co-movement in the very short term is a way of solving the predicament of disentangling speculative and fundamental influences on commodity prices. My findings do not support the notion of herd behavior and excess co-movement between energy and grain pricess.

My third essay examines hedging behavior in the oil market, and try to answer whether those who are classified as hedgers in the weekly Commitments of Trader reports (published by the U.S. Commodities Futures Trading Commission) are pure hedgers or whether they also take positions based on price expectations. Employing a State Space representation, I find that hedgers in the market for crude oil vary their positions substantially from month to month,

seemingly inconsistent with a risk minimizing hedging strategy. This suggests that there may be a speculative component to hedgers' trading decisions. My analysis of the relation between oil price variability and hedging commitments suggests that short hedgers focus on truncating their tails to avoid very costly outcomes, rather than pure variance reduction. This is consistent with the theory of selective hedging presented Stulz (1996). I find no significant relation between short hedging commitments and the OVX. Long hedging commitments on the other hand, is negatively related to expected price risk, as measured by the OVX. This is a puzzling phenomenon, as one would expect long hedgers to hedge more in an (perceived) increasingly risky market. The observed relationship might be due to long hedgers reducing the speculative component of their futures portfolio faced with turbulent market conditions.

My analysis supports the findings from Cheng and Xiong (2014)'s study on hedging in agricultural futures, namely that hedgers engage in significantly non-output related trading. However, although I find that hedgers in the oil market trade substantially more than what seems consistent with traditional risk minimizing, I do not agree with the main conclusion in Cheng and Xiong (2014). Since hedgers are typically speculating in the *physical* market (by adjusting production or leaving their positions exposed to price risk), considering regulations or policy measures geared towards this group appears redundant.

The forth essay is co-authored with Dr. Glenn Kristiansen, and analyses commodity market variability using an Extreme Value Theory (EVT) approach. We add to the literature on food price volatility by analyzing the tail segment of futures price return distributions 1995-2013. Finding no indication of systematically increasing tail risk in agricultural commodity markets, with a possible exception for grains, we conclude that there no general systematic change in the extreme risk associated with commodity investments. Our analysis further support the traditional view that agricultural price volatility is mainly driven by shocks to supply and demand, like adverse weather or dramatic political events. This is an important finding, because volatility driven by fundamentals cannot be tamed by regulation. To the contrary, one needs to look for good ways to manage this risk.

Forord

Denne avhandlingen består av fire empiriske studier av råvaremarkeder, med vekt på landbruksprodukter og energi. Vi benytter tidsserie-økonometri for å analysere markedsadferd, prisrelasjoner og risikostyring.

The første essayet undersøker langsiktige relasjoner og utvikling i produksjon og prissetting av hvete, mais og soyabønner. Med utgangspunkt i et relativt åpent forskningsspørsmål analyserer vi i hvilken grad den globale produksjonen av disse kornsortene er preget av kontinuitet eller strukturelle brudd. Våre funn viser at kornpriser er sterkt kointegrert, og at avvik fra langsiktig likevekt justeres hurtig. Vi oppsummerer viktige politiske og andre dramatiske hendelser, men finner at produsenter og forbrukere i landbruksmarkedet tilpasser seg endringer raskt og effektivt. Dette første essayet fungerer også som en introduksjon til de etterfølgende essayene, som har et mye mer kortsiktig perspektiv.

Det andre essayet er et bidrag til debatten om spekulasjon og uro i råvaremarkeder. Mange har hevdet at råvarepriser har blitt frikoblet fra fundamentale faktorer som tilbud og etterspørsel. Det hevdes at priser er drevet av psykologiske faktorer og at råvarerpriser varierer i takt, selv om de kun er svakt (fysisk) forbundet. Vi bruker et rammeverk kjent fra litteraturen om «event studies», og undersøker om sjokk i oljemarkedet umiddelbart (eller raskt) smitter over i markedet for korn. Jeg argumenterer for at å studere samvariasjon på veldig kort sikt er en måte å separere hvordan spekulasjon og fundamentale faktorer påvirker pris. Mine funn støtter ikke hypotesen om at spekulasjon har skapt unaturlig samvariasjon mellom energi- og kornmarkedet.

Mitt tredje essay undersøker hedging i oljemarkedet, og prøver å svare på om de som klassifiseres som hedgere[1] kun fokuserer på å minimere prisvarians, eller om de også tar posisjoner i futures markedet basert på forventninger om fremtidige priser. Vi finner at hedgere i markedet for olje handler mye og ofte, og langt mer en hva som samsvarer med risikominimerende strategi. Dette tyder på at det finner en spekulativ komponent i hedgerenes handelsbeslutninger. Min analyse av forholdet mellom oljeprisvariabilitet og hedging-

[1] i ukentlige rapporter om handelsposisjoner publisert av US Commodities Futures Trading Commission

forpliktelser tyder på at korte hedgere fokuserer på å minimere halerisiko for å forhindre svært dyre, potensielt katastrofale utfall, heller enn ren variansreduksjon. Dette er i tråd med teorien om selektiv hedging presentert Stulz (1996). Jeg finner ingen signifikant sammenheng mellom korte sikriforpliktelser og OVX. Den lange siden er derimot negativt knyttet til forventet prisrisiko, målt ved OVX. Dette er overraskende, da man forventer at lange hedgere sikrer mer i et mer risikabelt marked. Det vi observerer kan skyldes lange hedgere reduserer den spekulative delen av futuresporteføljen når de forventer turbulente markedsforhold. Min analyse støtter funnene fra Cheng og Xiong (2014)'s, de finner at hedgere handler langt mer enn hva som er naturlig i forhold til deres produksjon.

Det siste essayet analyserer volatilitet i råvaremarkedet og er skrevet sammen med Glenn Kristiansen. Vi metoder kjent fra ekstremverdi-analyse og analyserer hale-segmentet av fordelingen av avkastningene hos en rekke råvarer 1995-2013. Vi finner ingen indikasjon på at risikoen i råvaremarkedene har økt systematisk i denne perioden, med et mulig unntak for korn.

Vår analyse støtter videre den tradisjonelle oppfatningen om at priser i landbruket hovedsakelig påvirkes av sjokk på tilbud og etterspørselssiden, som ugunstig vær eller dramatiske politiske hendelser. Dette er et viktig funn, fordi volatilitet drevet av fundamentale faktorer vil være umulig å redusere ved hjelp av markedsreguleringer. Man må heller fokusere på å håndtere denne risikoen, for eksempel via hedging i futures.

Four Essays on Commodity Price Dynamics and Risk: Backdrop and Context

Introduction

When I began writing this dissertation, global commodity markets had recently experienced a period of boom and bust. In July 2008, WTI crude oil peaked at USD 145 per barrel, up from approximately USD 50 in January 2007. By December 2008, five months late, oil was traded in the vicinity of USD 45. Corn prices surged from USD 3.10 per bushel in July 2007 to USD 7.30 per bushel in June a year later. Prices then plummeted to USD 3.50 by November 2008.

The dramatic commodity price increases in 2007-08 gave rise to a heated debate on global food security, and whether more regulations are needed in order to secure the proper functioning of commodity markets. This dissertation is a contribution to this discussion, but I also focus on commodity markets in a broader context.

Looking back on some 15 years of volatile commodity prices it is easy to understand why the functioning of these markets attract the attention of policy makers, academics and market participants alike. Commodity prices and their fluctuations have a major impact on the global economy. Virtually all nations trade in food and raw materials and as such, changes in commodity prices have trade bill effects with a net outcome that depends on whether a country is a net commodity importer or exporter. International trade is closely related to welfare and growth. In a more domestic perspective, commodities make up an important part of the Norwegian economy. This goes way beyond production of oil and gas. Energy, in particular Norway's 130 TWh hydropower production, is processed downstream into fertilizer, aluminum, ferrosilicon, zink, and various alloys. Seafood, both farmed and wild fish, generates more than NOK 60 billion in export earnings (2016). For centuries forestry, and the production of lumber, fiber, paper and pulp for the international market, has played an important role in the Norwegian economy. On the consumption side, Norway imports roughly 50% of its food consumption, directly as fruits, cheeses, flour, sugar, coffee, tea etc., and indirectly as inputs into Norwegian agriculture and aquaculture (soymeal, soya oil, corn, wheat) and into food and beverage industries (organic oils, sugar, cocoa, malt, etc.).

Despite these key roles in the domestic economy, remarkably little systematic research on commodity markets (beyond electricity, oil and gas, and to some extent fish) has been conducted in Norway. This applies to individual commodity markets, but even more so to *the interrelationships* between different commodities –similar as well as physically unrelated. Likewise, commodity production, markets and trade occupy little space in the teaching at Norwegian business schools.

As previously mentioned, commodity trading is a key element in modern growth, and access to global markets is important for both developed and developing countries. Many developing nations are net importers of food and processed goods. For governments in these countries, increasing commodity prices in particular can have a significant and adverse impact on the import bill and welfare. Scarce foreign exchange reserves might dwindle quickly faced with a sudden spike in food prices if the demand-elasticity for food imports is low. This implies that commodity price volatility can create both import bill and concomitant exchange rate uncertainty (Gilbert and Morgan 2010). If governments with limited foreign exchange reserves are unable to import sufficient staple food commodities to meet domestic needs, it can ultimately lead to public unrest. Towards the end of the 2002-08's food price surge, public demonstrations against higher food costs were held in several developing countries (Trostle, Rosen et al. 2011), and contributed to political upheavals. Thus, food prices have been claimed to have a major impact on the events in Northern Africa 2010-12, i.e. "the Arab Spring".

Developed, industrial nations spend a lesser share of their import bill on food and raw materials, and are thus usually most concerned about the impact rising commodity prices might have on inflation (Kaldor 1987). A commodity price increase can cause inflation by pass-through of raw material costs onto the final prices faced by consumers, and through additional wage increases aimed at making up for the increased cost of living.

A key word in commodity finance is scarcity. Land is a finite resource, and sectors like agriculture, mining and housing all compete for land shares. Several commodities are also finite resources themselves, like e.g. oil, gold and minerals. Hotelling's rule (Hotelling 1931) states that the optimal extraction path of an exhaustible resource is one where the price of the resource, determined by marginal net revenue, grows at the rate of interest. It turns out that the underlying assumptions are too restrictive for this rule to accurately reflect real prices (see e.g. Gaudet 2007), still it is a useful way of conceptualizing the basic intuition that prices should rise in order to cover the opportunity cost of foregone income growth that would result from extraction. Hotelling's result is an early contribution towards the debate on "sustainable development", formally defined in the Brundtland, Khalid et al. (1987) as *"... development that meets the needs of the present without compromising the ability of future generations to meet their own needs".*

This dissertation will not deal with sustainability in the environmental sense, but touch on the topic of sustainability in relation to food security and population growth. The question of whether agriculture is able to feed a growing population has reoccurred periodically in the public debate ever since Malthus (1798) argued that population growth generally expanded in times of plenty until the size of the population relative to primary resources causes distress. Based on continuous improvements in food production, these worries seem to be unfounded at least so far. Over the last decades, we have witnessed significant technological changes in the field of agriculture where new varieties and more efficient production have led to increasing yields. Tilman, Cassman et al. (2002) show that cereal production has doubled in the time period 1960-2000. This growth is mainly caused by increasing yields due to greater inputs of fertilizer, water and pesticides, new crop strains, and other technologies. FAO (2015) reports major progress in the fight against hunger, but also notes that the progress towards improved food security continues to be uneven across regions. In this context, we believe it is important to recognize that food security is contingent on more than world available supplies of food. Food security also depends on income, and the population's access to the available supplies, which implies that there is a direct relationship between food security, world trade in food, and access to international commodity markets.

I also include the market for crude oil in my analysis. Crude oil is the world's most liquid futures market. Since the 1980s, oil producers, downstream processors and consumers have been able to hedge their price risk at futures exchanges. Oil has been the world's most important source of energy since the mid-50s. Its products contribute to modern societies in a wide range of areas, from heating homes to providing fuel for cars and airplanes. It is an important component in chemical plants and other industries, and plays a key role as provider of energy in mining and processing of metals and minerals. Through its role as energy provider oil is also a major input in the transportation sector and in agriculture. In many ways, one can say that the market for crude oil is connected to all other commodity markets as a source of energy and as input in the production of numerous chemical products. .

Commodity markets – a venue for allocating resources and risk

Commodities are as old as humanity, and exchanging food and materials have been around for as long as we have had modern civilizations. From the late 10th century onwards, factors like urbanization, regional specialization and improved infrastructure across the British Isles and Continental Europe led to the formation and organization of commodity markets (Dijkman 2010). These markets were not mere trade fairs that served to balance supply and demand, but rather marketplaces governed by rules, customs and practices that served to determine the risks and costs of exchanging goods. Typically, such markets develop to reduce the costs to trading. Transaction costs comprise a wide range of costs incurred when performing a transaction, such as information costs, i.e. the costs associated with acquiring adequate information on market opportunities and conditions, and bargaining and decision costs. Later on, the formalizing of commodity markets has been an important way of reducing uncertainty and allocating (exchanging) risk among the market participants.

This dissertation deals with commodity price dynamics and risk, with special emphasis on the grain markets. This commodity group is close to man in that it represents the mainstay of diets in many countries. Grains are also an important input in the meat and dairy industry, in other words one might say that the majority of the global population derive a large part of their calorific needs from grains in some way, shape or form. In addition to their apparent connection to dairy and meat markets, grains are more recently also linked to energy through the biofuel industry. Hence. There are close links between oil and agricultural commodities, in particular the major grains.

The modern grain trade originated with the massive demand for wheat that was created by the industrial revolution (Morgan 1979). The factory towns of England and Western Europe attracted tens of thousands of peasants and farmers; new laborers that were removed from their traditional food supply, now relying on buying bread as a staple in their diets. New trade routes formed, and Southern Russia and North America eventually became main suppliers of wheat for the British Isles, in particular to the industrialized cities of England. The world has changed in so many ways since the nineteenth century, but the demand for wheat remains relatively stable on a per capita global basis. Wheat continues to be the most important food grain source for humans, and is grown on more land area than any other commercial crop (Curtis 2002).

Wheat was also the first commodity to be traded at a modern exchange, when the Chicago board of Trade (CBOT) was founded in 1848. Since that time, traders have sought ways to simplify and standardize contracts to create convenient vehicles for transferring risk. Well-functioning futures markets are important in a social welfare perspective. By aggregating information, futures markets allow producers and investors to channel their resources to the most efficient use. This price discovery function is one of the two core functions of a futures market. The second is risk transfer. Through the exchanges, producers can hedge their risk and speculators are given access to an investment with diversification benefits due to low correlation with capital markets (Chong and Miffre 2010). Well-functioning exchanges contribute to low transaction costs and reducing counterparty risk.

When food prices rose to record high levels in 2008 and again 2011, it concerned policymakers and NGOs worldwide. Some, e.g. Michael Masters in his 2008 testimony to the senate, or Foodwatch in their 2011 report titled "The Hunger-Makers", blamed speculators for the price increase. Predictably, the suggestion that investment banks were *"speculating with food at the expense of the poorest"* caused moral outrage. At the same time, the academic discourse became focused on whether speculation or scarcity was driving the upsurge in commodity prices. Today, studies analyzing the effect of speculation in futures markets are abundant (see e.g. Irwin and Sanders (2011), Irwin and Sanders (2012), Tang and Xiong (2012), Kilian and Murphy (2014), Steen and Gjølberg (2013), Henderson, Pearson et al. (2014), Demirer, Lee et al. (2015), Bhardwaj, Gorton et al. (2016), Bruno, Buyuksahin et al. (2016)). Using different methods and datasets, these studies have produced mixed results on whether speculation is harmful or helpful. I will weigh in on this discussion during this dissertation, for now I merely note that speculators are an essential part of any futures market as liquidity providers.

Grains and oil: Some stylized facts on production and trade

Through its production, processing and extensive supply chains, commodity markets employ hundreds of thousands of people and make a major contribution to the world economy. To illustrate the size of these markets, we summarize global production of crude oil and grains in table 1. As can be seen, approximately 30 000 million barrels of oil are produced every year, amounting to some 1 300 billion dollars. To put these numbers into some form of context, one day's worth of oil production is larger than the GDP of Somalia and Djibouti – combined. It is three times the cost of building the Burj Khalifa in Dubai, which is currently the tallest skyscraper in the world and holds 30 000 homes, nine hotels, the Dubai Mall and an artificial lake.

Crude oil is the worlds most heavily traded commodity, and a large part of production is sold across borders. OPEC (Organization of the Petroleum Exporting Countries and Russia are the major producers and exporters. China and the United States also produce large quantities of oil, but consume the majority of their energy production domestically.

Table 1: Global production and trade – volume and value 2016

	Production volume	Value, billion dollars**
Crude oil (Million barrels/Year)*	30 000	1 300
Wheat (1000 MT/Year)#	745 000	120
Corn (1000 MT/Year) #	1 000 000	150
Soybean and oilseeds (1000 MT/Year) #	340 000	120

* Source: EIA - Monthly Energy Review
** Based on 2016 average prices, spot data from the EIA for crude oil, and front month futures from the CME for grains
# Source: United States Department of Agriculture, downloaded from www.indexmundi.com

Although modest compared to global oil production, the annual world production of wheat, corn and soybeans is substantial. Taken together, 2016 annual production amounts to some 390 billion dollars. A large part of this production is traded internationally. For instance, the United States and Russian Federation both exported nearly half their annual wheat production in 2016. The United States has a long history of agricultural trade and production, and has grown wheat for export since the colonial period. After the civil war in 1861-1865, better ploughing equipment came into use, hard winter wheat was introduced, railroads provided better access to world markets, and new and better trading facilities were built (Montgomery 1953). Today, agriculture is still a major industry on the American continent, and the Midwest in particular has evolved into a highly specialized cash-grain farming area. The United States are is still the leading global corn producer and exporter, but Brazil and Argentina are also producing large quantities of corn and soybeans for export. In 2016, Brazil exported some 60 million MT soybeans, which represents roughly 20% of global trade year exports that year.

While the United States and Russian Federation export nearly half of their wheat production and Canada one third, China keeps the majority of their production of wheat, corn and soybeans for domestic consumption. Further, we see that while the U.S. New technologies and improved resource management have made these countries develop into rich agricultural nations. Major increases in production has occurred, particularly in Brazil, where the region of Mato Grosso and large areas of savannah in central Brazil has been transformed from infertile land to productive farmland through new technologies (Arvor, Meirelles et al. 2012). We will discuss these developments in detail in essay 1.

The four essays

This dissertation consists of four independent essays. Their unifying theme is trying to contribute to a better understanding of price relationships and variability within and across different (physically related and unrelated) commodities. While essays 2-4 are written within a commodity-finance tradition, the first essay takes an economics history approach. This study is explorative in nature, and discusses an issue well known in economic history, namely continuity versus breaks. Beyond being interesting in itself, I believe a survey and analysis of long-term developments in the grain sector is relevant and useful in relation to the subsequent short-term price analyses (essay 2-4).

The first essay deals with long run development, interrelationships and possible structural breaks in the production and pricing of the three major grains, i.e. corn, wheat and soybeans. Participants in the public debate on commodity prices and commodity market volatility often appear to be myopic. Evaluations of the present situation and forecasts of what is going to happen are often formed by the very recent past. As an example, the public debate after the 2008 commodity price spike was to a large extent driver by what in retrospect turned out to be a short lived price boom. At that time, many of the participants in the debate seemed to have forgotten that short-term dramatic price changes have occurred several times throughout history. There is sometimes a need for putting recent developments in a long-term perspective. Essay 1 is a contribution in this respect. The aim of this essay, "Are grain markets infected by oil price shocks? An empirical analysis of the effects from dramatic oil price changes on grain prices", is to give an overview of how absolute and relative output, yields, and prices have evolved in world grain production during the last 54 years. This period was characterised by a number of dramatic political events like e.g. the collapse of the Bretton Woods system, two major oil crisis', and the disbandment of the Soviet Union. There were also significant technological innovation in the field of agriculture, and new varieties and more efficient production methods have contributed towards a massive increase in yields. Focusing on some of the events that pertain specifically to agriculture, I analyze long-run price equilibrium, and short-term adjustments of deviations from this equilibrium over this 54-year period. Asking whether world grain production has been characterised by continuity or structural breaks I perform statistical tests for structural breaks, where the null is in favour of the primer, i.e. continuity. This research question is relevant in two dimensions. First, a large part of the global population relies on grains as the main part of their staple diet, which means that variations in production and prices of these commodities can come at great human cost, especially in poorer nations. Second, virtually all economies trade in food, which means that dramatic changes in grain production and prices may lead to significant trade bill effects.

When the debate on whether more regulation is needed to reduce destabilizing trading impacts from purely financial investors, it is likely due to the difficulty of disentangling "speculative" and “fundamental” effects on prices. My main conclusion is that grain markets generally adjusts smoothly and continuously. This implies that producers and consumers adjust to dramatic events quickly and effectively, perhaps reducing the need for seemingly required regulations imposed by politicians. The first essay also acts as a primer on commodity markets, and what separates commodity trading from trading in other assets. Commodities are different in that they exist to be consumed, and not to generate future returns. In that sense, they are not financial assets. Long-term commodity prices are determined by a combination of fundamental factors and the interaction of supply and demand. In the short run, price changes are driven by inflow of information to the market place, forming expectations regarding future supply and demand dynamics.

Typically, agricultural price booms and periods of high volatility are caused by shocks to the supply side. Weather events or animal diseases that disturb the normal pattern of variation that is expected in agricultural production are examples of such shocks. As such, one would not expect a shock in one market to have an immediate effect on the price of a physically unrelated product.

Over the last couple of decades, academic and public debate on commodity price dynamics and volatility has centered around concepts like “excess volatility” and more recently “financialization”. Many have argued that commodity prices have been disconnected from their fundamental values. Instead, it is claimed, prices are driven by psychological factors and financial sentiments with similar impacts across commodities that are only remotely (physically) connected. My second essay, “Are grain markets infected by oil price shocks? An empirical analysis of the effects from dramatic oil price changes on grain prices”, is a contribution to this debate. Linking oil and grain markets, I ask whether commodity markets are moving too much in tandem, suggesting that herding behavior rather than fundamental factors are driving the prices. Adopting a framework known from event studies I examine whether oil price shocks, defined as a large price change from one day to the next, are immediately (or rapidly) transmitted to the grain markets. I hypothesize that if commodity markets have truly become a market of one, oil price shocks should be visible in grain market prices the same day, or at least on a next day basis. My main contribution to the literature is a study of price relationships and patterns one might fail to uncover using data on a monthly, or even weekly frequency (see Williams and Cook (2016) for a discussion on how low frequency data can be a challenge in examining short-term relations in financial markets). To date, weekly and monthly data is what has been typically used to study the effects of speculation and potential herding in commodity markets. I argue that studying co-movement in the very short term is a way of solving the predicament of disentangling speculative and fundamental influences on commodity prices. My findings do not support the notion of herd behavior and excess co-movement between energy and grains.

The question of how commodity markets, and in particular speculators, contribute to price stabilization (or volatility) has been debated for decades. There is a huge body of literature on this issue, which resurfaced in 2008 (see e.g. Haase, Zimmermann et al. (2016) for a recent and thorough review). Not surprisingly, many blamed speculators in the futures market for causing the oil price surge (see also Fattouh, Kilian et al. (2012) for critique and references), and the academic discussion typically focus on speculators and their trading activities. A notable exception is Cheng and Xiong (2014), who ask why hedgers engage in significant non-output related trading. In his essay "In defense of Destabilizing Speculation", Friedman (1960) suggests that the traditional dichotomy of "legitimate" producers buying "insurance" from the speculator may be flawed. Rather, Friedman argues, the futures market may be seen as a market where *"a "legitimate" producer engages as a side-line in selling "gambles" to speculators willing to pay a price for gambling and knowingly doing so"*. In my third essay, I follow up on this issue and examine whether weekly crude oil futures hedging commitments, as presented in the Commitment of Traders reports 2006-2016, are more consistent with hedging or speculative activities. In line with Friedman's conjecture, I consider the possibility that hedgers to some extent also speculate in futures by taking positions beyond what will minimize risk.

Employing a State Space representation, I find that hedgers in the market for crude oil vary their positions substantially from month to month, seemingly inconsistent with a risk minimizing hedging strategy. This suggests that there may be a speculative component to hedgers' trading decisions. My analysis gives some indication that hedgers scale their positions up or down with expectations of relative price changes (futures versus spot). However, as far as short hedgers are concerned, the scaling of commitments do not appear successful *ex post*.

There are asymmetric effects in how long and short hedging commitments relate to oil prices and oil price variability. My analysis of the relation between oil price variability and hedging commitments suggests that short hedgers focus on truncating their tails to avoid very costly outcomes, rather than pure variance reduction. This is consistent with the theory of selective hedging presented Stulz (1996). I find no significant relation between short hedging commitments and the OVX. Long hedging commitments on the other hand, is negatively related to expected risk conditions, as measured by the OVX. This is a puzzling phenomenon, as one would expect long hedgers to hedge more in an (perceived) increasingly risky market. The observed relationship might be due to long hedgers reducing the speculative component of their futures portfolio face with turbulent market conditions.

My analysis supports the findings from Cheng and Xiong (2014)'s study on hedging in agricultural futures, namely that hedgers engage in significantly non-output related trading. However, although I find that hedgers in the oil market trade substantially more than what seems consistent with traditional risk minimizing, I do not agree with their main conclusion in Cheng and Xiong (2014). Since hedgers are typically speculating in the *physical* market (by adjusting production or leaving their positions exposed to price risk), considering regulations or policy measures geared towards this group appears redundant.

As previously mentioned, people can be shortsighted on the wake of dramatic events. Sumner (2009) is an exception. He compares the 2006-08 price developments with other episodes of extreme commodity price fluctuations in the 19th and 20th centuries. He concludes that the price increases from 2006 through 2008 (using grains as an example) were among the largest during the last 140 years. However, Sumner demonstrates that extreme booms (and busts) have occurred several times in the past.

I complete my dissertation by broadening the scope and examining a wide range of agricultural commodities in the final essay. This paper is written with Dr. Glenn Kristiansen. In "Commodity market risk from 1995 to 2013: an extreme value theory approach", we ask whether the amount of extreme price deviations have increased during an 18 year period. This period includes the 2006-08 and 2011-12 run-up in commodity prices. We add to the literature on food price volatility by analyzing the tail segment of futures price return distributions. Measuring dispersion around the mean can give a good gauge of movements around a trend or a central tendency, but fails to capture the risk associated with the extreme events that manifest themselves as outliers in the data. We ask the reader to note that our analysis is not meant as a replacement of traditional measures of risk like e.g. the standard deviation, but rather as a way of supplementing existing analyzing techniques.

In this study, we employ a variation of the block maxima estimation method known from Extreme Value Theory (EVT). This framework use asymptotic results that hold for a wide range of parametric distributions, and provides the possibility of focusing on the two tails of the distribution separately, which is appropriate when faced with the skewed distributions one typically find in commodity markets. To circumvent the problem that extreme events are by definition very rare, we use the bootstrap to estimate all test statistics and make assessments about inference. With a possible exception for the major grains, we find no indications of systematically increasing tail-risk for the commodities in our sample. Analysis of estimated shape-parameters of the Generalized Extreme Value distribution further supports the conclusion that there is no general systematic change in the extreme risk associated with these commodity investments.

Closing remarks

Finally, a few sentences on style of presentation. Empirical analysis requires formal modelling and statistical techniques; this dissertation is no exception. However, my aim has been to give priority to economic understanding and simplicity. There are several graphs to be found in the four subsequent essays, the models are generally parsimonious, and there is little fancy econometrics. There are, obviously, potential dangers in taking this approach. Graphs can give a distorted view of reality, and sometimes lead to erroneous conclusions if accepted at face value. Standard and simple econometric techniques may be to "rough" to give accurate descriptions, and can be unsatisfactory on some levels. On the other hand, complicated methods can make it hard to distinguish the weaknesses of a given model. Black (1982) discusses how econometric modelling can sometimes present correlations disguised as causal relationships. The more opaque the model, the easier it can be to confuse the two. Leamer (1983) follows up on this and other articles, when he debates the fragility of inference and prescribes a need for "*taking the Con out of Econometrics"*.

I have chosen to rely on simple models, and this has been a deliberate choice. Even when the econometrics gets somewhat fancy in essay 4, I try to present the results in a way that is intuitive and easy to grasp, because my focus has been on applied research and market understanding. The empirical analysis, reasoning and conclusions in the four essays are presented in a way that invites criticism, since academic criticism and debate is what moves our knowledge and understanding forward.

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Structural Breaks or Continuous Adjustments in Grain Production and Prices 1961-2014? An Explorative Study

Abstract

This article analyses grain production and prices 1961-2014. We first describe the development in aggregated and relative allocation of land worldwide for wheat, corn and soybeans, and the growth in production volumes and yields. We then proceed by analyzing long-term price relationships. Finding that grain prices are strongly co-integrated, we estimate and Error Correction Model to see whether deviations from the long-run equilibrium is quickly adjusted. Furthermore, we investigate whether changes in land allocations for these principal field crops are best described as a continuous process or as a series of structural breaks, hypothesizing that events like the introduction of GM technologies and the "energizing" of corn after 2005 caused structural breaks in acreage shares and relative prices.

Given the major and sometimes dramatic political events and technological changes during this period, one would expect to find significant structural breaks in grain production, yields and prices. However, our main conclusion is that grain markets generally adjust smoothly and continuously. Prices adjust quickly towards long-run equilibrium, and the results from a series of Chow tests indicate that the changes in relative land allocations have progressed as a relatively smooth process with few structural breaks.

1 Introduction

This article is a contribution to the understanding of long-run trends and structural changes in grain production and prices. We discuss global developments for three principal field crops, namely wheat, corn, and soybeans. Analyzing production, prices, yields, and long-term land allocation over more than half a century (1961-2014), we try to capture changes from one harvest to the next, leaving the short-term movements *within* the marketing year aside. Our focus is fluctuations in production (metric tons, MT hereafter), acreage (hectares, Ha hereafter), prices and yields (MT/Ha).

Empirical analyses of commodity markets often deal with relatively short horizons. A few years of monthly (or weekly or daily) observations are used as input in econometric models in order to test out hypotheses related to market behaviour and price dynamics. Such studies are, obviously, highly relevant for decision makers. Still, such short-term horizons should be supplemented with studies that cover the longer run and using observations with lower frequencies in order to capture trends and possible structural breaks. Such breaks may be identified as “a new era”. As pointed out by Zulauf (2016) in his study of factors affecting long-term corn and soybean prices, economists often disagree on what constitutes a new era, see e.g. Irwin and Good (2009, 2016) on whether recent years can be defined as the introduction to a new era of higher agricultural prices. Using recent data on e.g. relative prices and volatility may occasionally result in near-sighted conclusions. Psychological myopia is a well-known trait in human judgements, as we often seem to believe that the recent past represents something completely new or different (see e.g. Hsee, Yu et al. (2003) for a survey).

Wheat, corn and soybeans play a central role in societies worldwide in terms of nutritional content (energy, protein). Grains also represent a major commodity in international trade. Wheat was one of the first domesticated food crops, and is a major diet component in the civilizations of Europe, West Asia and North Africa. Historically, no commercial crop has been as widely grown or heavily traded. Corn and soybeans have many uses, including human consumption, but today their primary use is as feedstock in meat production (pork, beef, chicken). With the introduction of the Renewable Fuel Standard (RFS) through the US Energy Policy Act of 2005, corn has also become a major input in the production of biofuels.[1]

Looking back, the previous decades have been characterized by globalization, dramatic political events, and significant technological innovation in the field of agriculture. Our article aims to identify whether events like wars, economic recessions, political reforms, and technological changes influence adjustments to agricultural by causing structural breaks in relative land allocations, prices and risk. Focusing on some of the events that pertain specifically to agriculture, we employ formal tests where the null is in favour of the primer, i.e. continuity. This research question is relevant in two dimensions. First, a large part of the global population relies on grains as the main part of their staple diet, which means that variations in production and prices of these commodities can come at great human cost, especially in poorer nations. Second, virtually all economies trade in food, which means that dramatic changes in grain production and prices may lead to trade bill effects of significant magnitudes.

Concerns about rising food prices and commodity price variability are widely recognized in the literature. Wright (2011) discusses the economics of grain price volatility and the importance of understanding the relationship between consumption, available supplies and stocks. Other relevant studies include Gilbert and Morgan (2010) who examine historical food price volatility; Radetzki (2006) analysing recent commodity booms, and Jacks (2013) who takes evidence on real commodity prices and discusses long-run trends, medium-run cycles, and short-run boom/bust episodes in a very long perspective. There is also a large body of literature on whether the recent influx of index trackers and financial investors have had an adverse effect on the functioning of commodity markets. Haase, Zimmermann et al. (2016) review this literature in a recent survey, and find that the results from analyzing speculation and its impact on commodity futures markets are mixed.

The contribution of this article is survey of the development in relative allocation of agricultural land worldwide for wheat, corn and soybeans, and the growth in production and yields since 1961. We further examine long-term price dynamics and risk, and investigate whether changes in

[1] The RFS requires a minimum annual quantity of ethanol content in gasoline, and the bulk of US ethanol is produced from corn. This new source of demand has been claimed to have caused a permanent increase in world corn prices (Carter, C., et al. 2012), and thereby influenced the price and production of other agricultural commodities as producers have reallocated land to corn production and away from other crops.

land allocations for these principal field crops adjust continuously. Specifically, we perform a series of 1-step ahead Chow tests to see if whether major political events or technological changes manifests themselves as structural breaks in grain production. Through this approach, we seek to present empirical evidence on how producers adjust to external events and changing consumer preferences. We also study the long-run relationship among grain prices.

The remainder of this article is organized as follows. Section 2 gives an overview of important global events which are likely to have influenced price dynamics and land allocation among the main grains, and consequently impacted global grain production. Section 3 presents the data, while section 4 gives some stylized fact on grain production and prices. In section 5, we look at long run equilibriums and short-term price adjustments in the grain markets, while section 6 tests for structural breaks in land use. Section 7 offers some concluding remarks.

2 An historical flashback

From 1961 through 2014, a number of important events took place in the world economy and in international trade, events that presumably had significant impacts on the production and trade in agricultural commodities. One such event was the collapse of the Bretton Woods system, which dissolved between 1968 and 1973 (IMF). Virtually all standardized contracts on agricultural commodities are priced in US dollars. While many feared that the collapse of the Bretton Woods system would destabilise the global economy, the transition to floating exchange rates turned out to be a blessing. When oil prices surged in 1973, floating exchange rates to some extent helped alleviate the impact of this external shock for many economies. The oil crisis in 1973 arose when the Arab members of the Organization of Petroleum exporting Countries (OPEC) proclaimed an oil embargo against the United States. The embargo was a response to American involvement in the 1973 Yom Kippur war, and extended to other countries that supported Israel in this conflict, including the Netherlands, Portugal, and South Africa. By the end of the embargo, global oil prices had quadrupled, and US oil prices were even higher. Energy is a major input in agricultural production through channels like farm equipment, fertilizer production and processing, packaging and transportation. One would expect changes in energy prices to have an impact on grain prices, and also on relative land allocation in global grain production. Wheat, and even more so corn, requires substantial amounts of nitrogen fertilizer in order to obtain high yields, while the soybean is a legume and can use the nitrogen in the atmosphere for plant growth. The second oil crisis of 1979, which began with a decrease in oil output due to the Iranian revolution, also resulted in widespread panic and elevated petroleum prices. An outcome of these events was a growing political willingness to reduce protectionist trade barriers like tariffs and subsidies. In particular, several countries came together on this subject through the General Agreement on Tariffs and Trade (GATT), and even though agriculture is still the most heavily protected sector in world trade, these changes in the political climate also affected agricultural trading. Given these political and economic events, one would expect to find structural breaks in global grain production and relative prices during the 1970s.

During the 80s and 90s, the global marketplace grew substantially as a number of centrally planned economies opened up towards free trade (or less protection in trade). Most notable in this context is the collapse of the Soviet Union, which was formally disbanded on December 26, 1991. Agricultural production in the former Soviet Union generally suffered from low productivity due to inefficient rural management, complex socially oriented problems, and cumbersome and confusing agricultural policies. These problems were obviously not solved overnight, but dramatic improvements had taken place by the end of the millennium. By 2014, the Russian Federation had become the 4th biggest exporter of wheat globally which is reminiscent of the region's golden era prior to the First World War when Russia was the world's largest wheat producer and exporter. In 2016, Russia became the world's biggest exporter of wheat for the first time in modern history, with some 30 million MT.

Parallel to these major events in the global economy and politics there were significant developments that pertain specifically to the grains sector. New varieties and more efficient production methods contributed towards a significant increase in yields. World cereal production doubled in the time period 1960-2000 (Tilman, Cassman et al. 2002), and this growth was predominantly caused by increasing yields due to improved agronomic practices, including more optimal use of fertilizer, water and pesticides, new crop strains, and other technological advances. From 2000 onwards, there has also been rapid growth in the use of genetically modified varieties (GM)[2]. Though controversial in some parts of the world, the use of GM

[2] GM refers to any organism where the genetic material has been changed through genetic engineering techniques. In agriculture, the DNA of various crops is typically altered to obtain resistance to pest and diseases, to be grown in different climates, or to be resistant to certain chemical treatments (typically some herbicide).

technologies is widespread in corn and soybean production, and has contributed towards more efficient production of these crops. The widespread adoption of GM varieties likely comes from improved profitability over traditional methods. Other factors like producer flexibility, consumer preferences, and farmer attributes and perceptions might also influence adoption (Fernandez-Cornejo and McBride 2002). Looking to the US, GM varieties are now dominating the market for both corn and soybeans; the adoption of GM crops is approaching 100% of planted acreage, see figure 1. As can be seen, GM varieties were introduced around the turn of the century, and their use increased rapidly. For soybeans, the relative GM share grew from about 50 to almost 90% between 2000 and 2006. Likewise, corn GM acreage grew from some 25% in 2000 to more than 80% by 2008. One would expect to see such fundamental technological changes reflected in e.g. relative prices of corn and soybeans versus wheat, where GM technologies has yet to be introduced.

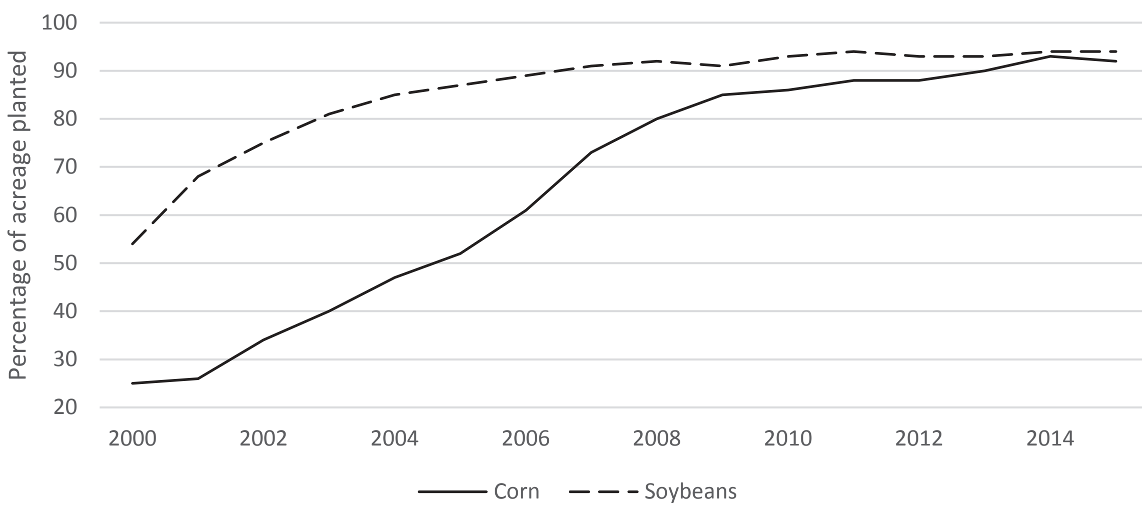

Figure 1: GM corn and soybean varieties as percentage of planted acres of the respective crops, United States, 2000-2015. Source: USDA, National agricultural Statistics Service, June Agricultural Survey for the years 2000-2015.

Another driving factor behind the increase in agricultural production has been expansive government policies and the cultivation of new land, in particular in Brazil. Annual soybean production increased by nearly 2 000% 1968-1997, in part due to the government providing fixed nominal rate loans for equipment and operating expenses, as well as subsidising tractors and fertilizer (Frechette 1997). Furthermore, the Cerrado, a vast savannah that stretches for more than 1 000 miles across central Brazil, has been transformed from infertile land to a prosperous agricultural region by adding appropriate proportions of phosphorus and lime to the soil. Researchers developed tropical varieties of soybeans to make this crop suitable for the Amazonian region, and there has been massive agricultural expansion in Mato Grosso, which is the main production area for soybeans in Brazil. According to Arvor, Meirelles et al. (2012) the net area used for soybean production in Mato Grosso expanded by 275% from 1992 to 2012. Soybean yields in Mato Grosso (3.08 tons per hectare) were estimated to be 17% higher than the Brazilian average (2.63 tons per hectare) in 2009. The increase in yields were largely caused by improved agricultural management practices like double cropping and no till farming, better soil and water management and more efficient use of fertilizer. This region also produces large amounts of corn, and the land allocated to corn crops expanded by a fivefold during the same period. Simultaneously, yields increased by 56 and 117% for soybeans and corn, respectively.

The turn of this century was characterized by growing demand for a number of key commodities, including agricultural products. Rapidly increasing commodity prices in 2006-08 and 2010-11 can, at least in part, be explained by this (unexpected) growth in demand in conjunction with tightening supplies. Some also suggest that monetary expansion and exchange rate movements following the financial crisis were central explanatory factors of the commodity price boom in 2007-08. A good overview of macroeconomic factors that likely contributed to the price spike in 2008, is given in (Pies, Prehn et al. 2013).

Another important development is the American political aim of promoting energy independency and environmentally friendly technologies through increased ethanol production. The US Energy Independence and Security Act of 2007 stipulated a near doubling of mandated ethanol use. Fortenbery and Park (2008) find that growth in ethanol production is important in explaining corn price determination. According to estimates by Carter, Rausser et al. (2012) the 2007 expansion in the Renewable Fuel Standard caused a 30% increase in world corn prices. Both articles also discuss the considerable expansion in ethanol production capacity that occurred between 2005 and 2007. Abbott (2013) presents figures that document a large and persistent new demand from corn from this industry; the amount of US corn used in ethanol production increased from 12.4% in crop year 04/05 to over 38.5% in 10/11. The demand from the biofuel industry has remained at this high level. Again, one would expect effects on acreage allocation and relative prices. S ummarizing, global grain production has been exposed to major economic, political and technological "shocks" over the past 54 years. It appears reasonable to expect that these shocks would cause dramatic and tangible effects on production, land allocation and relative prices. On the other hand, farming has a long history of adapting rapidly to changing production conditions. The next sections of this paper will elaborate on this issue.

3 Data

We focus on wheat, corn and soybeans because these commodities are chiefly grown in the same temperature zones, and thus compete for the same land resources[3]. Beyond being substitutes in production, they are also to some extent substitutes in consumption, in particular when used for animal feed. That corn, wheat and soybeans share a number of common factors becomes evident when we study their price history. In figure 2, we saw that while there are deviations in the price trajectories, the three commodities share similar cycles and long-term trends.

Prices in this article are continuous front month futures prices from the Chicago Mercantile Exchange (CME) Group[4]. We use futures contracts because this market is forward looking by construction, quickly incorporating news and changes in expectations. Our sample covers 1961-2014. We base our analysis on annual data because prices and price expectations are dominated by the annual harvest cycle. Grain prices tend to fluctuate the most within the growing season, as supply expectations can shift significantly due to weather conditions and changes in expectations regarding harvested acreage and growing conditions. For this reason, we use prices observed in the 4th quarter each year (the southern hemisphere has "inverse" seasons compared to the northern, and by measuring prices in December, i.e. between harvests, we average out this effect). At this point, the market should have full information about the size of the current crop

[3] Rice is the staple food in the larger part of Asia, and also widely imported and consumed in the Caribbean and Central and West Africa. When we chose to exclude this commodity from our analysis, it is due to fundamental differences from the other grains. Rice is mainly consumed in different geographical regions than wheat, corn and soybeans. Furthermore, rice production requires different temperatures and different types of agricultural land to be successful, which implies that this crop does not compete with the other grains when land is allocated to food crops. We also chose not to include grains like rye, barley and oats etc., as these grains represent only a marginal part of total grain production. In 2013, global production of e.g. barley was roughly 30 million MT, or 4% of global wheat production that year.

[4] All price series are downloaded through Quandl, a search engine for numerical data that offers access to a multitude of financial, economic and social datasets. See www.quandl.com for more information.

year's output for corn and soybeans, and a reasonable basis for forming expectations regarding next years' market conditions based on prevailing price and storage conditions. While it is not ideal to measure wheat prices in the middle of the marketing year, we do so to obtain synchronicity across prices.

Statistics on production (MT), acreage (Ha) and yields (MT/Ha) are obtained from the Statistics Division of the Food and Agricultural Organization of the United Nations (FAOSTAT hereafter). FAOSTAT mainly collects information about agricultural output by the cooperation of governments, which supply information about primary crops through annual questionnaires (FAOSTAT). FAOSTAT also collaborate with various non-governmental agencies, to achieve conformity in the presentation of international statistics. The time reference for reporting on harvested area and crop production is based on the calendar year. More precisely, the statistics for a particular crop are reported under the calendar year in which the entire harvest or the bulk of it took place. The harvest of the crops we analyze in this paper is generally limited to a few weeks in each region. Figures are reported by the countries in various time frames like e.g. calendar year, marketing year, etc., before being allocated to the calendar year in which the entire harvest or the bulk of it took place.

4 Stylized facts on grain prices and production 1961-2014

Relative prices, rather than absolute prices, are the relevant input parameter in the farmer's decision process. When planning for the upcoming season, a farmer will take into account the relative prices of agricultural inputs like e.g. fertilizer, land and so on. Assuming the farmer is rational in an economic sense, she will then allocate land and other resources to the crop that yields the highest expected revenue (at similar risk levels). Because corn, wheat and soybeans to a large extent are substitutes in consumption, the relative demand for these commodities mainly depend on price. Consequently, the relative price differences between the three commodities are bound due to the consumer's ability to substitute. Short term, and sometimes violent, price variations do occur, mainly because supply is inelastic within season (a farmer cannot reap what he has not sown). However, in the longer term, the relative price differences will move towards equilibrium. This effect is illustrated in figure 2, which displays relative grain prices 1961-2014.

As can be seen, there is no long-term (upward or downward) trend in the price ratios, and peaks do not persist (only last for a couple of years).

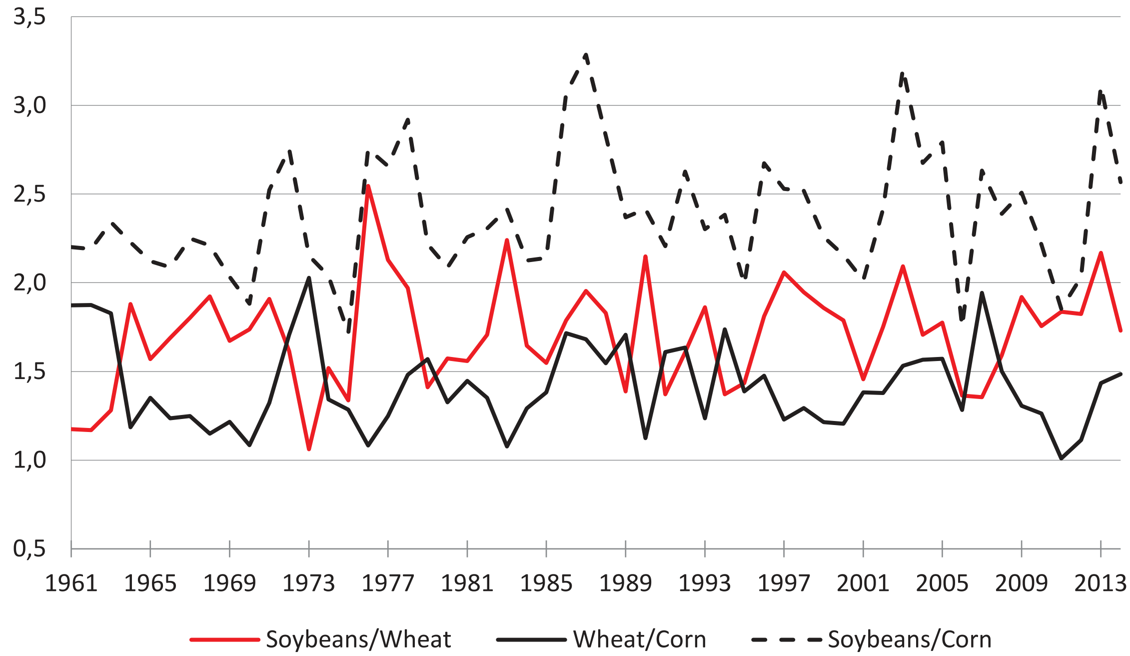

Figure 2: Relative front month futures prices (4th quarter) from the Chicago Mercantile Exchange Group, 1961-2014, annual observations.

Acreage of harvested wheat, corn and soybeans increased from 334 million Ha in 1961 to 523 million Ha in 2014 (see figure 3). In other words, the total acreage allocated to produce these grains increased by roughly 50% over half a century, which corresponds to an annual trend growth of 0.7%. Growth was particularly strong 1970-81 and 1999-2014, at a rate of 1.5% annually in each period. From 1970 to 1981, the total harvested acreage of corn, wheat and soybeans increased by 67 million Ha, i.e. an area that is roughly the total size of France. From 1999 to 2014, the increase was even larger, at some 94 million Ha.

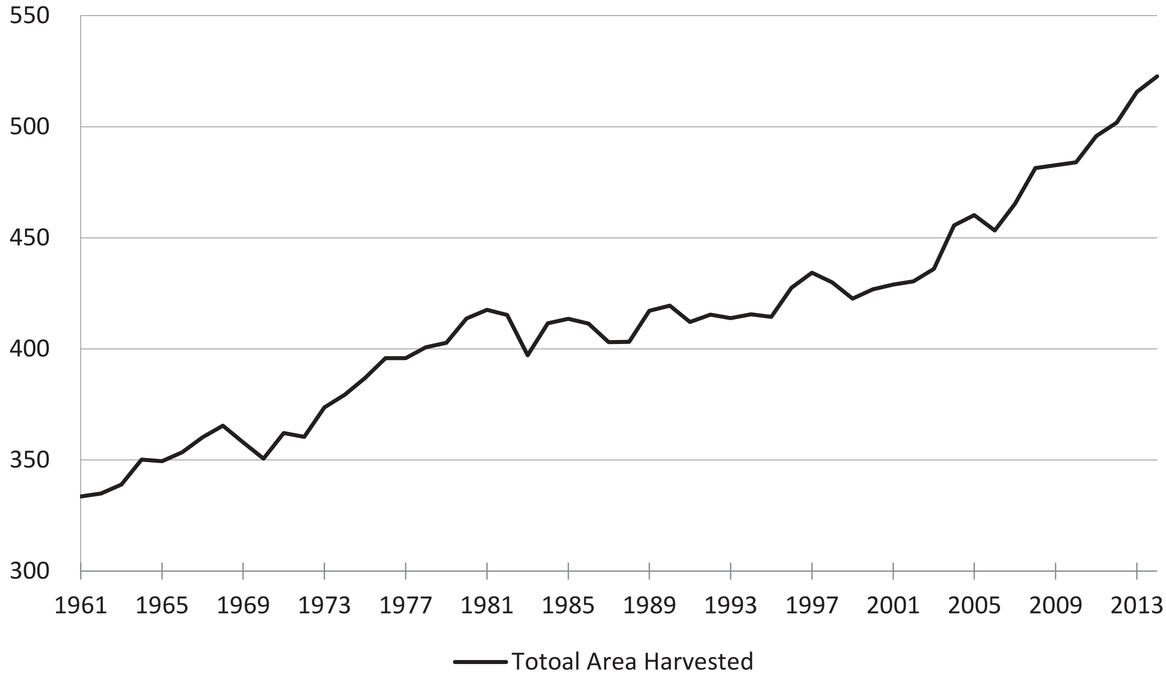

Figure 3: Total grain area harvested (wheat, corn, soybeans) in million Ha, annual data 1961-2014. Source: FAOSTAT.

Figure 4 displays the evolution of harvested acreage for each grain individually. From 1961 to 1968, the amount of harvested wheat acreage increased by approximately 21 million Ha, i.e. roughly 2/3 of the total increase in harvested grain acreage during that period. After two years of declining acreage, growth picked up again and increased by 31 million Ha 1970-1981. This area corresponds to about half of the total agricultural land in Canada today. From 1982 onwards, there has been a downward trend in the area allocated to wheat production. This trend is reversing in 2004. The areas allocated to corn and soybean production have increased steadily throughout the last five decades. Corn area harvested has experienced a trend growth of 0.9% annually from 1970 to 2014. The growth has been even stronger for soybeans, where area harvested has increased by more than a fivefold from some 24 to 118 million Ha 1961-1970, see figure 4. This implies an annual trend growth of 2.4%.

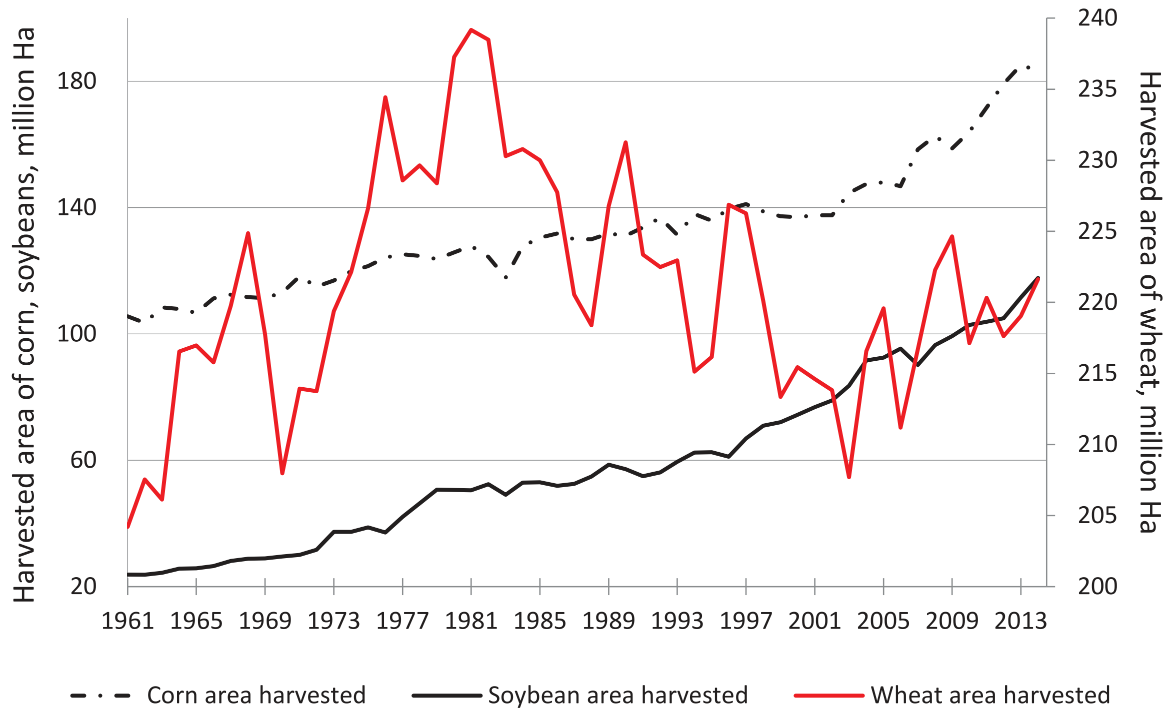

Figure 4: Harvested areas of wheat, corn, soybeans (million Ha), annual data 1970-2013. Source: FAOSTAT.

Considering the distribution of land towards production of the three main grains, wheat has been losing acreage shares. Wheat area harvested decreased from 61% of total in 1961 to 42% in 2014. The area allocated to corn production remains relatively constant throughout the period we examine (up from 32 to 35% of total), while the acreage share of soybeans has increased dramatically from 7 to 23%.

A large part of the increase in soybean acreage is located in the region of Mato Grosso, which is the main production area for soybeans in Brazil, accounting for 31.3% of national production as of 2009 (Arvor, Meirelles et al. 2012). Here, agricultural expansion has played an important part in increasing agricultural production, as previously mentioned the net area used for soybean production expanded by 275% from 1992 to 2012. Further, large areas of savannah in central Brazil have been transformed from infertile land to a rich agricultural region through new technologies.

4.1 Production and yields

Agricultural development has led to large increases in food supply feeding a growing world population. From 1961 to 2014, world population increased from some 3.000 billion people to more than 7.000 billion and a large part of this population have grains as main source of daily caloric intake. As previously mentioned, some of the growth in world grain production came about due to cultivation of new land, and more cropland has been oriented towards grain production. Nevertheless, increasing yields have been the major driving force behind the growth in grain and oilseed production from the 1960s onwards. Figure 5 shows that this increase has been largest for corn and wheat. Wheat yields have increased from 1.1 to 3.3 tons per hectare in 54 years, while corn yields are up from 1.9 to 5.6 tons per hectare. In both cases, this is equivalent to an annual trend growth of 1.9%. The trend growth in soybean yields was 1.4% during the same period, and in absolute terms, soybean yields increased from 1.1 to 2.6 tons per hectare from 1961 to 2014. Masuda et. al. 2009 projects a 2.2% annual growth in soybean production up to 2030, but also highlight a need for significant investments in yield improving research by agribusiness policy makers and managers.

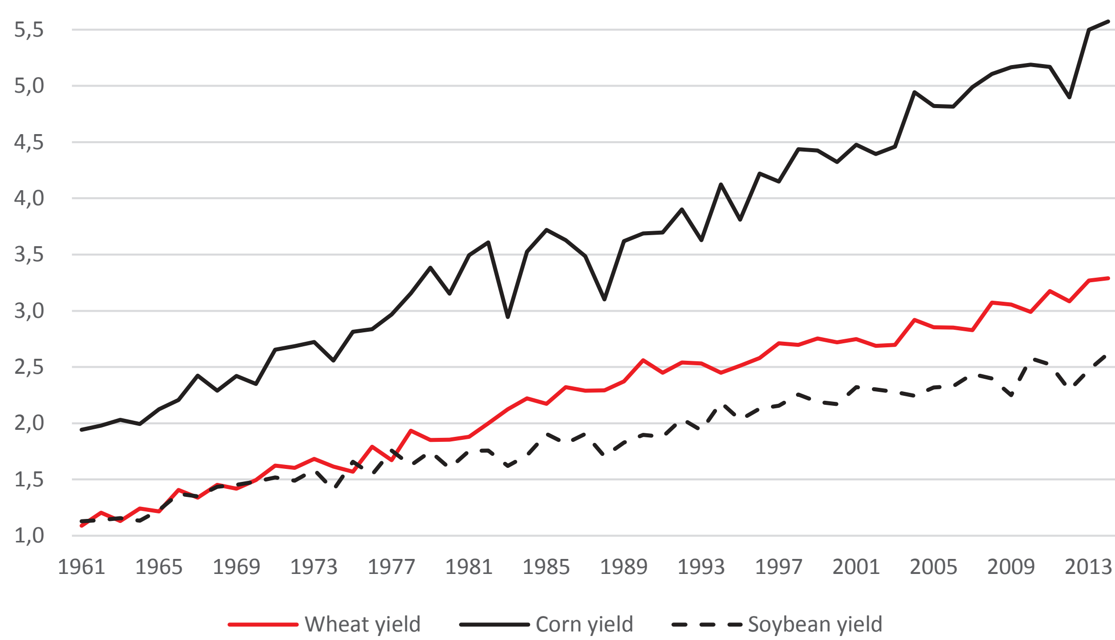

Figure 5: Global grain yields; wheat, corn, soybeans (tons per hectare), annual data 1961-2014. Source: FAOSTAT.

Wheat, corn and soybeans all experienced significant increase in yields at the global level from the 60s onwards. However, behind the average yields reported in figure 5 there are large regional differences, and there is still room for yield growth and more efficient grain production in important agricultural regions. Large areas in Africa would benefit from better water management and modern agronomic practices, including greater inputs of fertilizer, herbicides and pesticides. Considering the African continent's climatic and soil conditions, tropical soybean varieties can be cultivated in about half of Africa's land (Kolapo 2011). This implies that the technologies employed in Brazil could be possibly be imported to countries in Africa, like e.g. Mozambique or Zambia. There is also a greater potential for improved soybean yields in certain regions with the introduction of newly developed GM drought tolerant soybean strains.

Further, there are still parts of the former Soviet Union were agricultural production suffer from low productivity and inefficient agricultural management. To put this potential into context, we note that in 2012, the agricultural land in the Russian Federation, Ukraine and Kazakhstan combined amounted to approximately 465 million Ha (source: The World Bank). A large part of this area is allocated to wheat production, and increasing yields in this region would have a significant impact on the world supply of wheat. To illustrate the changes that have occurred in this region, we use the year 2000 as our baseline. This year, the Russian Federation exported 696 million tons of wheat, while the total exports from the Russian Federation, Ukraine and Kazakhstan combined were 4 746 million tons. These are marginal magnitudes on a global basis. By 2014, the Russian Federation had become the 4th biggest exporter of wheat globally. Total exports from the Russian Federation, Ukraine and Kazakhstan combined amounted to 37,5 million tons, which made this region the biggest exporter of wheat worldwide that year (source: USDA). In 2016, Russia was expected to be (and became) the world's biggest exporter of wheat for the first time in modern history tons (Financial Times, August 18, 2016). In other words, we have seen huge efficiency gains in this region through the last decade, but there are still opportunities for improving agricultural management and technologies in the former SU.

Based on our discussion of the development in harvested acreage and yields, we know there has been a significant growth in grain production from 1961 to 2014. This growth is illustrated in figure 6. The annual trend growth of wheat, corn and soybean production was 1.9%, 2.8% and 4.4%, respectively. Harvested acreage of wheat actually declined during the time period we study, which implies that the increase in production came from increasing yields alone. The increase in corn production was a combination of increasing yields and harvested acreage, as were the increase in soybean production. In terms of soybeans, a large part of this increase was caused by cultivation of new land in Brazil. Looking at grains as a whole, production has increased from 450 million MT to 2 059 million MT from 1961 to 2014, equivalent to a trend growth of 2.5%. Annual trend growth was even higher from 2000 to 2013, at 3.0%. For comparison, world population growth has been roughly 1.1% during the same period, which implies that grain production is now growing faster than world population.

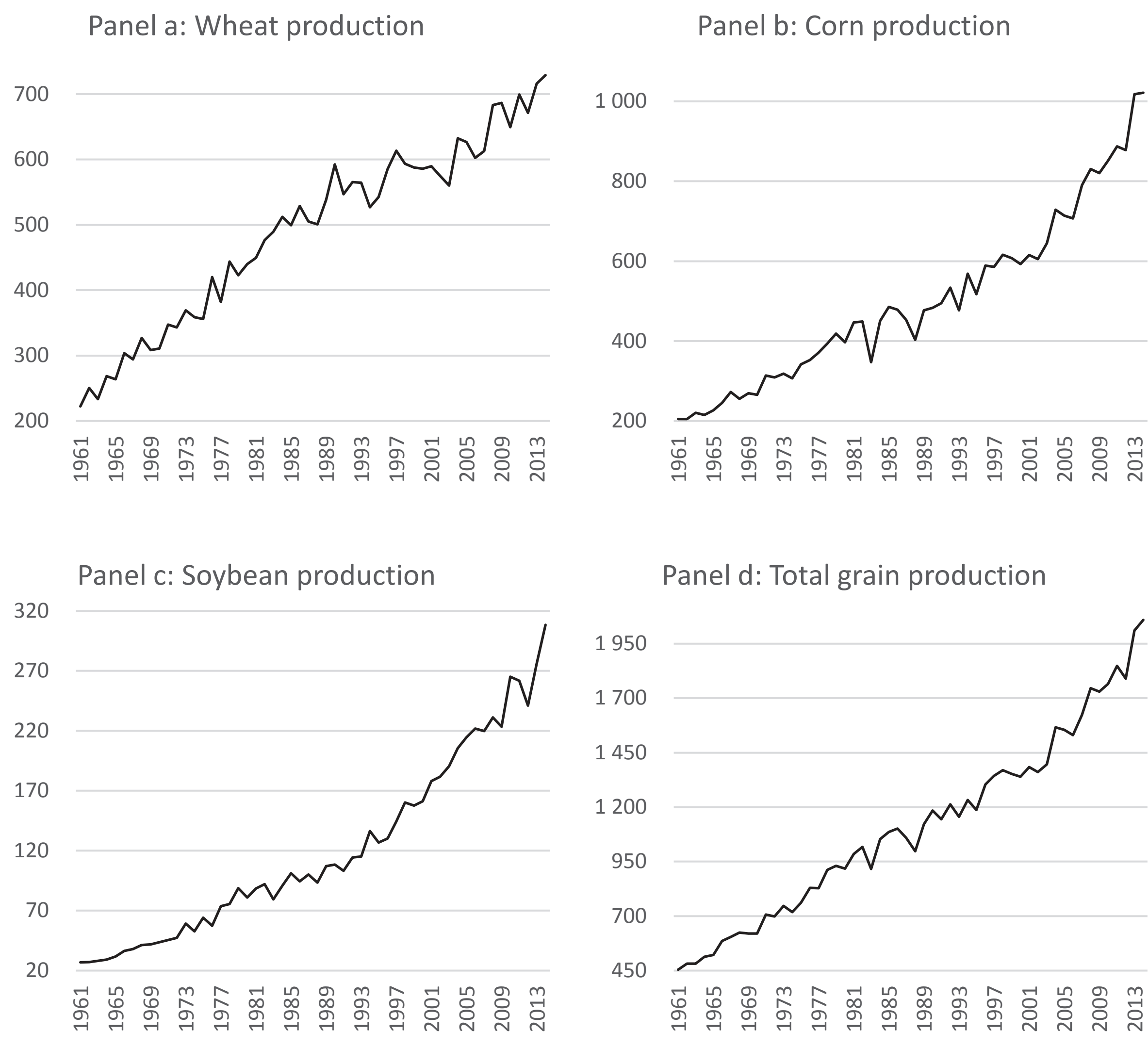

Figure 6: Grain production, wheat, corn, soybeans, total (million tons), annual data 1961-2014. Source: FAOSTAT.

4.2 Prices and risk

Despite massive increases in production and yields, concerns regarding land use and food security remain central on the international agenda. In particular, there was much talk about a global food crisis proceeding the summer of 2008, when the prices of several important agricultural commodities had nearly doubled from the beginning of 2007. The peak in grain prices (and most other commodities) were short-lived, and in the autumn of 2008 prices fell almost as fast as they had increased just a few months earlier. However, food commodity prices rose sharply again between June 2010 and February 2011, even surpassing the record 2008 peak that had worried policymakers and non-governmental organizations across the world.

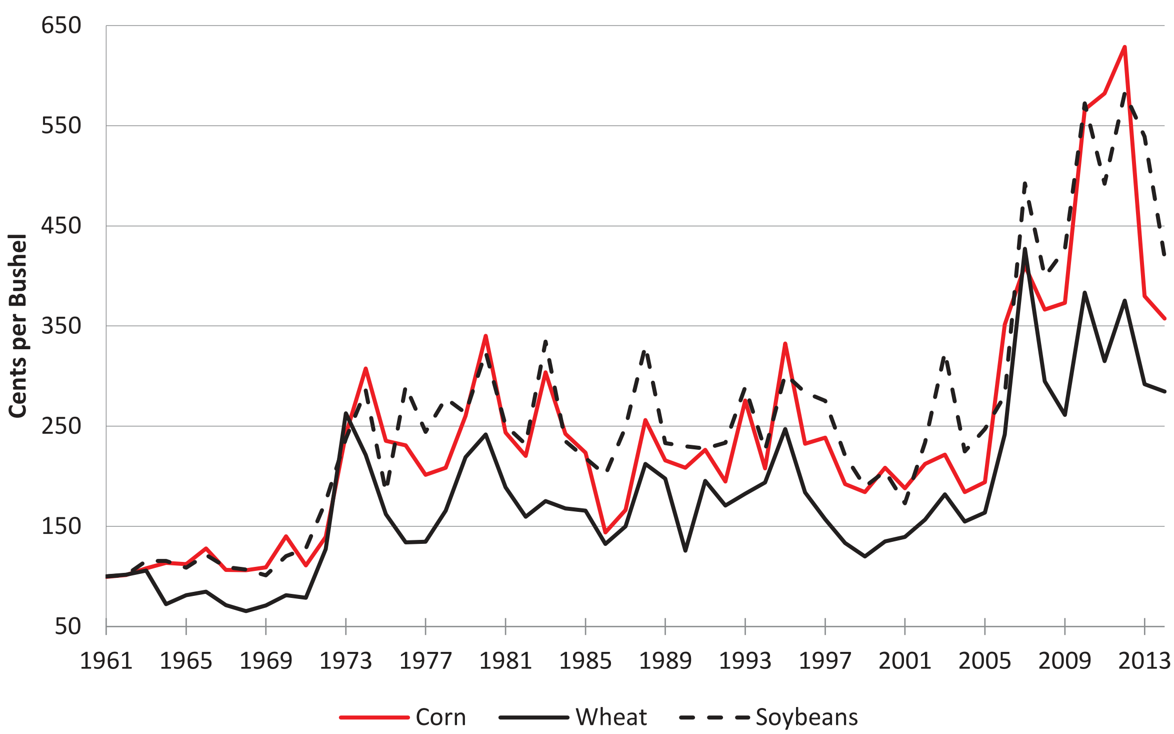

Figure 7: Front month futures prices (4th quarter) from the Chicago Mercantile Exchange Group, 1961-2014 (Rebased, 1961 = 100).

Both 2007–08 and 2010–11 were characterized by adversely affected crops in several important regions for agricultural production (Trostle, Rosen et al. 2011). Typically, agricultural price booms and periods of high volatility are caused by shocks on the supply side. In the short run, price changes are driven by inflow of information to the market place, forming expectations and speculation regarding future supply and demand dynamics. In the long run, agricultural commodity prices are determined by fundamental drivers, namely supply, demand and available inventory (Geman 2015). Factors like demographic changes and income variations influence demand, while weather patterns and adverse events like droughts or pests are key drivers on the supply side. Table 1 presents summary statistics for corn, wheat and soybeans.

Table 1: Descriptive statistics, 1961-2014, percent changes

	Wheat	Corn	Soybean
Average	2%	2%	3%
St. Dev.	24%	24%	22%
Kurtosis	0,49	0,09	-0,35
Skewness	0,61	0,26	0,08
Min	-45%	-50%	-40%
Max	72%	59%	56%
N=	54	54	54

annual observations, front month futures prices from the Chicago Mercantile Exchange Group, 1961-2014

The price changes of all three grain varieties are positive on average during the time period we consider. We note that as our data consist of nominal prices, the positive price changes in table 1 likely represent inflation rather than actual positive returns. The standard deviation of corn and wheat are identical at 24%. These commodities display similar return distribution characteristics, although the statistics on wheat suggests that this distribution has slightly fatter tails compared to corn, and also moderately more positive skewness. The statistics for soybean indicates less price variability, with a standard deviation of 22% and a platykurtic distribution. To get a more dynamic impression of variability and risk, figure 8 displays the evolution in standard deviations based on a rolling window of 12 observations, 1973-2014.

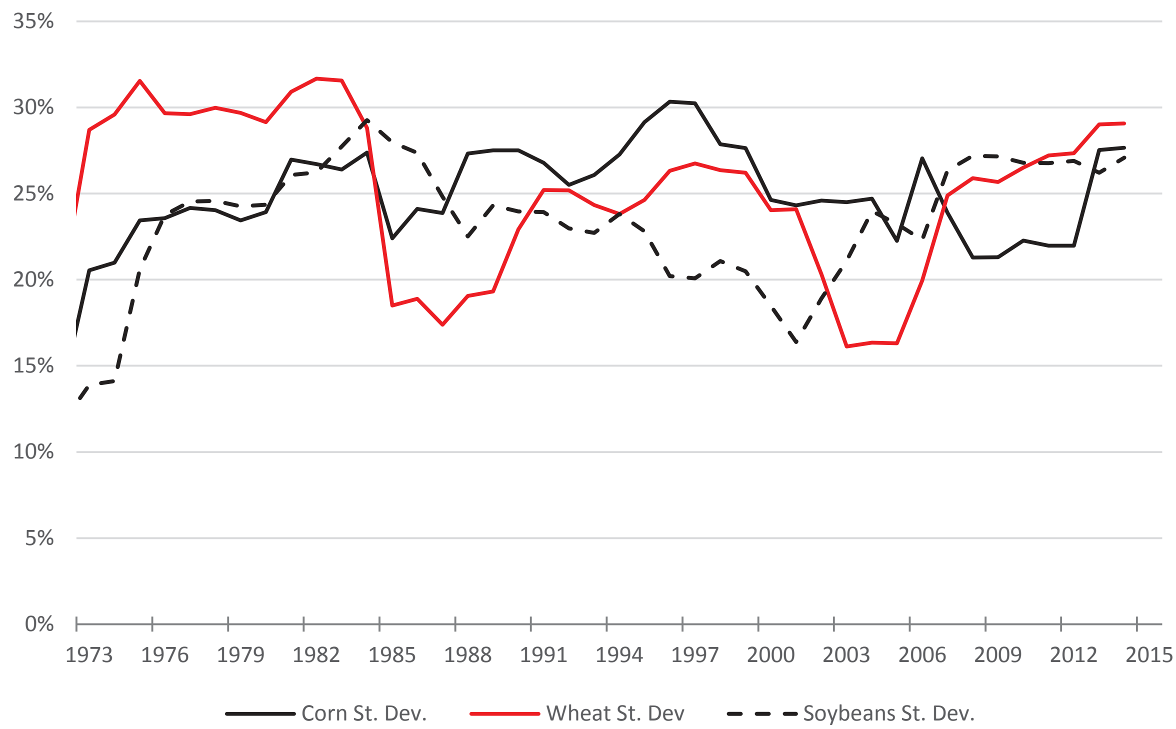

Figure 8: Standard deviations for wheat, corn and soybean price changes, 12 year rolling window, 1961-2014, annual observations.

In the recent debate on food prices, many have claimed that price risk has increased significantly since 2005 (see e.g . Haile, Kalkuhl et al. (2016)). Whether or not price volatility has increased does however depend on which window we look through. This is demonstrated in figure 8, where the standard deviations of the three grains based a 12-year moving window show no increasing trend in volatility. Comparing commodity risk, we see that annual volatility fluctuates within the range of 15-30% for all three grain varieties. There are individual differences in the trajectories, but the three rolling samples share common cycles. The figure shows that soybeans have lower annual volatility compared to corn and wheat.

5 Price Dynamics: Long-run equilibrium and short term adjustments

Considering how grain prices share common trends and cycles, it is reasonable to expect some form of long-run relationship between the three price series. A series of Augmented Dickey-Fuller (ADF) tests reveal that grain prices observed annually 1961-2014 are non-stationary. We further find that all series are stationary when differenced once.

Following the standard Engle-Granger (1987) two-step procedure, we begin by performing the first step in establishing a co-integration relationship:

$$p_{i,t} = \alpha + \beta p_{j,t} + u_t^{i,j} \tag{1}$$

for all the pairs (i, j), i.e. corn-wheat, corn-soybeans and wheat-soybeans. Testing the residuals from these regressions for stationarity clearly demonstrates that grain prices are co-integrated, i.e. tied together in a long-run equilibrium (table 2).

Table 2: Step 1 - ADF-tests for stationarity of $\hat{u}_t^{i,j}$

	t-values	Number of lags#
Corn-wheat	-5.05**	0
Corn-soybeans	-3.53*	4
Wheat-soybeans	-5.27	2

number of lags determined by minimizing AIC
Critical values from Engle and Yoo (1987): * 5% = -3.29; ** 1% = -4.14

Having found that all three grain prices are co-integrated, we proceed by estimating Error Correction Models (ECMs). Since the OLS estimate of β is superconsistent (Stock 1987)[5], the sampling error from estimating it through a cointegrating equation is less important than the

[5] This means that the variance of β converges to zero at a rate $1/n^2$ instead of the usual $1/n$.

sampling error of the error correction model estimates asymptotically. This justifies the two-step approach, and we estimate an ECM specified as:

$$\Delta p_{i,t} = \alpha + \sum_{i,j=1}^{2} \rho_{i,j}(p_{i,t-1} - \hat{\beta} p_{j,t-1}) + \varepsilon_t \qquad (2)$$

where Δ is the first-difference operator, the variable $p_{i,t}$ represents the log-price of commodity i at time t, and $p_{j,t-1}$ is the log-price of commodity j at time $t-1$. The expression inside the brackets is the error correction term from the cointegration regression of $p_{i,t}$ on $p_{j,t}$. Since the two variables are cointegrated with cointegrating coefficient $\hat{\beta}$, all variables in (2) are stationary. (2) describes the short-run relationship between deviations from the long-run equilibrium and changes in p_i. ρ is an estimate of the speed at which p_i returns to a long-run equilibrium after a change, or "shock". As such, the ECM recognizes that previous time periods' deviations from the equilibrium influence short-run dynamics.

Table 3: ECM model estimation results, 1961-2014

	α	$\rho_{c,s}$	$\rho_{w,s}$	$\rho_{c,w}$
Wheat	0.02		**-0.62**	-0.29
	(0.59)		(-2.59)	(-1.16)
Corn	0.02	-0.33		**-0.50**
	(0.80)	(-1.39)		(-2.30)
Soybeans	0.03	0.00	0.39	
	(0.90)	(0.01)	(1.91)	

t-values in brackets, values significant at the 5% level is marked in bold

From table 3 we see that deviations from the long-run equilibrium between wheat and soybean prices have a significant effect on changes in wheat prices the subsequent period. The coefficient representing speed of adjustment implies that 62% of the short-run disturbance is corrected the following year. Similarly, the price of corn is "pulled back" towards the long-run equilibrium after a shock in the price of wheat. Once more, the correction is relatively swift; the estimated coefficient suggests half of the disturbance is corrected the subsequent period. The error correction mechanism between soybean prices and the other grains are not as distinct, but we see that the coefficient representing the relationship between wheat and soybeans is significant at the 10% level. The speed of adjustment is 39%. As regards the topic of this article, namely whether grain prices adjust continuously, these results support the notion of prices that move rapidly back into equilibrium after an initial disturbance or shock.

6 Testing for structural breaks in land use

There are several studies on the acreage effects from agriculture price changes. These at least date back to the classic articles by Mark Nerlove, e.g Nerlove (1956) , and a number of studies in the 1970s (e.g. Houck and Ryan (1972)). In their recent study, Haile, Kalkuhl et al. (2016) find significant and positive price elasticities on acreage using a panel data approach.

Taking a time series approach, we examine whether relative prices have a significant effect on land allocation among the main grains. Performing regressions with harvested acreage (Ha) as dependent variable we study changes in acreage caused by changes in grain prices, adjusted for area growth.

$$lnHa_t^j = \alpha_0 + \gamma TIME + \alpha_1 lnHa_{t-1}^j + \sum_{i=1}^{3} \beta_i lnp_{i,t-1} + \varepsilon_t \qquad (3)$$

where the variable $lnHa$ represents the logarithm of harvested acreage, the superscript j indicates commodity, and the variable lnp is the natural log of the price of commodity i at time t. The parameter γ represents long-term trend growth, while the lagged value of $lnHa$ controls for short-term adjustments in acreage.

Using natural logs for variables on both sides of the econometric specification is convenient because it allows for a straightforward interpretation of the regression coefficients. All parameter estimates have a natural interpretation as percentage changes, and information about the effect of relative price differences is given by the quotient rule which states that $lnx - lny = ln(^x/_y)$. We expect $\beta \neq 0$, i.e. that changes in prices lead to short-term (annual) adjustments in harvested acreage. Table 4 presents the results.

Table 4: the relationship between harvested acreage and last years' prices, 1961-2014

	α_0	γ	α_1	β_w	β_c	β_s	R^2
Wheat	**7.11**	**-0.001**	**0.61**	**0.04**	0.01	0.00	74%
	(4.36)	(-3.71)	(7.14)	(1.98)	(0.33)	(0.86)	
Corn	**5.65**	**0.002**	**0.68**	-0.02	**0.09**	-0.03	98%
	(3.33)	(2.80)	(7.29)	(-0.86)	(3.70)	(-1.20)	
Soybeans	**4.58**	**0.001**	**0.70**	-0.04	**-0.14**	**0.23**	99%
	(4.07)	(3.67)	(10.3)	(-1.34)	(-4.14)	(6.87)	

t-values in brackets, values significant at the 5% level is marked in bold
w = wheat, c = corn, s = soybeans

It should be mentioned that the variables in (3) are non-stationary. Hence, inference regarding the estimated parameters must be conducted with care. That being said, our results suggest that a substantial part of the variation in harvested acreage of wheat, corn and soybeans, respectively, is explained by a combination of last year's harvested acreage and relative prices. From (3) we expect high R-squared values, as it is reasonable to expect that most farmers will carry their planting patterns over from one year to the next. Further, we see that the estimated coefficients for long-term area growth are modest in size, and they all have the expected sign (see figure 5).

Our results indicates that last year's prices of corn and soybeans have no significant effect on harvested acreage of wheat. Wheat acreage is however sensitive to changes in wheat prices, and (statistically) tend to increase with 4% in response to a 1% increase in last years' wheat prices, adjusted for area growth. This estimate is significant at the 5% level. Moving the discussion to harvested corn acreage we find very similar results, harvested acreage of corn respond to last years' harvested acreage as well as last years' price of corn. Adjusted for trend growth, corn acreage increases with 0.09% in response to a 1% increase in the price of corn the previous year.

Soybeans are the only field crop where we find a statistically significant relationship between harvested acreage and last years' prices of another grain variety. Adjusted for area growth, harvest soybean acreage decrease with 0.14% in response to a 1% increase in the price of corn the previous year. This crop also sensitive to changes in last years' prices. Harvested soybean acreage increases with 0.23% in response to a 1% increase in the previous years' soybean prices. Using the quotient rule, this implies that the response towards a change in the ratio of corn vs soybean prices is -0.37, i.e. that a 1% increase in last year's price of corn relative to the price of soybeans leads to a 0.37% decrease in harvested soybean acreage.

Overall, these results are not surprising; one expects to find the closest lead-lag relationship between corn and soybeans. These commodities are to some extent substitutes in both consumption and production, they share a similar 5-month growth cycle and require similar climatic conditions. Using the US as an example, the bulk of corn and soybeans are produced in the Midwest region, where planting starts in the beginning of April and last through June. The main harvest begins in September and is finished by the end of November at the latest. The largest exporters of corn and soybeans globally are the US, Brazil and Argentina. From 2000 onwards, Ukraine has also become a major exporter of corn, increasing their exports from some 400 000 MT in 2000, to 15 500 000 MT in 2015.

While it is relatively easy to switch between planting corn or soybeans, wheat stands out with its own unique growth cycle and harvest time frames. In the US, winter wheat is planted from mid-August through October, and the harvest run from mid-May to July. Further, wheat is a sturdier crop compared with corn and soybeans, and can be grown commercially in harsher climates. It follows that wheat production benefits from taking place in a number of regions, and the largest exporters of wheat are the European Union, the Russian Federation, the US, Canada, Australia and Ukraine. Kazakhstan and Argentina are also noteworthy wheat exporters.

To examine whether there have been structural breaks in the relationship between harvested acreage and last year's grain prices, we run Recursive Least Squares (*RLS*) estimations with specifications as outlined above. Recursive estimations start with a minimal number of observations, and statistics are recalculated adding one new observation at a time. The coefficients of the regression are thus estimated sequentially, and studying these estimates provides information about parameter consistency and structural breaks. We employ the classical test for structural breaks, namely the 1-step-ahead Chow test, which uses an F-test to determine whether a single regression is more efficient than two separate regressions splitting the data into two sub-samples (Chow 1960). Formally, the 1-step-ahead Chow test statistic follows an F-distribution with $F(1, t-k-1)$ under the null of constant parameters, for $t = M, \ldots, T$. The test statistic is calculated by comparing the residual sum of squares across sub-periods:

$$\frac{(RSS_t - RSS_{t-1})(t-k-1)}{RSS_{t-1}} = \frac{v_t^2/w_t}{\hat{\sigma}_{t-1}^2}$$

where RSS represents Residual Sum of Squares for each t, t denotes sample size, k is the number of parameters, and v_t and w_t represents the standardized innovations (standardized recursive residuals). Normality is required for the statistic to be F-distributed.

Figure 9 presents the outcome of the 1-step-ahead Chow test when regressing harvested wheat acreage (Ha) on changes in relative grain prices, adjusting for trend growth and short-term area adjustments. There is support for the hypothesis of a structural break in 1976 and 1994, but even though these years are statistically significant, it is hard to think of historical events that might have caused these instabilities. Both years were characterized by moderate price levels, stocks were however much lower in 94 compared to 76. Referring back to figure 5, we believe that these breaks merely represents the beginning and end to a downward trend in the land allocated to wheat production, rather than changes of a structural character.

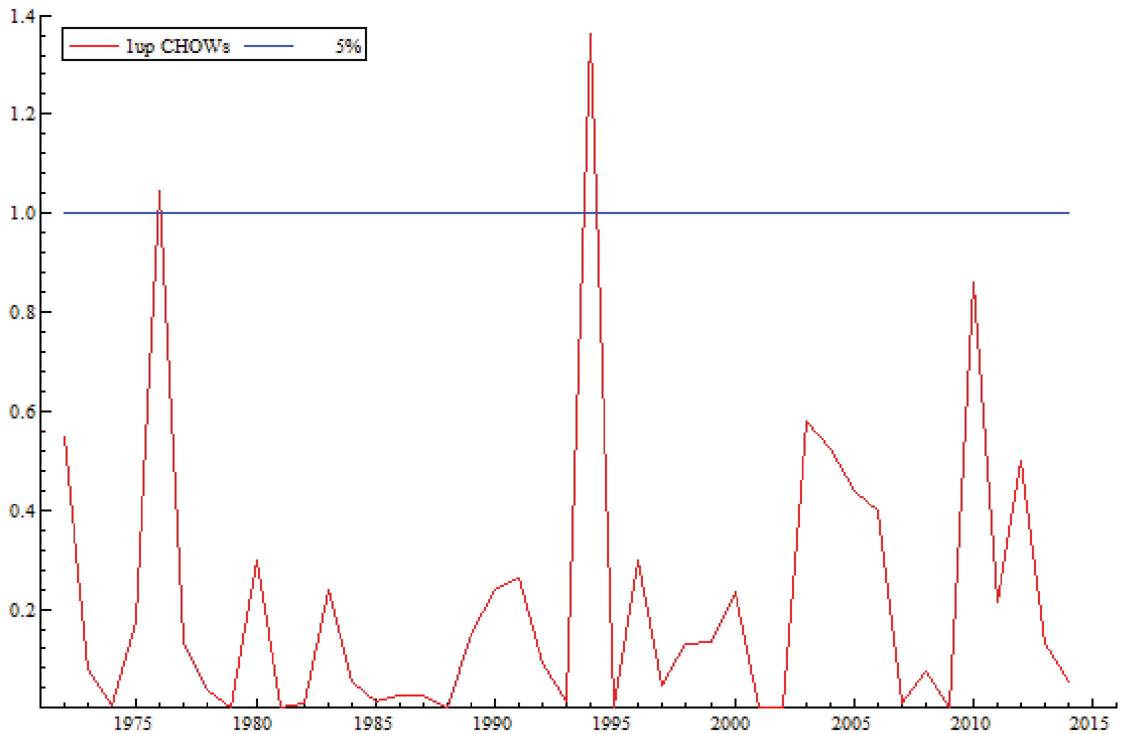

Figure 9: 1-step ahead Chow test, harvested wheat acreage (Ha) on changes in relative grain prices, adjusted for trend growth and short-term area adjustments, 1961-2014.

The 1-step Chow test on corn acreage (figure 10) identifies structural breaks in 1983 and 2007. While it is hard to identify the exact cause of a break in 1983, some reasonable conjectures can be made. In the US, it is common to speak of 1973-80 as an agricultural boom period, while the 80s was a bust decade with poor performance and low farm income. This view is supported by a 35% increase in US farm export volume from 1973-1980, an increase that was sustained by production shortfalls in other countries, a fall in the dollar's real exchange value after the collapse of the Bretton Woods system, rapid growth in foreign real income and strong support from domestic commodity programs (Belongia 1986). By the beginning of the 80s, farm fundamentals such as real income and relative prices were generally bearish – and even though farm productivity was increasing farmers continued to leave the sector. Turning to the Federal Reserve Bank of St. Louis' February forecasts for agriculture, 1983 was expected to be the fourth consecutive year of low farm income in the US (Belongia 1983). A record harvest in 1981, declining exports, and large carryover stocks had all contributed to depressed grain prices.

Ideal weather conditions and record yields in 1982 did nothing to alleviate the situation, and the US at now held about 76% of global corn stocks and 39% of world wheat stocks (Belongia 1983). Policy actions had been taken to encourage wheat and corn producers to reduce their planted acreage and thus reduce grain output[6], but with little success – at least in terms of supporting grain prices. What ultimately made grain prices recover in 1983 was a drought induced production shortfall, when intense heat affected crops across numerous states in the Midwest and the Great Plains. This yield related disturbance had major effect on grain prices, especially for corn and soybeans. That we find no evidence of this shift in wheat prices lends support to this supposition, as wheat benefits from being produced in a number of regions, while the world relied heavily on US corn and soybean exports during the 80s. We believe that the political incentives towards reducing grain acreage in the US and the drought induced price spike were important contributors towards the structural instability detected in 1983.

Further, we find evidence of a structural break in the relationships related to harvested corn acreage in 2007. This break is likely related to the political aim of promoting energy independency and (assumed) environmentally friendly technologies through increased ethanol production in the US. The role of biofuels as a determinant of corn prices is controversial, but based on our results, we argue that the expansion of the RFS through The US Energy Independence and Security Act of 2007 created a new and persistent demand for corn that lead to a structural shift in corn production.

[6] The 1981 US Farm Bill encouraged grain farmers to participate in a new acreage reduction program by offering deficiciency payments and price support loans in return for ideling a crop-specific percentage of their base acreage. This was an essential alteration from the former set-aside program; prior to 1981 acreage reductions were based upon current year plantings, and most importantly, the reductions were not crop-specific.

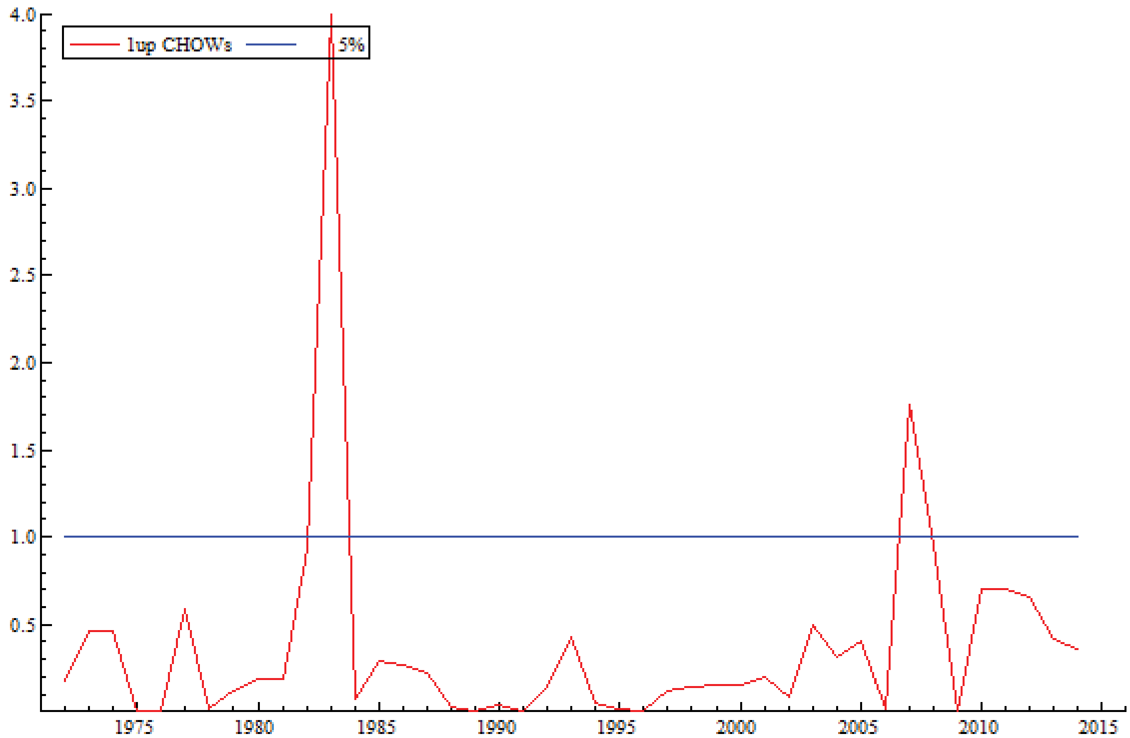

Figure 10: 1-step ahead Chow test, harvested corn acreage (Ha) on changes in relative grain prices, adjusted for trend growth and short-term area adjustments, 1961-2014.

Moving to soybeans in figure 11, we find indications of several structural breaks. We find no obvious cause of the instability in ‘74, ‘78 and ‘87, but merely note that this could be related to the major growth in area allocated to soybean production in South America which we have already discussed. The clear evidence of a structural break in 1983 lends further support to our conjecture that this instability was caused by US agricultural policies and adverse conditions in the US Corn Belt. Finally, we detect structural breaks in 2000 and 2002. This instability is likely related to GM technologies, which was introduced at the beginning of this century. No other commercially grown crop has adopted GM varieties to the same extent as soybean farming. Finally, there is a structural break in the regression of harvested corn acreage in 2007. Since we discovered a lead-lag relationship between corn and soybean prices, this might be related to the increased use of corn for ethanol production. Again, we stress that this is merely a reasonable conjecture rather than implied by the statistical test statistics.

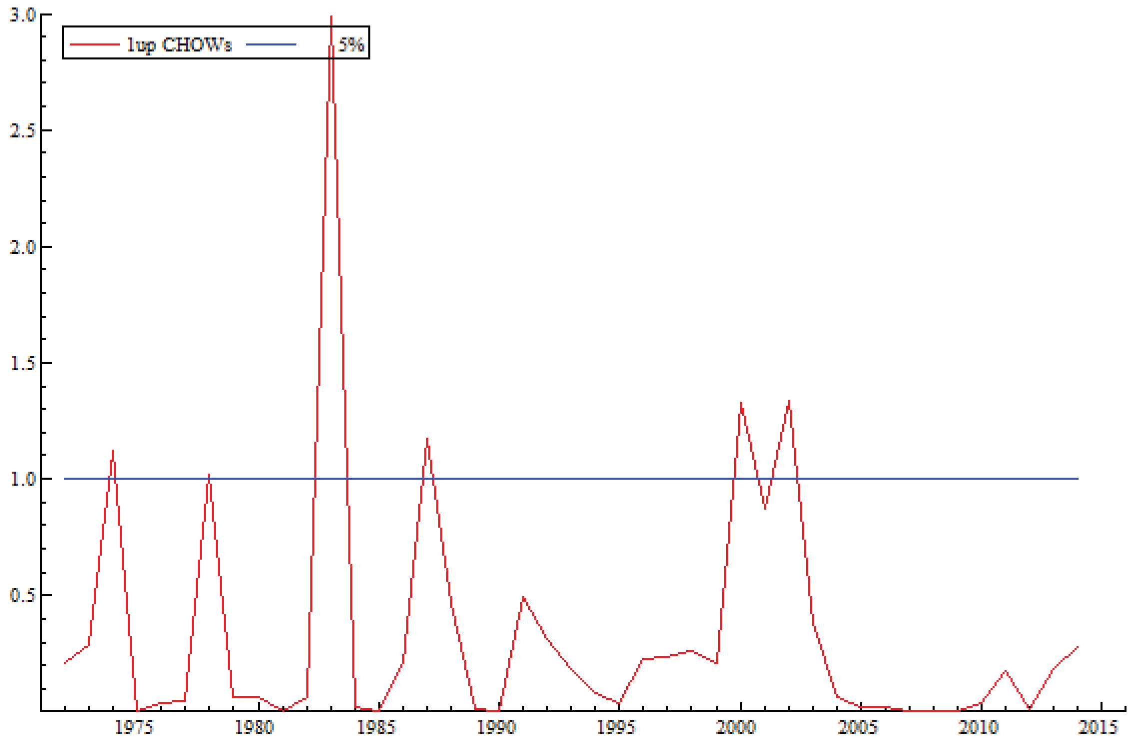

Figure 11: 1-step ahead Chow test, harvested soybean acreage (Ha) on changes in relative grain prices, adjusted for trend growth and short-term area adjustments, 1961-2014.

7 Conclusion

In this article, we have described grain acreage, yields and aggregate production, as well as price relationships for wheat, corn and soybeans in an historical setting 1961-2016. During this period, agriculture has been exposed to a number of dramatic changes related to input prices, agricultural technology, geopolitical events and rapid changes in consumers' income and preferences. Oil price shocks, the collapse of the Soviet Union, the introduction of GM-technology and new demand for corn as input for biofuels are examples of events that have added to the uncertainties normally faced by farmers. One would expect such dramatic events to be reflected in grain production and prices as erratic changes or structural breaks. However, the analysis of acreage allocation, prices, production and yields tells a story of gradual adjustments and continuity – with some exceptions. Grain farmers seem to have been able to adjust successfully to both positive and adverse external events. Production, yields and grain acreage have grown at a steady rate, and the changes in land allocation towards the different crops have been relatively smooth. Likewise, price risk as measured by standard deviations have been fairly stable over the long-run, as have fluctuations in relative prices.

Considering how wheat, corn and soybeans are substitutes in production, and to some extent substitutes in consumption, it is reasonable to expect a long-run relationship between grain prices. This link is confirmed through a co-integration analysis. Estimates from ECMs shows that grain prices are cointegrated, with rapid adjustments of deviations from the long-run equilibrium. In sum, we find that despite massive international events like wars, technological changes, and so on, adjustments in agriculture are continuous and relatively smooth. Some of this continuity should be attributed to global markets that allow producers and consumers to share risk, information, and forming expectations.

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Are Grain Markets Infected by Oil Price Shocks? An Empirical Analysis of the Effects From Dramatic Oil Price Changes on Grain Prices*

Abstract

In a number of scientific articles, and in public and political debates it has been claimed that commodity markets have become "financialized", i.e. that commodity prices are driven by financial sentiments rather than fundamental factors. In this narrative, oil is typically accused of driving other commodity prices, including those physically unrelated to oil. Empirical studies considering this issue typically employ standard time-series methods analysing co-variance over time, or study structural shocks through a vector autoregressive framework. The present study takes a somewhat different approach, focusing on whether dramatic events in the global oil market have an effect on grain price changes. Specifically, we study whether oil price shocks are immediately (or rapidly) transmitted to the grain markets. Adopting a framework known from event studies we find no evidence of shock contagion from oil to grain price changes, which contradicts the notion of herd behaviour and excess co-movement in commodity markets, here represented by oil and grains.

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1 Introduction

This paper is a contribution to the debate on "excess" co-movement in commodity markets. We investigate shock contagion across commodities, examining whether oil price shocks, defined as a large price change from one day to the next, are immediately (or rapidly) transmitted to grain markets. Commodity markets constitutes a major part of the global economy, and well-functioning futures markets are important due to their crucial role in price discovery and risk transfer. As such, it is important to reveal whether speculation is having adverse effects on the functioning of these markets.

Against a backdrop of high and volatile commodity prices 2006-2008, policymakers, the media and academics alike have discussed whether the prices of both physically related and unrelated commodities are moving too much in tandem, suggesting that speculative influences rather than fundamental factors are driving price fluctuations. This debate has a long history, with a milestone represented by Pindyck and Rotemberg (1990) claiming that herd behavior rather than fundamentals was driving commodity prices. This paper was later criticized for model misspecifications[1], but the discussion regarding herd behavior and "financialization" of commodity markets remains central on the political agenda. The term "financialization" implies that the surge in derivatives trading by purely financial traders has had a significant impact on commodity prices and fluctuations, and thereby caused highly correlated returns across different and unrelated asset classes (see e.g. Tang and Xiong (2012), Henderson, Pearson et al. (2014), Bruno, Büyükşahin et al. (2016)). Despite numerous policy papers and articles written on the issue, the question of whether the influx of long-only index traders and large institutional investors in commodity markets have been harmful or helpful is still under debate.

Leaving the question of "excess" co-movement aside for now, it remains an undisputable fact that the extent of commodity index traders' presence in commodity markets increased radically during the beginning of the 21st century. Numbers collected by Barclays Capital and presented in Irwin and Sanders (2011) suggests that asset totals invested in commodity index products grew from \$50 billion by late 2004, to roughly \$250 billion in mid-2008 (see also Henderson, Pearson et al. (2014)). Commodity index investing, like most derivatives trading, experienced a sharp

[1] Such as arbitrarily selected variables and failure to account for conditional heteroscedasticity (see e.g. (Deb, P. et al. (1996) and Le Pen, Y. and B. Sévi (2013)).

decline during the financial crisis, but resumed growing in 2009 and reached a new peak of about \$300 billion in 2010.[2] Those who claim that index traders were responsible for artificially inflating commodity prices and creating excess co-movement, argue that the size of this new investor group overwhelmed the normal functioning of these markets. The discussion continues to be relevant, with investment flows of \$54 billion into commodity markets from January through August 2016 (Financial Times, September 15, 2016). According to Barclays, this is an all-time high of flows into this asset class for the first eight months of any year. Sanders, Irwin et al. (2010) provide an interesting perspective to this debate reviewing earlier research on the adequacy of speculation in agricultural commodity markets, comparing historical findings with current levels of speculative versus hedging positions. Interestingly, previous studies of grain and livestock futures markets (going back as far as 1947) tend to be mainly concerned with *insufficient* speculative activity, and worry that there is not enough speculators to support hedging demands. Most of this research rely on “Working’s T”, which is an index measuring speculation in futures markets based on the notion that futures markets are predominantly hedging markets, where speculation tends to follow hedging volume (Working 1960). Sanders, Irwin et al. (2010) calculate and evaluate the Working’s T index from 1995 through 2008, finding that speculative levels remain within the range of historical levels, even after accounting for index trader positions.

Despite a large body of literature that rejects the notion that speculative influences are causing price distortions in commodity markets (see e.g. Irwin and Sanders (2011), Irwin and Sanders (2012), Kilian and Murphy (2014), Steen and Gjølberg (2013), Demirer, Lee et al. (2015), Bhardwaj, Gorton et al. (2016)), the controversy surrounding index traders and institutional investors lives on. It is however difficult to ascertain whether derivatives trading is causing excess co-movement, due to the difficulty of disentangling “speculative” and “fundamental” effects on prices. The side that believes index investors are overcrowding commodity markets have successfully applied political pressure to limit speculative positions in commodity futures markets. The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 is a tangible result of these efforts, outlining a new regulatory framework that grants the Commodity Futures Trading Commission (CFTC) wide authorities in setting aggregate limits on speculative

[2] Measuring the size of index investments is not a straightforward task, and these numbers are not universally agreed on. This is acknowledged in Irwin and Sanders 2011 p.5.

positions in US commodity markets.[3] Predictably, these regulations are met with little enthusiasm by investors and trading houses, which continue to voice concerns about the rules regarding capital requirements, position limits and limited hedging exemptions (see e.g. Financial Times April 26, 2015). It is likely that both sides of the debate will continue to lobby their case in the future, as the Dodd-Frank act is a massive piece of legislation and the exact implementation is still subject to revisions.

In this article we discuss agricultural commodities in the form of grains, and whether grain and oil prices are displaying co-movement beyond what is reasonable to expect based on fundamentals. Oil is typically considered a driver of commodity prices, and modern grain production has a long history of being linked to energy through input channels. Fuel and power are used directly in production through activities like planting, harvesting, transport and processing, while fertilizer and pesticides represent two important inputs through which agriculture indirectly consumes large amounts of energy. More recently, grain and oil prices are also connected through a second channel, namely biofuel production. The introduction of the Renewable Fuel Standard (RFS) in 2005, a federal program that requires transportation fuel sold in the United States to contain a minimum volume of renewables, created a source of corn demand that is directly linked to the market for gasoline. The RFS requires large quantities of corn being converted into ethanol for fuel use, and with the increased use of (predominantly) corn for ethanol production, grain crops are getting increasingly linked to energy.

There is already a large body of literature that discusses financialization of commodity markets. We will review the works most closely related to our research in section 2. Papers that are concerned with excess co-movement typically focus on the evolution of correlations and the covariance structure over time, or employ a structural vector autoregressive (SVAR) framework. SVAR models are used to quantify the average contribution of structural shocks to the variability of the data, and allows for historical decompositions that measure the cumulative contribution of each structural shock to the evolution of a particular variable over time (Kilian 2011). A common factor of both approaches is that they examine the issue of excess co-movement in a long-term perspective. Here, we chose to come at this subject from a somewhat different angle and

[3] Information about the rule-writing process can be found at http://www.cftc.gov/LawRegulation/DoddFrankAct/index.htm

investigate shock contagion in commodity markets. Rather than focusing on long-term macro variables we examine whether oil price shocks, defined as a large price change from one day to the next, are immediately (or rapidly) transmitted to the grain markets. Using daily data we hypothesise that if commodity markets have truly become a market of one, oil price shocks should be visible in grain market prices the same day, or at least on a next day basis. We argue that studying co-movement in the very short term is a way of solving the predicament of disentangling speculative and fundamental influences on commodity prices. Even seemingly unrelated commodities will *over time* be driven by common factors like interest rates, business cycles and so on. By taking the analysis down to a same day frequency, we reduce the need to identify these drivers. The futures markets for grains are highly liquid, as is (of course) the futures market for oil and oil products. In such markets, price relevant information and news travel fast. Thus, assuming that oil is infecting grain prices, one would expect an incubation period of just a few hours, or at most one day. Swift transmission of oil price shocks to grain markets cannot be explained by traditional transmission channels like e.g. fuel use in grain production, and can thus indicate that grain prices are no longer based on fundamental values, but rather on short-term "infection" from basically unrelated bodies. As such, our contribution to the literature is a study of price relationships and patterns one might fail to uncover using data on a monthly, or even weekly frequency (see Williams and Cook (2016) for a discussion on how low frequency data can be a challenge in examining short-term relations in financial markets).

The remainder of this article is organized as follows. Section 2 gives a brief overview of the current literature on herd behaviour and speculation in commodity markets. In section 3 we outline a methodological framework for evaluating shock contagion between markets in the very short term. Section 4 presents data and stylized facts on wheat, corn, soybeans and crude oil prices, observed daily from April 1983 through June 2016. Section 5 discusses our econometric results, while section 6 contains concluding remarks.

2 Related literature

Hirshleifer and Hong Teoh (2003) define herding to include *"any behavioural similarity brought about by actual interactions of individuals"* (Hirshleifer and Hong Teoh (2003) p. 27). Examples of situations where investors may "herd" include deciding whether or not to participate in a market, and when forming general sentiments on whether to buy or sell. Such behaviour can manifest itself as "bull" or "bear" markets, and is not necessarily harmful to price discovery *per se*. But if investors irrationally converge in their action and beliefs, herd behaviour could be deemed harmful. As mentioned above, some argue this is the case with commodity markets, stating that prices are driven by the sentiments of commodity index trackers and large institutional investors rather than fundamental factors like supply and demand. Herd behaviour also erodes the benefit of holding commodities as a diversification tool.

The recent focus on changes in the investor base of commodity trading is hardly uncalled for, as several studies on financial markets have suggested that herd behaviour among large institutional investors can distort market prices and/or create excess volatility (see e.g. Sias (1996), Dennis and Strickland (2002), Gabaix, Gopikrishnan et al. (2005), Chiang and Zheng (2010), and also Spyrou (2013) for a literature review). There is currently a large and growing body of literature that focus on the magnitude of financial institutions' positions in commodity derivatives, and whether the inflow of purely financial investors to this market has brought about adverse effects like herd behaviour. Irwin, Sanders et al. (2009) and Sanders, Irwin et al. (2010) are early contributions on whether recent speculative influences were damaging to the functioning of agricultural commodity markets. These studies find little evidence that speculation was responsible for the run-up in commodity prices prior to 2008, or otherwise harmful to the trading place. Demirer, Lee et al. (2015) reach similar conclusions when they find no significant effect of the stock market on herd behaviour in commodity futures markets. Steen and Gjølberg (2013) also revisit Pindyck and Rotemberg's question from 1990 asking whether commodity markets are characterized by herd behaviour. They find little evidence of financialization or contagion from the market activities of financial investors prior to 2008.

McPhail, Du et al. (2012) use a SVAR model and variance decomposition to measure the contribution of different factors in explaining corn price variation. They find that speculation has explanatory power, but only in the short run. In a long-run perspective, their findings indicate that energy prices followed by global demand are the most important drivers of corn prices. Kilian and Murphy (2014) get comparable results when they study the role of inventories and speculation with regard to crude oil prices. Evidence from their SVAR model suggests that global demand rather than speculative trading caused the run up in oil prices 2003-2008. Using a different structural model framework, Bruno, Büyükşahin et al. (2016) study the impact of index investors on food commodity prices. The authors find that equity-commodity return correlations have dropped dramatically in the aftermath of the financial crisis in 2008, suggesting the global business cycle rather than index investors are driving changes in the co-movement of commodity and equity prices. Bhardwaj, Gorton et al. (2016) arrive at a similar conclusion, focusing on a wider range of commodities (27 in total).

Somewhat contrary to these results, Tang and Xiong (2012) look at co-movement between the price of non-energy commodity futures and oil prices and find that the increase in this correlation is much more pronounced for commodities in two popular commodity indices. The authors conclude that this represents evidence that commodities have become “financialized”. Examining a much broader range of commodities, Silvennoinen and Thorp (2013) find that return correlations between commodities and traditional asset markets generally increased around 2000, suggesting a closer integration of commodity and equity markets. Büyükşahin and Robe (2014) use trader position data, and find that the activities of hedge funds are helpful in predicting fluctuations in equity-commodity co-movements. On the other hand, the positions of other participants in commodity futures markets, like e.g. index traders and swap dealers, contain little predictive power for cross-market correlation patterns. As such, their study reports mixed evidence as far as the financialization hypothesis is concerned. Ohashi and Okimoto (2016) study excess co-movement in commodity markets, and find a significant increase in the residual return correlation of several seemingly unrelated commodity pairs after 2000. Moreover, the authors find no significant increase in the residual correlation among non-index commodities. These results are consistent with the predictions in Basak and Pavlova (2016) who analyse how institutional investors entering commodity futures markets may influence prices, volatilities, and correlations. Their model suggests that all increase with financialization, but more so for index futures than non-index ones.

The body of scientific papers, newspaper articles and policy papers discussing the impact (or lack) of index funds and speculative traders on commodity prices is rapidly increasing. Afull review of the literature is outside the scope of this text. We refer to Irwin and Sanders (2011), Pies, Prehn et al. (2013), and Cheng and Xiong (2013) for a more comprehensive overview of prior research. It does however seem to be little evidence in the literature that index trackers and institutional investors influence returns and/or volatility dynamics in commodity markets. A recent metastudy of the impact of speculation on commodity markets by Haase, Zimmermann et al. (2016) concludes that speculation most likely reinforce trends in prices, but little impact on returns and risk premiums.

3 Methodological approach

Our aim is to examine whether shock contagion occurs from oil to grain markets. To obtain a short-term measure of potential shock effects from crude oil price changes onto the grain markets we adapt ideas known from event studies, a method used in several financial market studies to quantify how the value of a firm is affected by one specific event. This approach is convenient to the researcher as, given rationality in the marketplace, the impact of an event will be immediately reflected in security prices (MacKinlay 1997). As such, it is also suitable for our purposes.

To reveal changes in market behaviour that suggest commodity markets have become "financialized", we split the data sample in January 2004. The cut-off point is informed by previous literature, which typically finds that this is when hedge funds and other purely financial investors' began to dramatically increase their exposure to commodity markets (see e.g. Irwin and Sanders (2011), Steen and Gjølberg (2013), Bhardwaj, Gorton et al. (2016)).

The first undertaking of an event study is to define the event of interest. Here, we consider an "oil price shock" as the event. We further define an oil price shock to be daily price changes twice the historical standard deviation, i.e. the 2.5% largest positive and negative price changes given a normal distribution., Thus, the "shock" variable is an empirically based estimate, originating from observations April 4th 1983 June 13th 2016. Sticking loosely to the terminology of event studies we define the event window, which is the period over which we examine the potential shock effect, to be three days. Note that the estimation is done sequentially, so that we are able to examine the potential effect of a shock on day one, two and three separately.

The final step in the appraisal of an event's impact on price changes consists of specifying an econometric design. Here, we estimate the following model using ordinary least squares:

$$r_{t+n}^{x} = \alpha_0 + \alpha_1 r_t^{oil} + \alpha_2 shock_t^{+} + \alpha_3 shock^{-} + \alpha_4 \left[shock^{+} r_t^{oil}\right] + \alpha_5 \left[shock^{-} r_t^{oil}\right] + \varepsilon_t^{x} \qquad (1)$$

where r_{t+n}^{x} represents the logarithmic price change of either wheat, corn or soybeans on time $t+n$ for $n = 0, 1, 2$; the variable r_t^{oil} denotes the log price change of oil at time t, and the two $shock$ variables are dummies defined as:

$$shock^{+} = \begin{cases} 1\ if\ r_t^{oil} > +2 \times \mathrm{st.dev.} \\ 0\ otherwise \end{cases}$$

$$shock^{-} = \begin{cases} 1\ if\ \ r_t^{oil} < -2 \times \mathrm{st.dev.} \\ 0\ otherwise \end{cases}$$

The parameter α_1 controls for how oil price changes affect simultaneous and subsequent changes in the price of grain. Since both variables are on logarithmic form this parameter is readily interpreted as a percentage. The parameters α_2 and α_3 indicate whether oil price shocks have a significant influence on grain price changes. The interaction terms, associated with the parameters α_4 and α_5, provide information about the strength of this effect. This model allows us to trace out whether there exists a significant relationship oil and grain price changes, and whether shocks to the oil price influence subsequent grain price changes. Significant parameter estimates in relation to the shock variables would indicate that dramatic events in the oil markets are immediately ($n = 0$) or rapidly ($n = 1,2$) transmitted to the grain markets, supporting the notion of herd behaviour among investors in commodity markets. We estimate the model on current and subsequent values of the left hand side variable to allow for delayed effects of a shock. Under the null, events (shocks) in the oil market have no impact on price changes in the market for global grains.

To provide more information about how the *magnitude* of oil price movements influence grain price changes we proceed by estimating piecewise linear regressions using intervals of either positive or negative oil price changes as the left hand side variable. Specifically, we model daily grain price changes as:

$$r_{t+n}^{x} = \alpha_0 + \alpha_1 r_t^{oil} + \alpha_2 r_t^{\mathrm{oil2-4}} + \alpha_3 r_t^{\mathrm{oil4-6}} + \alpha_3 r_t^{\mathrm{oil6+}} + \varepsilon_t^{x} \qquad (2)$$

where r_{t+n}^{x} represents the logarithmic price change of either wheat, corn or soybeans on time $t + n$ for $n = 0, 1, 2$; the variable r_t^{oil} denotes log price changes in oil between 0-2% on time t, and the remaining variables represent "bins" of oil log price changes of 0-2%, 2-4%, 4-6%, and >6%, respectively. The parameter α_1 measures the grain markets' general response to oil price changes, the parameter α_2 measures the effect of a moderate oil price shock, α_3 measures the additional impact if the shock is substantial, and α_4 measures the additional impact of very dramatic oil price changes. Hence, we are able to differentiate between the contagion effects of oil price shocks of different magnitudes.

We then proceed with an analysis of possible volatility contagion from the oil market to grain. In this analysis we use a multivariate GARCH approach based on Engle (2002) to study the dynamics of volatility and interdependence between the different markets. Specifically, we employ a dynamic conditional correlation (DCC) model, which has the flexibility of univariate GARCH models coupled with a parsimonious parametric structure for the correlations. The DCC approach is based on two steps; modelling the volatility of each individual asset and then modelling the co-variances based on the standardized residuals from the first step.

Consider the following model:

$$r_t = \gamma_0 + \sum_{j=1}^{p} \gamma_j r_{t-j} + \varepsilon_t$$

$$\varepsilon_t | I_{t-1} \sim (0, H_t) \tag{3}$$

where r_t is an $m \times 1$ vector of price returns, γ_0 is a $m \times 1$ vector of long-term drifts, γ_j for $j = 1, \dots, p$ is an $m \times m$ matrix of parameters, and ε_t is a $m \times 1$ vector of forecast errors of the best linear predictor of r_t, conditional on past information (I_{t-1}) and with variance-covariance matrix H_t. As in a standard VAR representation, the elements of $\gamma_j, = 1, \dots p$, can be interpreted of own- and cross-mean dependence between markets.

The conditional variance-covariance matrix, H_t, is defined as:

$$H_t = D_t R_t D_t \tag{4}$$

where D_t is a diagonal matrix of conditional standard deviations, $D_t = diag(h_{11,t}^{1/2}, \dots, h_{mn,t}^{1/2})$ where each $h_{ii,t}^{1/2}$ evolves according to a univariate GARCH specification of the form $h_{ii,t} = s_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{ii,t}^2$ and R_t is a matrix of conditional quasicorrelations:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{5}$$

with the $m \times m$ symmetric positive-definite matrix $Q_t = \left(q_{ij,t}\right), i, j = 1, \dots, m$ given by

$$Q_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1 \tilde{\epsilon}_{t-1} \tilde{\epsilon}_{t-1}' + \lambda_2 Q_{t-1} \tag{6}$$

where $\tilde{\epsilon}_{it} = \varepsilon_{it} / h_{ii,t}^{1/2}$. The R in (6) is an $m \times m$ matrix of correlations, and λ_1 and λ_2 are non-negative adjustment parameters that govern the dynamics of conditional correlations and satisfy $0 \leq \lambda_1 + \lambda_2 < 1$.

The DCC model is appropriate in our context since it approximates a dynamic conditional correlation matrix that permits us to examine variations in the correlation between markets over time. Further, the variance-covariance matrix in (4) allows us to model the degree of volatility interdependence between markets across time. We estimate the model using a $Student's\ t$ density to account for the leptokurtic distribution of time series returns.

4 Stylized facts

We have collected daily prices for three grains (wheat, corn and soybeans) and crude oil, covering April 4th 1983 to June 13th 2016; 8 319 observations in total. Specifically, we use front month futures prices from the CME group, which is the largest commodity futures exchange in the world.[4] The contracts are rolled over on the first day of the delivery month of the first nearby contract, to avoid expiry effects that can occur when trading volume decreases close to maturity.

[4] All price series are downloaded from Quandl, which is a search engine for numerical data that offers access to a multitude of financial, economic and social datasets. See www.quandl.com for more information.

To circumvent artificial jumps in the data on rollover dates, price adjustments are implemented according to the calendar-weighted method. The price gap between consecutive contracts is smoothed by gradually shifting from 100% front and 0% back weighting, to 0% front and 100% back weighting, over a period of 5 days. This price adjustment corresponds to a mechanical roll strategy wherein the trader rolls 20% of the position every day, for 4 days before the roll date.

Crude oil is the world's most heavily traded commodity, with a futures market that is very liquid for at least one year ahead. There is a new contract expiring each calendar month, and the December contract trades nine years into the future. Wheat and corn trade with fewer maturities per year, namely March, May, July, September and December, while soybean futures trade with January, March, May, July, August, September, and November contracts. The available maturities reflect the seasonality of these crops.

Grain and oil prices are influenced by several common factors, but these products have important differences in production. Most importantly, oil is produced continuously and trade with futures contracts expiring every month while the major grains are seasonal crops, with product being stored for gradual consumption and a marketing period of (typically) one year. Taking US corn as an example, planting starts in the beginning of April and lasts through June. The main harvest begins in October, and is finished by the end of November. This leads to a pattern of seasonality, with prices increasing throughout the marketing year as available stocks decline.

Figure 1 shows the development of grain and crude oil prices over the period 1983–2016, rebased so that January 1983 = 100 for each series. We see that (nominal) commodity prices remained stagnant from the beginning of this period up until late 2001, when crude oil prices started to increase. A steep upsurge in grain prices followed a few years later, before all commodities climaxed in a price spike in the summer of 2008. Prices subsided dramatically at the onset of the financial crisis and remained depressed for approximately two years, before increasing to pre-spike levels in 2010. Grain prices reached unprecedented levels again in 2012, due to meagre harvests in the "corn belt" when the US experienced its worst drought in more than half a century. Crude oil prices also regained their strength after the collapse in 2008, but experienced a new steep decline in early 2014. The main cause of this price drop was a near doubling of US domestic oil production, crowding out import of oil barrels that used to be designated for this market. Canadian, Iraqi and Russian oil producers were also pumping oil at record levels, which further contributed to a flooded market. In February 2016 WTI crude oil was quoted at $26.21 a barrel, which is equivalent to a price drop of 75% compared to June 2014 levels.

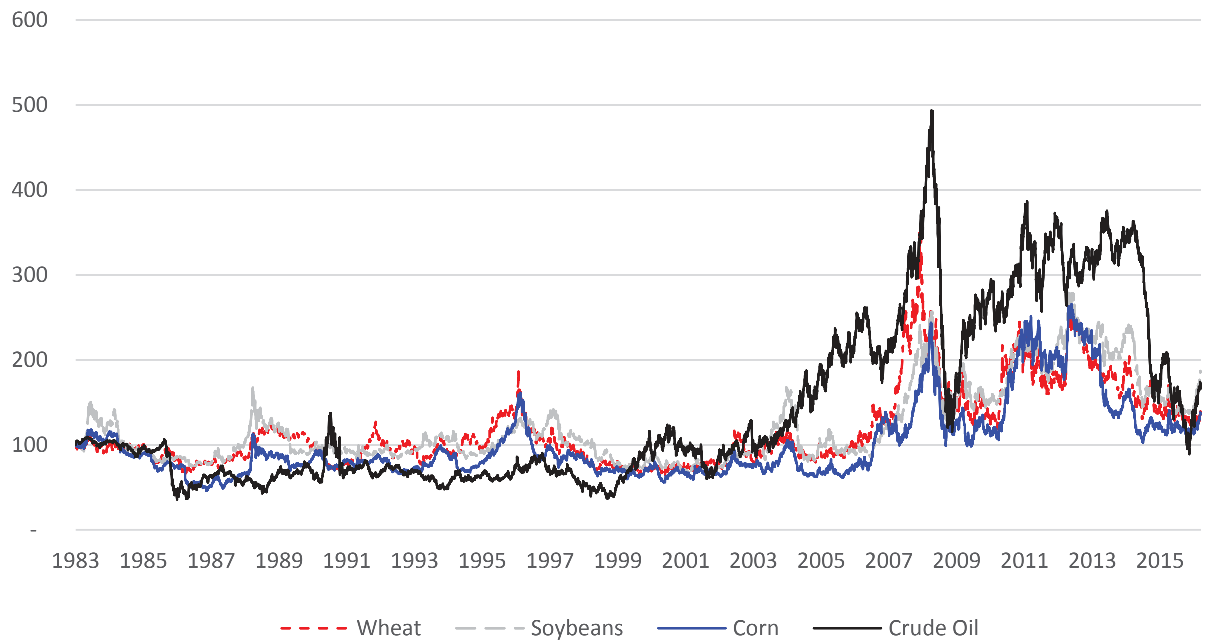

Figure 1: Front month futures prices, daily observations April 4th 1983 - June 13th 2016 (Rebased, April 4th 1983 = 100).

Table 1 summarizes risk and return statistics for the grains and crude oil 1983-2016. The mean return of all commodities are zero. The variability in price returns are similar across the grain varieties, with annualized standard deviations in the range of 23-27%. Risk is much higher for crude oil, with a volatility of 36% annualized. The higher variability in crude oil returns is also visible through the minimum and maximum values. The min/max values of grain returns are all in the interval of ±10%, while crude oil returns ranges from -41 to 14%. A negative price change of 41% from one day to the next is extreme, and this was a one-time occurrence in January 91 due to a release of strategic American oil reserves. Oil prices have however fluctuated wildly during the beginning of this millennium as well, in particular around the financial crisis, with several price changes of more than 10% from one day to the next. All price return distributions display high peaks and fat tails relative to the normal distribution. The three grain varieties all have excess kurtosis of roughly 2.5 relative to the Gaussian, while the crude oil return distribution display extremely fat tails with excess kurtosis of 16.93. All four return distributions are moderately skewed, once more this is effect is more pronounced for crude oil returns with a negative skewness of 0.83.

Table 1: Descriptive statistics, grain and crude oil returns, 1983-2016

	Wheat	Soybean	Corn	Crude oil
Mean	0,00	0,00	0,00	0,00
St. Deviation*	27 %	23 %	24 %	36 %
Kurtosis	2,50	2,35	2,67	16,93
Skewness	0,05	-0,25	-0,04	-0,83
Min	-10,0 %	-7,4 %	-7,9 %	-40,8 %
Max	8,8 %	6,6 %	9,0 %	14,0 %
N	8 319	8 319	8 319	8 319

Price return series are calculated as $r_t = ln(p_t/p_{t-1})$
*annualized by multiplying with $\sqrt{252}$

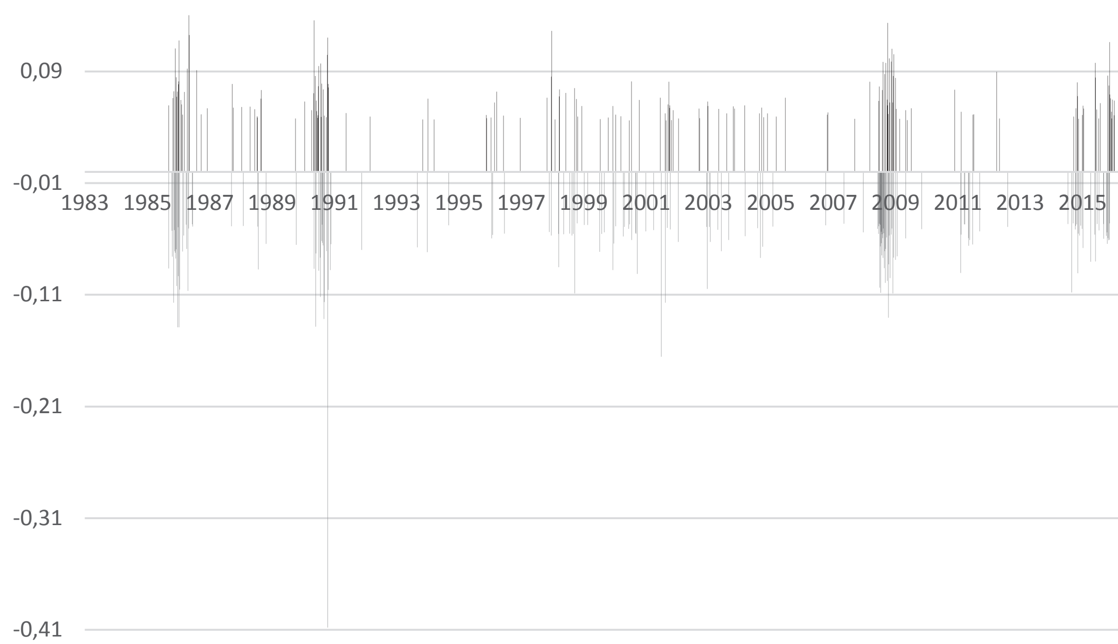

Figure 2: Positive and negative oil price shocks, daily returns, April 4th 1983 to June 13th 2016.

Our dataset consists of 8 319 observations and a positive price change of more than two daily standard deviations occurred 178 days, i.e. 2.1% out of total. Negative returns in excess of two standard deviations occurred 193 days, or 2.3% out of total. Figure 2 displays positive and negative oil price shocks against time. We see that large price deviations tend to cluster together, and 1986 was a year with several major price changes from one day to the next, both positive and negative. The 1980s were characterised by a large surplus of crude oil caused by falling demand following the elevated energy prices during the 1973 and 1979 energy crisis. OPEC (Organization of the Petroleum Exporting Countries) not only failed to maintain oil price levels, but was also loosing market shares despite lowering production. Some member countries began to actively counteract the internal OPEC production quota system, and against this backdrop, Saudi Arabia publicly announced their intention to regain their market share in December 1985. As reported by Bloomberg (Loder 2016): *"In 1986, the Saudis opened the spigot and sparked a four-month, 67 percent plunge that left oil just above $10 a barrel. The U.S. industry collapsed, triggering almost a quarter-century of production declines, and the Saudis regained their leading role in the world's oil market".*

The second period of very volatile oil prices came in the aftermath of Saddam Hussein's invasion of Kuwait in August 1990 (Hamilton 2009). This was the second time the Iraqi regime invaded another OPEC member country, and even though the impact on prices was less severe than during the 1973 and 1979 energy crisis, volatility was just as high. In this period we also find the most extreme negative return, when oil prices dropped by more than $10 on January 17th 1991after increasing by $3-5 during the first half of April. This price drop was a direct response to the first ever Presidentially-directed release of strategic American oil reserves, when the US joined its allies in pledging global oil supplies as the war broke out in the Persian Gulf.[5]

Referring back to figure 2, we see that what we define as oil price shocks are spaced out further apart from the beginning of 1991 onwards. During the rest of the 90s, OPEC's member countries largely succeeded in their aims of achieving market stability and minimizing price volatility (see e.g. Hamilton (2011)). There is a small cluster of large price changes to the upside in the final

[5] A summary of strategic petroleum releases can be found at www.energy.gov.

months of 2001 following the terrorist attacks on 9/11, before the next period of extreme market turbulence occurs at the onset of the financial crisis during the summer of 2008. Another event, which is easily identified in figure 2, is a new release of strategic oil reserves in the summer of 2011. This release was a reaction to the disruption in global oil supplies caused by political instability in the Middle East and North Africa. Markets then remained stable until the collapse of the oil price beginning in 2014. As previously mentioned, the main cause of this drop was a massive increase in US oil production in conjunction with lack of cooperation between OPEC member countries. Large non-OPEC oil-producers, like e.g. Russia, also refused to coordinate efforts towards more stable oil prices.

A brief, and very preliminary, look at our data highlights how the markets for crude oil and grains by tradition have been two separate entities. As previously mentioned, 1986 was a turbulent year in the global oil market, with large production surpluses and internal disagreement among the members of OPEC. This turbulence is reflected in table 3, which gives an overview of the 20 most dramatic days in the oil market 1986-2016, i.e. the 20 days with largest price changes from one day to the next (10 positive and 10 negative). Four out of ten of the largest positive price changes occurred in 1986. As can be seen, on those four days of dramatic oil price increases, corn and soybean prices dropped. Wheat price changes were also negative of three out of four of those days.

Table 3: 20 dramatic days in the oil market and simultaneous grain price changes, April 4th 1983- June 13th 2016

Largest positive daily price changes					Largest negative daily price changes				
Date	**Oil**	**Wheat**	**Soybeans**	**Corn**	**Date**	**Oil**	**Wheat**	**Soybeans**	**Corn**
24.02.1986	11,04 %	0,30 %	-0,48 %	-1,28 %	04.02.1986	-11,72 %	0,62 %	-1,40 %	0,61 %
07.04.1986	11,76 %	-3,27 %	-2,35 %	-0,75 %	24.03.1986	-13,91 %	-1,22 %	-0,75 %	0,43 %
04.08.1986	14,03 %	-0,10 %	-2,18 %	-1,54 %	08.04.1986	-13,90 %	-2,36 %	-0,57 %	-2,17 %
05.08.1986	12,24 %	-2,02 %	-0,84 %	-0,31 %	27.08.1990	-13,86 %	-1,15 %	1,89 %	-0,14 %
06.08.1990	13,57 %	0,62 %	-0,51 %	-0,10 %	30.11.1990	-13,17 %	3,14 %	0,73 %	1,26 %
14.01.1991	12,03 %	-1,50 %	0,57 %	0,53 %	05.12.1990	-11,64 %	-0,67 %	1,97 %	0,21 %
23.03.1998	12,62 %	1,36 %	-0,65 %	-0,47 %	17.01.1991	-40,81 %	1,79 %	0,76 %	0,00 %
31.12.2008	13,34 %	0,99 %	2,94 %	2,68 %	24.09.2001	-16,54 %	0,28 %	0,85 %	-0,12 %
19.02.2009	11,02 %	1,70 %	-0,34 %	1,14 %	15.11.2001	-11,71 %	-0,18 %	-0,45 %	0,60 %
12.02.2016	11,62 %	-0,16 %	-0,09 %	-0,42 %	07.01.2009	-13,07 %	-4,81 %	-2,59 %	-2,61 %

More generally speaking, nothing in table 3 suggests that a dramatic oil price changes immediately contaminate grain markets. There is only one day where we see a positive price change across all markets, namely on 31st December 2008. Similarly, only two out of the ten days with dramatic oil price decreases show corresponding drops in all three grain markets. We identify the 1990s as a highly volatile period for oil prices (the aftermath of Saddam Hussain's invasion of Kuwait in August that year), and there is oil market turbulence following the 9/11 terrorist attacks on the United States. But again, there is no pattern to the corresponding price changes of wheat, corn and soybeans, which suggests that these markets are mainly driven by fundamental factors unrelated to oil. Again, we note the initiation of Operation Desert Storm and the first ever Presidentially-directed release of strategic American oil reserves which manifest itself as a 41% price drop in oil prices on 17th January 1991. On that day, grain price changes were all positive (≈ 0 in the case of corn).

5 Econometric results

We have specified an econometric model that aims to identify the impact of oil price shocks on grain price changes and thus detect potential contagion effects from oil to grain markets. Table 4 presents the results from 1983-2003, i.e. prior to the period when commodity markets are said to have become financialized. Within the confines of our models, oil price changes were not an important determinant of grain price changes during this period. We see that the coefficient measuring the impact of oil price changes is only significant in the case of corn. Negative oil shocks have a significant effect on price changes of wheat, but the estimated coefficients are low in value and the explanatory power of this model is extremely low at 0.2%. Oil shocks influence the subsequent price of wheat, but once more the R^2-value is very small. Overall, the regressions displays negligible explanatory power and few significant coefficient estimates.

Table 4: The impact of oil price shocks 1983 - 2003, daily observations

	r_t^{oil}	$shock_t^+$	$shock_t^-$	$[shock_t^+ r_t^{oil}]$	$[shock_t^- r_t^{oil}]$	R^2
r_t^{wheat}	0.02 (1.66)	0.00 (0.99)	**-0.01** **(-2.46)**	-0.07 (-1.06)	**-0.08** **(-2.24)**	0.20%
r_t^{corn}	**-0.03** **(-2.63)**	0.01 (1.26)	-0.00 (-0.81)	-0.05 (-0.85)	0.01 (0.23)	0.17%
$r_t^{soybeans}$	-0.01 (-0.67)	0.01 (1.38)	-0.00 (-1.56)	-0.09 (-1.46)	-0.05 (-1.52)	0.09%
r_{t+1}^{wheat}	-0.00 (-0.07)	**0.01** **(2.80)**	-0.00 (-1.59)	**-0.17** **(-2.48)**	-0.05 (-1.56)	0.21%
r_{t+1}^{corn}	0.01 (0.81)	0.00 (0.76)	-0.00 (-0.53)	-0.05 (-0.83)	-0.03 (-0.78)	0.03%
$r_{t+1}^{soybeans}$	0.01 (0.60)	0.00 (0.51)	-0.00 (-1.30)	-0.04 (-0.66)	-0.04 (1.64)	0.05%
r_{t+2}^{wheat}	0.00 (0.03)	-0.00 (-0.76)	-0.00 (-0.83)	0.06 (0.87)	0.00 (0.13)	0.09%
r_{t+2}^{corn}	0.00 (0.20)	-0.00 (-0.35)	-0.00 (-0.05)	-0.00 (-0.03)	0.02 (0.64)	0.07%
$r_{t+2}^{soybeans}$	0.01 (1.32)	0.00 (0.41)	-0.00 (-0.97)	-0.03 (-0.43)	-0.03 (-0.80)	0.08%

N = 5 200
t-values in brackets, values significant at the 5% level marked in bold
constant excluded for brevity

Table 5 presents the results from the regressions 2004-2016. The significant r_t^{oil}-parameter and the noticeable higher R^2-values indicates that oil prices have gained importance as a driver of grain price changes. The parameters are also much larger in absolute value compared to the figures in table 4. In the instance of wheat, the estimated parameter increase from 0.02 through 1983-2003, to 0.21 when we exclude observations prior to 2004. The latter estimate indicates a 2.1% price change in the price of corn as an immediate response to a 10% change in the price of oil. We also find that there is a significant relationship between oil price changes and the subsequent value of wheat and soybean returns. Somewhat puzzling, the parameter representing the response of next day wheat price changes to oil price fluctuations is negative.

Table 5: The impact of oil price shocks 2004 - 2016, daily observations

	r_t^{oil}	$shock_t^+$	$shock_t^-$	$[shock_t^+ r_t^{oil}]$	$[shock_t^- r_t^{oil}]$	R^2
r_t^{wheat}	**0.21**	0.01	**0.02**	-0.18	**0.30**	5.56%
	(10.1)	(1.02)	**(2.21)**	(-1.43)	**(2.40)**	
r_t^{corn}	**0.20**	0.00	0.01	-0.06	**0.22**	6.24%
	(10.8)	(0.21)	(1.47)	(-0.56)	**(2.00)**	
$r_t^{soybeans}$	**0.17**	-0.00	**0.02**	-0.04	**0.32**	7.29%
	(10.6)	(-0.23)	**(2.39)**	(-0.39)	**(3.28)**	
r_{t+1}^{wheat}	**-0.05**	0.00	-0.01	-0.01	-0.17	0.39%
	(-2.24)	(0.15)	(-1.22)	(-0.11)	(-1.32)	
r_{t+1}^{corn}	-0.03	-0.00	0.00	0.10	0.11	0.18%
	(-1.69)	(-0.82)	(0.45)	(0.82)	(0.99)	
$r_{t+1}^{soybeans}$	**0.05**	**-0.01**	-0.01	**-0.27**	-0.16	0.51%
	(3.07)	**(1.97)**	(-0.90)	**(-2.67)**	(-1.58)	
r_{t+2}^{wheat}	-0.02	-0.01	-0.01	0.15	-0.19	0.16%
	(-0.81)	(-0.81)	(-1.70)	(1.16)	(-1.45)	
r_{t+2}^{corn}	-0.03	-0.00	-0.01	0.08	-0.12	0.16%
	(-1.44)	(-0.31)	(-1.48)	(0.72)	(-1.11)	
$r_{t+2}^{soybeans}$	-0.02	-0.01	-0.01	0.13	-0.16	0.20%
	(-1.27)	(-0.99)	(-1.87)	(1.27)	(-1.60)	

N = 3 118
t-values in brackets, values significant at the 5% level marked in bold
constant excluded for brevity

Focusing on oil price shock effects, table 5 shows that positive oil price shocks have no significant impact on grain price changes the same day. There is a significant influence on the subsequent price of soybeans, but the estimated parameter is close to zero and the explanatory power of this regression is marginal at 0.51%. We find that negative oil price shocks have a significant effect on changes in wheat and soybean prices, but surprisingly the estimated coefficients are negative. In other words, major price drops in the oil market are accompanied by positive changes in the price of wheat and soybeans the same day, which is the opposite of what one would expect in a market characterized by herd behaviour. The magnitude of the interaction terms suggests this effect to be stronger after 2004, and all the estimated parameters are statistically significant. Finally, we note that as in the previous regressions, using subsequent price changes as left hand side variable provides few significant effects.

We note that although statistically significant, our findings are not necessarily economically significant in the sense that one could use this information for e.g. hedging price risk (taking opposite positions in the grain and oil market in times of market turbulence). Regardless, the statistical results are clearly not supporting the claim that that oil price turbulence is spilling over into the grain markets.

Our results so far suggest that oil price changes, and to some extent oil price shocks, have a significant effect on grain price changes after 2004. Piecewise linear regressions provide additional information about the influence of oil price shocks, i.e. on whether “size matters”. Table 6 presents estimation results from 1983-2003, confirming that oil price changes played a minor role in determining grain price changes prior to 2004. All R^2-values are very low, regardless of whether we consider positive or negative oil shocks. Furthermore, we see that there are very few significant parameter estimates, and those statically significant are marginal in size. For instance, the estimated impact of a 2-4% oil price change on corn price changes is only -0.07% (all prices changes are multiplied by 100 prior to the estimation). Finally, we note that the estimated coefficient is negative, i.e. the price changes in oil and corn are of opposite sign. We see the same effect in the response of soybean price changes to negative oil price shocks. While the estimated coefficients are too small to be economically significant, we note that these opposite price changes are not supporting the notion of herd behaviour in commodity markets.

Table 6: Piecewise linear regressions - 1983-2003

	r_t^{oil} positive				
	0-2%	**2-4%**	**4-6%**	**>6%**	R^2
r_t^{wheat}	0,04 (1,20)	0,03 (1,23)	0,04 (1,28)	0,01 (0,46)	0,09 %
r_t^{corn}	-0,03 (-0,73)	**-0,07** **(-3,20)**	-0,01 (-0,29)	0,02 (-1,00)	0,23 %
$r_t^{soybeans}$	0,05 (1,32)	-0,00 (-0,03)	0,00 (0,12)	-0,00 (-0,18)	0,03 %

	r_t^{oil} negative				
	0-2%	**2-4%**	**4-6%**	**>6%**	R^2
r_t^{wheat}	0,05 (1,19)	0,02 (0,90)	0,02 (0,71)	0,00 (0,15)	0,05 %
r_t^{corn}	-0,06 (-1,62)	-0,02 (-0,77)	0,00 (0,02)	-0,01 (-0,60)	0,06 %
$r_t^{soybeans}$	0,07 (1,85)	-0,01 (-0,26)	**0,05** **(2,13)**	-0,01 (-1,22)	0,14 %

N = 5 200, t-values in brackets, values significant at the 5% level marked in bold, constant excluded for brevity

Table 7 presents piecewise linear estimation results 2004-2016. Again we find evidence of a closer relationship between crude oil and grain prices after 2003. All estimated coefficients are statistically significant, the R^2-values are however still ranging from 3.38 to 6.28%. Consequently, the influence of oil price changes is marginal. We see that the estimated coefficient on oil price changes above 6% is only 0.18, which implies that the impact of such dramatic oil price changes are only 0.18% and hardly relevant in a financial setting. If we look at table 7 as a whole, no estimated coefficient is above 0.05 which again suggests that the explanatory power of dramatic oil price changes are marginal in this context. Finally, we note that the estimated parameters in relation to negative oil price changes all have positive signs. In other words, oil market turbulence affect grain price changes by a uniform price increase. Running these regressions using subsequent values of grain price changes as left hand side variables provides little information beyond what we have found previously, the results are thus excluded for brevity.

Table 7: Piecewise linear regressions - 2004-2016

	r_t^{oil} positive				
	0-2%	**2-4%**	**4-6%**	**>6%**	R^2
r_t^{wheat}	**0,42** **(6,28)**	**0,33** **(7,47)**	**0,25** **(4,20)**	**0,18** **(3,09)**	3,34 %
r_t^{corn}	**0,45** **(6,86)**	**0,34** **(9,10)**	**0,18** **(4,18)**	**0,22** **(4,69)**	4,44 %
$r_t^{soybeans}$	**0,42** **(8,00)**	**0,25** **(7,47)**	**0,15** **(3,26)**	**0,16** **(3,62)**	3,71 %

	r_t^{oil} negative				
	0-2%	**2-4%**	**4-6%**	**>6%**	R^2
r_t^{wheat}	**0,34** **(5,02)**	**0,31** **(7,21)**	**0,21** **(3,65)**	**0,36** **(5,45)**	4,26 %
r_t^{corn}	**0,42** **(7,14)**	**0,27** **(6,78)**	**0,25** **(5,08)**	**0,36** **(6,38)**	5,35 %
$r_t^{soybeans}$	**0,30** **(5,49)**	**0,26** **(6,86)**	**0,24** **(5,66)**	**0,35** **(7,51)**	6,28 %

N = 3 119, t-values in brackets, values significant at the 5% level in bold, constant excluded for brevity

Moving on to the relationship between the oil and grain markets in terms of volatility contagion, we adopt a DCC GARCH model and examine volatility dynamics and time varying correlations. The estimation results 1983-2003 (table 7) indicate that crude oil and grain markets are not interrelated at the mean level. In the condition mean equation, the γ_{1ij} coefficients capture cross-market dependence, i.e. the dependence of the return in market i on the lagged return in market j. With the exception of corn, which is influenced by past wheat and crude oil returns, we find no significant cross-market dependence. Wheat and corn exhibit significant and positive own mean dependence, and crude oil own mean dependence is significant at a 6.5% level. The soybean market exhibit significant negative own mean dependence. The latter finding can be explained by substitution effects in demand. If large soybean price changes are associated with an increase in soybean prices, this will reduce the demand for corn and increase demand for substitutes like e.g. corn for animal feed. As can be seen, the adjustment parameters, λ_1 and λ_2, sum to 0.944, indicating high persistence in the conditional variances. That the parameter estimates sum to less than unity supports the notion of a mean reverting process, but in this instance the return towards a long-run mean level are estimated to be very slow. The relative size of the lambdas further suggests that the evolution of the conditional co-variances depend more on their past values than on lagged residuals' innovations. Finally, we see that none of the estimated unconditional correlation coefficients are significantly different from 0 in this time period.

Table 7: DCC-GARCH estimation results 1983-2003 (obs=5199)

	Wheat i=1	Soybeans i=2	Corn i=3	Crude Oil i=4
Conditional mean equation				
γ_0	-0.005 (0.750)	0.006 (0.689)	0.006 (0.656)	0.009 (0.606)
γ_{11i}	**0.032 (0.012)**	-0.012 (0.341)	-0.006 (0.616)	0.013 (0.315)
γ_{12i}	0.023 (0.059)	**-0.029 (0.042)**	0.000 (0.981)	-0.008 (0.445)
γ_{13i}	**0.562 (0.000)**	-0.010 (0.507)	**0.093 (0.000)**	**0.035 (0.023)**
γ_{14i}	0.010 (0.175)	0.001 (0.856)	0.006 0.289	0.026 (0.065)
Conditional variance-covariance equation				
s_i	**0.051 (0.001)**	**0.020 (0.000)**	**0.022 (0.000)**	**0.007 (0.032)**
α_i	**0.071 (0.000)**	**0.073 (0.000)**	**0.080 (0.000)**	**0.090 (0.000)**
β_i	**0.896 (0.000)**	**0.917 (0.000)**	**0.909 (0.000)**	**0.915 (0.000)**
λ_1				0.004 (0.084)
λ_2				**0.940 (0.000)**
corr(rwheat,rsoybeans)				-0.023 (0.130)
corr(rwheat,rcorn)				0.022 (0.166)
corr(rwheat,rcrude)				0.018 (0.225)
corr(rsoybeans,rcorn)				0.000 (0.978)
corr(rsoybeans,rcrude)				0.016 (0.257)
corr(rcorn,rcrude)				-0.019 (0.211)
Wald joint test for adjustment coefficients				**947.47 (0.000)**

N = 5 199, P-values in brackets, values significant at the 5% level in bold

Considering the time period beginning in 2004, the results in table 8 indicate very high persistence in the conditional volatility. We see that the adjustment parameters sum to 0.985, i.e. close to unity, which implies that shocks to volatility remain in the system for a very long time. Once more we see strong evidence of ARCH and GARCH effects, and the joint test for the adjustment coefficients further supports a model approach that allows for time varying correlation. Examining the levels of mean dependence there are no dramatic changes compared to the previous period. Interestingly, wheat now displays significant cross-market dependence towards all other markets. In terms of crude oil and soybeans the estimated coefficients are modest in size and thus not necessarily economically significant, but the cross-market dependence of corn on wheat returns is still strong (0.149 compared to a value of 0.562 in the first period) and highly significant.

All estimated unconditional correlation coefficients are statistically significant in this sample, the correlation among the grain varieties being in the range of 0.36-0.65. Interestingly, we also find significant and positive unconditional correlation between oil and grain markets, with coefficient estimates in the range of 0.17-0.24. In the case of corn, one might argue the considerable expansion in the use of biofuels and ethanol production capacity has led to closer integration between corn and energy markets (see e.g Carter, Rausser et al. (2012), Gardebroek and Hernandez (2013)). On a more general basis, several authors have argued that this increase in correlation is caused by "financialization" (see e. g. Tang and Xiong (2012), Henderson, Pearson et al. (2014), Ohashi and Okimoto (2016), while another strand of literature suggests time-varying correlation is tied to business cycles and/or large price movements during economic recessions (see e.g. Steen and Gjølberg (2013), Bruno, Büyükşahin et al. (2016)). Our analysis does not attempt to identify the source behind this closer integration between grain and oil markets, we merely note that correlations have increased after 2004 (see also figure 3) and shocks to conditional volatilities are generally very persistent.

Table 8: DCC-GARCH estimation results 2004-2016 (3119)

	Wheat i=1	**Soybeans i=2**	**Corn i=3**	**Crude Oil i=4**
Conditional mean equation				
γ_0	-0.000	**0.067**	0.026	0.041
	(0.988)	**(0.002)**	(0.298)	(0.192)
γ_{11i}	-0.019	-0.005	-0.033	-0.001
	(0.395)	(0.757)	(0.086)	(0.956)
γ_{12i}	**-0.066**	**-0.076**	-0.032	-0.007
	(0.002)	**(0.000)**	(0.122)	(0.778)
γ_{13i}	**0.149**	0.176	**0.151**	**0.050**
	(0.000)	(0.000)	**(0.000)**	**(0.044)**
γ_{14i}	**-0.033**	0.008	-0.005	-0.026
	(0.026)	(0.435)	(0.637)	(0.169)
Conditional variance-covariance equation				
s_i	**0.057**	**0.033**	**0.044**	**0.032**
	(0.002)	**(0.000)**	**(0.003)**	**(0.013)**
α_i	**0.054**	**0.058**	**0.060**	**0.065**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
β_i	**0.935**	**0.929**	**0.929**	**0.933**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
λ_1				**0.030**
				(0.000)
λ_2				**0.955**
				(0.000)
corr(rwheat,rsoybeans)				**0.364**
				(0.000)
corr(rwheat,rcorn)				**0.651**
				(0.000)
corr(rwheat,rcrude)				**0.170**
				(0.001)
corr(rsoybeans,rcorn)				**0.481**
				(0.000)
corr(rsoybeans,rcrude)				**0.237**
				(0.000)
corr(rcorn,rcrude)				**0.212**
				(0.000)
Wald joint test for adjustment coefficients				**1.9e+05**
				(0.000)

N = 3 119, P-values in brackets, values significant at the 5% level marked in bold

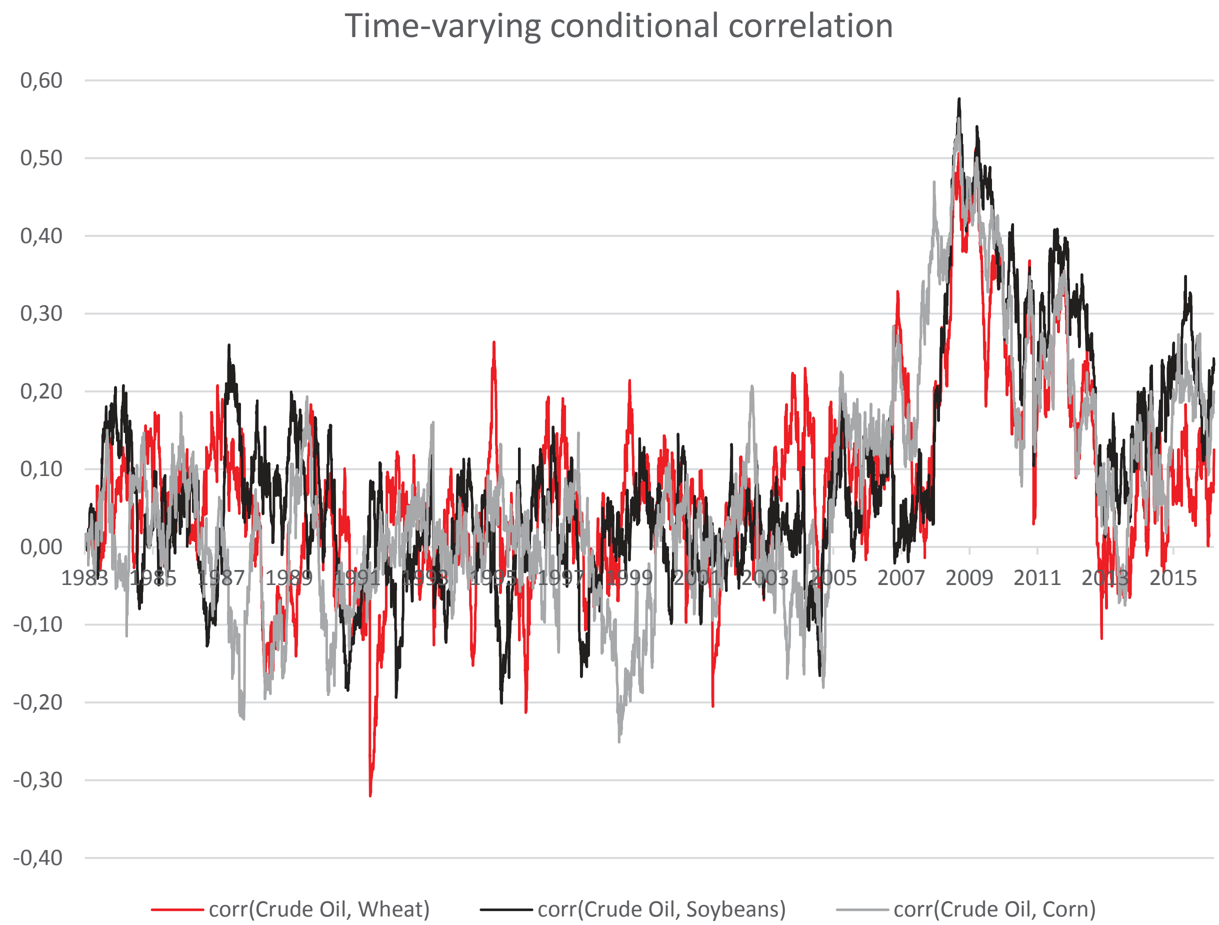

Figure 3: Time-varying conditional correlation estimation results based on DCC-GARCH(1,1), daily returns, April 4th 1983 to June 13th 2016.

Figure 3 presents a visual depiction of the time-varying correlation between crude oil and wheat, corn and soybeans, respectively, 1983-2016. The estimates are based on the DCC-GARCH(1,1) model outlined above. As can be seen, the correlations were generally confined between ±0.2 until the summer of 2007, when there is a steep increase in all three cross-market linkages. All series display a decreasing trend from the onset of 2009 and had fallen back to historical levels by the end of 2012. However, we see a new high peak in the correlation between oil and the major grains in the autumn of 2015, and it is interesting to note that the correlations between crude oil and grain markets now seem to be moving much more in tandem, compared to pre-2004.

6 Conclusion

In the introduction to this article we argue that studying co-movement in the very short term is a way of avoiding the predicament of disentangling speculative and fundamental influences on commodity prices. Adopting a framework known from event studies we find little evidence of such rapid shock transmission from oil to grains. If commodity markets were characterized by herd behaviour (by large institutional investors or other groups) one would expect dramatic changes in the oil price to be transmitted rapidly onto the prices of other commodities.

Examining volatility dynamics and time-varying correlations in an mGARCH framework we find little support for oil and grain market integration at the mean level. We do, however, find that the correlation between oil and grain markets increased significantly from the summer of 2007 onwards, peaking by the end of 2008. Whether this development was caused by financialization and herd behaviour or macro-economic factors like e.g. business cycles is impossible to determine based on our analysis.

Failing to find evidence of a contagion effect from oil to grain price changes supports the conjecture that fundamental factors and macroeconomic conditions continues to be the central elements explaining commodity price and returns dynamics. As such, it seems unnecessary to impose more stringent regulations on commodity trading, as price changes driven by fundamentals cannot be controlled by regulatory measures like position limits. Generally speaking, in a market environment where the volatility is driven by fundamental factors one should rather focus on securing sufficient liquidity to meet hedging demands.

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Are hedgers rational? An essay on hedging behavior in the crude oil markets 2006-2016*

Abstract

This article analyzes crude oil futures hedging commitments 2006-2016 and questions whether the observed market behavior of hedgers is consistent with a rational hedging strategy. Hedgers in the market for crude oil vary their positions substantially from month to month, and beyond what seems consistent with a risk minimizing hedging strategy. The question of why hedgers' trade so much has been raised, and we ask whether the frequent adjustment of positions might stem from a speculative component to hedgers' trading decisions. The large variation in hedgers' commitments may indicate that market participants who self-report as hedgers scale their commitments up or down according to price expectations.

Our analysis suggests that hedgers have had little success in adjusting their positions prior to relative price changes. The central message from our research is that short hedgers should review their trading strategies. Our results further indicate that hedging behavior among long hedgers is driven by perceived future risk as measured by the OVX (the "Oil VIX"). Short hedgers on the other hand do not seem to adjust their positions based on expectations of future price volatility, but we find a significant relationship between short hedging commitments and tail risk. Finally, we emphasize that hedgers in the crude oil market will typically speculate in physical positions rather than futures. If so, attempts to curb volatility of price increases through regulations of the futures markets appear futile.

*I am very grateful to Ron Ripple and Sjur Westgaard for insightful and constructive comments on an early version of this essay. The remaining weaknesses are my responsibility.

1 Introduction

A number of studies on commodity price dynamics and risk are devoted to the issue of whether speculation in futures markets drive commodity prices and price volatility. This issue has emerged repeatedly in academic and popular debates, in particular at times of high price volatility, e.g. after the dramatic market movements in 2008. Among the recent contributions to the debate as regards the oil market are Büyükşahin and Harris (2011) and Brunetti, Büyükşahin et al. (2016), who study co-movement of energy commodities. A central topic in the debate has been whether excessive speculation in futures has destabilized markets and made prices deviate from their fundamental values. In many of these studies, (e.g. Till (2009)) the metric applied to reveal possible excess speculation has been the "Working's Speculative T Index", originally proposed by Holbrook Working (1960) (see also Irwin, Sanders et al. (2009), Sanders, Irwin et al. (2010)). The present article addresses this issue in a different way, focusing on hedgers' behavior in the NYMEX futures market for crude oil. This a is highly liquid market that allows oil producers, downstream processors and consumers to hedge their price risk up to 9 years ahead[1]. We raise the question of whether the trading activities of market participants who classify as hedgers in the weekly Commitments of Traders (COT) reports[2] are more consistent with speculative rather than hedging behavior. In line with modern hedging theory, we consider the possibility that hedgers to some extent also speculate.

The term "speculate" requires some clarification. To many, speculation involves some sort of active investment, e.g. buying stocks or commodities with the sole purpose of selling at a later time. However, another understanding of speculation is that of not covering one's positon in the physical commodity market, i.e. leaving oneself exposed to market risk. With this view on speculation, an oil producer who is hedging less than what would be the risk minimizing position (i.e. under-hedging) may be

[1] The CME Group WTI crude oil futures (NYMEX) lists nine years forward using the following listing schedule: consecutive months are listed for the current year and the next five years; in addition, the June and December contract months are listed beyond the sixth year. The ICE Brent Crude futures contract is listed 96 consecutive months ahead, i.e. 8 years.
[2] The Commitments of Traders (COT) reports are published by the U.S. Commodity Futures Trading Commission and provide a breakdown of each Tuesday's open interest for all major commodity markets. See http://www.cftc.gov/Marketreports/CommitmentsofTraders/index.htm for more information.

considered a speculator. Note that this does not imply that the hedger is speculating in futures, by under-hedging she is taking a speculative position in the physical commodity market. Conversely, a producer taking a short position above the risk minimizing hedge ratio speculates in futures. In other words, being over-hedged or under-hedged relative to the optimal hedge ratio may be considered speculation. This point of view is argued in several academic contributions to the literature on hedging versus speculation (e.g. Culp 2011). In this paper, we apply the latter understanding of speculation, asking whether hedgers have been successful in predicting movements in relative spot/futures prices – and in that sense have been behaving rationally.

The COT reports, published weekly by the U.S. Commodity Futures Trading Commission, breaks down the market open interest into (among others) hedgers[3] and money managers' positions. If hedgers take a view on prices similar to pure speculators it calls for caution in how we interpret these numbers. Commercial traders are typically producers and consumers of the underlying commodity, and hence report as hedgers in futures markets. Our article aims to shed light on whether these market participants are routine hedgers (strictly risk minimizing), or whether they also step out of their role as hedgers and engage in speculation through their trading operations. The recent debate on financialization of futures markets has revolved almost solely around the behavior of financial speculators, which we find peculiar as anecdotal evidence suggests that far from being passive market participants, most hedgers take an active view on future market prices. This conjecture is supported by the findings in Cheng and Xiong (2014), who reveal that commercial hedgers engage in significant non-output related trading. They question why hedgers trade so much. Analyzing hedgers' commitments in corn, wheat, soybeans and cotton, they find that although hedgers' positions are much smaller than physical output, the volatility in their positions is much higher than the volatility in output of these productions. While volume risk may explain why producers do no hedge 100% of their production, the high and stable correlation between spot and futures price changes (as documented in

[3] The official name of this category is "Producer/Merchant/Processor/User", we use "hedgers" for brevity.

several studies) should imply a relatively stable hedging activity, assuming that the hedgers' are strictly risk minimizing.

We believe Cheng and Xiong (2014) raise a highly relevant question in asking *"What cause hedgers to trade?"*. It is important to increase our knowledge about the behavior of hedgers in commodity markets, because these participants play a key role in the price discovery process by anchoring the futures price to the underlying market fundamentals and physical products. Speculators also contribute towards well-functioning markets as providers of liquidity, but they cannot support the price discovery function of a futures market by themselves. A study on hedgers' behavior is a contribution to the debate on financialization of commodity markets and possibly adverse effects from speculative activities. So far, the discussion as well as policy measures have been oriented towards the purely financial side of the market. If the commercial traders – typically thought of as the hedgers – also participate in speculative activities, the behavior of these players warrants further attention.

The article is organized as follows. We start out by discussing what it means to be a hedger, and to hedge rationally. During this discussion, we question whether the observed market behavior of hedgers is consistent with a risk minimizing hedge strategy. Section 3 gives a detailed presentation of the data on crude oil futures hedging commitments, as presented in the weekly COT reports 2006-2016. Through this descriptive analysis, we develop a set of hypotheses on hedging behavior. Section 4 gives an outline of the econometric method, while section 5 presents the estimation results. Concluding remarks are given in the final section.

2 What does it mean to be a (rational) hedger?

Futures markets serve two core functions, namely price discovery and risk transfer. Price discovery occurs when the market participants aggregate and evaluate all information that is relevant to the equilibrium price level, and – based on this information – enter into transactions for future delivery. Risk transfer allows those who deal with the physical commodity to exchange risk (e.g. between producers and downstream consumers), or to transfer the risk of price changes to speculators that are more willing or capable to bear such risk. The possibility of reducing risk through hedging is often emphasized in the discussions regarding the need for well-functioning futures markets.

This raises the issue on what it means to be a hedger as opposed to being a speculator. The weekly COT reports define hedgers as those market participants who have a commercial interest in the underlying physical commodity (e.g. oil producers, refiners, airline companies etc). Speculators are those who buy/sell futures contracts with no activity in the physical product on which the futures contract is written. While the dichotomy “hedger/speculator” based on this formal definition is simple and relatively clear it poses problems regarding the understanding and analysis of behavior and trading motivation. Cootner (1967) concluded that many studies of futures markets were hampered by an inadequate understanding of what motivates trading behavior. While speculators’ motivations are easy to interpret (they buy because they expect prices to rise, and *vice versa*), hedgers’ motivations and behavior are much harder to perceive.

Price risk can be reduced for a producer (consumer) by going long (short) in futures. A perfect hedge against price risk based on a forward agreement requires a perfect correlation between the changes in the price of the underlying commodity and that of the futures contract. Nevertheless, hedgers rarely hedge their entire production/consumption, and most futures contracts are liquidated by taking offsetting positions prior to delivery. Liquidating positions prior to the time of delivery as stipulated by the futures contract may reduce the effectiveness of the hedge, since the perfect hedge (zero risk) is based on the fact that the spot and futures prices converge towards delivery (assuming the futures and spot product are identical in terms of quality, and disregarding transportation and transaction costs). These observations made Working (1953a, b, 1962) challenge the notion of the hedger as a passive market player aiming to minimizing risk. He emphasized the concept of a profit maximizing hedger, and argued that rather than focusing on absolute prices, physical players use the spot-futures price relation as an indicator of prospective gain or loss from storage. In other words, Working describes a hedger that is typically concerned with changes in the *basis*, i.e. the difference between the futures and spot price. As pointed out by Johnson (1960), *“since the hedger is not motivated primarily by desire to reduce risk, it is also misleading (…) to judge the effectiveness of hedging* *according to the degree to which futures price and spot price movements are parallel".* Thus, Johnson concludes that if the hedger has expectations regarding the relative spot/futures price, his hedge may contain a speculative component and in that respect the distinction between the hedger and the "ordinary" speculator disappears. *"The only essential distinction between them is that the hedger has a primary market which in this model gives rise to a merchandising profit"* (Johnson 1960, p. 150).

In a much later follow up, Ederington (1979) discusses three major theories of hedging; the traditional theory, which emphasizes the risk avoiding potential of futures contracts, the theories of Working, and the portfolio theory. Building on works by Johnson (1960) and Stein (1961), he shows how the risk avoidance of traditional hedging and the profit maximization emphasized by Working can be integrated by viewing hedging as an application of basic portfolio theory.

Let y define the *physical* position, e.g. as measured in barrels of oil. $y > 0$ represents a long position (producer or cash-and-carry trader of e.g. oil), while $y < 0$ implies a short position, i.e. a consumer of the commodity. Let x define the *futures* position. $x > 0$ represents a long position in futures, while $x < 0$ indicates a short hedge. In a simple one-period framework, the profit or loss long-short (or short-long) portfolio of physical and futures positions is given by the spot price change for the physical commodity (s_t) and the futures price change (f_t) weighted by x and y, i.e.:

$$\pi = ys_t + xf_t \tag{1}$$

The variance of π is:

$$Var(\pi) = y^2\sigma_s^2 + x^2\sigma_f^2 + 2xy\sigma_{sf} \tag{2}$$

where σ_s^2 and σ_f^2 are the variances of the spot and futures price changes, and σ_{sf} denotes their covariance. The minimum of this variance can be expressed in terms of the futures position as:

$$x^* = -y\,\frac{\sigma_{sf}}{\sigma_f^2} \tag{3}$$

or as the optimal (risk minimizing) hedge ratio:

$$\beta = \frac{x^*}{y} = -\frac{\sigma_{sf}}{\sigma_f^2} = -\rho_{sf}\,\frac{\sigma_s}{\sigma_f} \qquad (3')$$

where ρ_{sf} is the correlation between the spot and futures price changes.

Ederington's model is now the standard textbook theory on risk minimizing hedging. It states that for a routine hedger, the optimal (i.e. minimum price risk) hedge ratio is given by the product of the correlation coefficient between the changes in the spot and futures prices and the relative risk (standard deviation) for spot and futures price changes. Ederington's optimal hedge ratio focuses on price risk only. In e.g. agricultural production, there is also a substantial production (volume) risk. Thus, even in the case when the Ederington hedge ratio is 1.0 farmers tend to hedge less than 100% of their production, simply because weather conditions may cause actual production to deviate from the expected. If major production areas have experienced adverse weather condition causing a reduction in aggregated output, prices tend to increase and a 100% hedge will represent too high of a hedge ratio. Hence, producers often choose to under-hedge (see Rolfo (1980) and Hirschleifer (1991)). In the case of oil, production uncertainty is far less than in biological productions, and production quantities are relatively stable. Given a β close to unity (as we will document later), this should imply stable hedging activities[4].

Since Ederington proposed this model in 1979, numerous studies (see e.g. Gjølberg and Johnsen, 1985, 1986 and more) have concluded that the risk minimizing hedge ratio in the oil market is close to unity, fairly stable over time, and that the risk reduction as measured by R^2 is substantial (as will be demonstrated later in this paper). Given the fact that oil production and consumption are relatively stable in the short run, one would expect to find hedging activity in the crude oil market to be relatively constant over time, with minor variations caused by changes in production volumes and consumer demand. However, Cheng and Xiong (2014) find that

[4] Barring the inference of production uncertainty, Anderson and Danthine (1983b) find that mark-to-market makes the hedge less than the routine hedge in which the futures position is equal in size to the expected output.

producers' futures positions in agricultural commodity markets are several times more volatile than the corresponding output uncertainty. This may indicate that hedgers in commodity markets trade for reasons that are unrelated to maintaining a minimum variance hedge ratio.

Today it is widely accepted that hedger's in commodity markets are able to entertain two thoughts at once. As discussed in an early study on risk management in the oil markets Gjølberg and Johnsen (1986) (see also Anderson and Danthine (1983)) show that an optimal hedge x^*, can be divided into two distinct entities; one pure hedge position that minimizes risk, and one pure speculative position which allows the hedger to take a view on future price movements:

$$x^* = -\beta y + \gamma \frac{E(F_1) - F_0}{\sigma_F^2} \qquad (4)$$

where y is the hedger's physical position. As before, $y > 0$ indicates a producer or cash-and-carry trader, and $y < 0$ represents a consumer of the commodity. β represents the risk minimizing hedge ratio defined in (3'). The first element of (4)represents the hedger's pure hedge position and minimize risk, while the second part represents the hedger's pure speculative position. γ represents the risk tolerance level, and implies that the hedge will deviate from the risk-minimizing position $-\beta y$ to the extent that the hedger holds an opinion on the future futures price versus that of today. The actual hedge will be scaled up and down compared to the risk-minimizing hedge based on whether the hedger expects a price increase or decrease. $\frac{E(F_1)-F_0}{\sigma_F^2}$ represents the expected risk adjusted return of the speculative position.

Expression (4) represents an intuitive and possibly realistic representation of hedging behavior in commodity markets. In short, the speculative part of the expression adjusts the risk-minimizing hedge to exploit an expectation of futures returns. The willingness to adjust the "pure" hedge is determined by the size of these returns, the additional risk associated with the investment, and our risk tolerance level. As such, there is no principal difference between a hedger and a speculator when it comes to speculating in futures. Another implication from (4) is that whether or not the hedger commits to a speculative position only hinges on the expected return from this particular position, and not on the associated risk (or the features of other current investments). Risk and risk tolerance levels only influence the *size* of the position. If risk tolerance is low, the speculative component will be minor.

Taking this notion one step further, we propose that commercial traders engage in selective hedging according to the theory of risk management presented in Stulz (1996). He argues that rather than focusing blindly on mitigating cash flow volatility, the primary goal of risk management is to eliminate the probability of costly lower-tail outcomes. His theory also suggests that some companies might acquire a comparative informational advantage through its day-to-day business activities, like e.g. production of a commodity, which might lead some companies to take speculative positions in commodities or currencies. Note that for a producer (i.e. a short hedger), this means speculating in physical commodities (through storage or changes in production schedules). It is, however, not unlikely that this assumed informational advantage leads to selective hedging, where the risk managers allow their view of future market conditions to influence the ratio of the (commodity) exposure to be hedged.

There is considerable empirical evidence consistent with the notion of selective hedging, as well as extensive survey evidence that companies routinely speculate within the context of their hedging programs (see e.g. Dolde (1993), Glaum (2002) and Géczy, Minton et al. (2007)). Adam, Fernando et al. (2015) use data from the gold mining sector and examine whether this behavior creates corporate value in the way Stulz (1996) argues it has *the potential* to do. Their results show that smaller firms speculate more than larger firms, and the authors argue that this is indicative of speculation induced wealth transfer or financial constraints motives. However, their study does not rule out thyue rationale for selective hedging that is highlighted by Stulz (1996), namely that managers engage in selective hedging because they (perhaps erroneously) believe they can "*beat the market*".

For the time being we refrain from hypothesizing about whether a hedger can beat the market, and merely state that foregoing profit could be considered irrational for any market participant. The two concepts are however closely related, as the hedger's ability to profit from futures trading hinges on his or hers ability to successfully predict future price movements. This will be explored further in the subsequent section. We will take a simplistic approach to examine whether hedgers' trading yields better results than simply following a routine hedging strategy. In this analysis, we touch on the issue of whether the "flip side" of the trade, i.e. the pure speculators, are compensated for their role in the hedging balance. In a study on this issue, Chatrath, Liang et al. (1997) conclude that speculators in general do not impose an (instantaneous) risk premium on agricultural commodity hedgers. They find that the presence of speculators enhances market efficiency and may lower the cost to hedgers (See also Chang (1985), So (1987) and Miffre (2000)). Here, we will present estimates on hedging performance for long and short oil futures hedgers since 2006, and thus indirectly reveal the risk premium.

3 Stylized facts

Since the early 1980s, oil producers, downstream processors and consumers have had access to liquid futures markets in which they can hedge their price risk several years ahead. The liquidity feature makes this market ideal for analyzing hedging behavior. We use trader positions data from the disaggregated Commitment of Traders (COT) report, issued weekly (Fridays) by the Commodity Futures Trading Commission (CFTC). This report comprises U.S. futures markets above a certain size and breaks down Tuesday's aggregate positions held by five categories of market participants, namely "Producer/Merchant/Processor/User", "Swap Dealers", "Money Manager", "Other Reportable" and "Non-Reporting". We focus on the Producer/Merchant/Processor/User category, which consists of traditional commercial users, i.e. producers, processors and consumers of the physical commodity who are supposed to be using the futures contracts to hedge price risk. We combine these data with Tuesday spot prices for WTI light sweet crude oil delivered FOB at Cushing Oklahoma, downloaded from the U.S. Energy Information Administration (EIA). Weekly prices for futures contracts with the same underlying are found on the New York Mercantile Exchange (NYMEX). As measure of volatility we use the CBOE Crude Oil ETF Volatility Index (Oil VIX; Ticker: OVX), an index that measures the market's expectation of 30-day oil price volatility by applying the VIX methodology to United States Oil Fund options. The OVX is a forward-looking risk measure by construction. Assuming that hedgers' commitments are influenced by expected risk levels, we expect a relationship between the OVX and hedging commitments.

To make it easier to identify patterns in trader commitments, we conduct the majority of our analysis at a monthly frequency. We observe spot and futures prices on the Tuesday just prior to the termination of the contracts[5]. In the futures market for crude oil there are contracts for each consecutive calendar month. Trading in the current delivery month ceases on the third business date prior to the 25th calendar day of the month preceding the delivery month. Hence, observing the 2nd and the 3rd contract on (roughly) the 20th each month, these are contracts with close to constant time to maturity (2 and 3 months). Our data covers June 2006 through December 2016.

3.1 Traded volumes, open interest and hedgers' commitments

We begin by presenting some major statistics on trading activity in oil futures contracts, focusing on volume and open interest before moving on to hedgers' commitments.

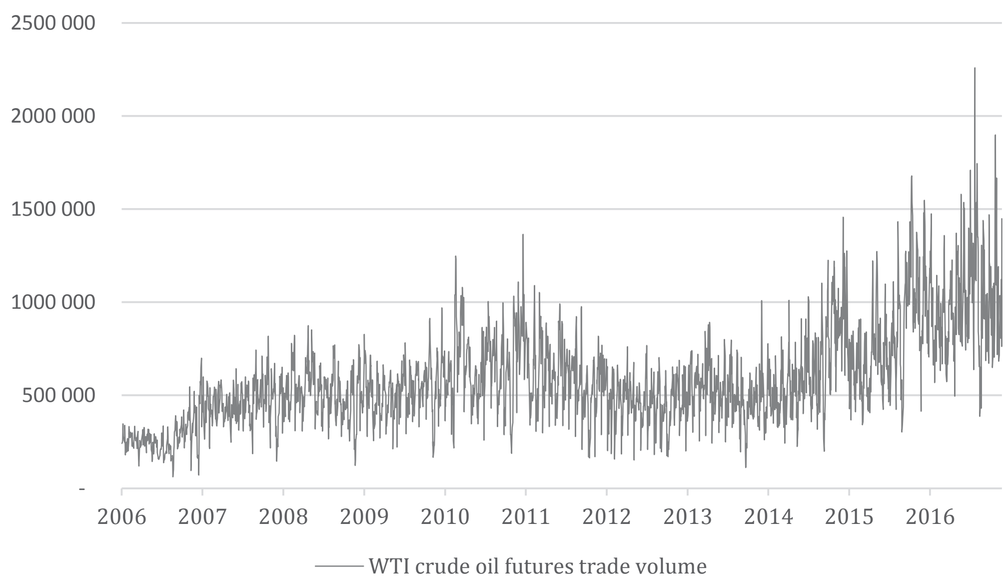


Figure 1: WTI crude oil futures traded volume in number of contracts, daily observations June 2006 – November 2016.

[5] When presenting an earlier version of this essay it has been questioned whether using prices observed that close to maturity means that we are studying instable prices due to the number of contracts being rolled just prior to maturity (expiry effects). We have looked into this issue and found no particular price movements around the 20th day of the month.

As can be seen from figure 1, traded volumes in (WTI) crude oil contracts at NYMEX are substantial. The average daily volume (aggregated over contracts 1-9) between June 2006 and November 2016 is roughly 584 000 contracts. Given the fact that each contract is written on 1 000 barrels, traded volume on average amounts to more than 7 times daily world production. We also note that trading has increased significantly over recent years. In parallel with falling oil prices during the last couple of years, trading reached a record level of more than 2 million contracts July 27, 2016. The graph further reveals that traded volume is very volatile. The standard deviation is approximately 256 000 contracts, equivalent to a coefficient of variation of 44 per cent.

Open interest (OI) is important and may indicate whether new money is coming into the marketplace. Figure 2 demonstrates that activity in the futures market for crude oil has grown significantly over the last 10 years, as measured by OI. OI nearly doubled from approximately 1 million contracts in June 2006 to 2 million contracts by the end of 2016. Obviously, the large majority of these contracts are terminated before maturity, but the numbers still illustrate the size and liquidity of the crude oil futures market. As can be seen from figure 2, OI is subject to a substantial variation. If hedging mainly takes place in nearby contracts, OI can be quite low since positions are reversed prior to maturity. The opposite occurs if hedging is predominantly conducted in contracts further out on the curve. In other words, OI changes with variations in the OI compositions, and the longer the average maturity, the less volatile OI will be.

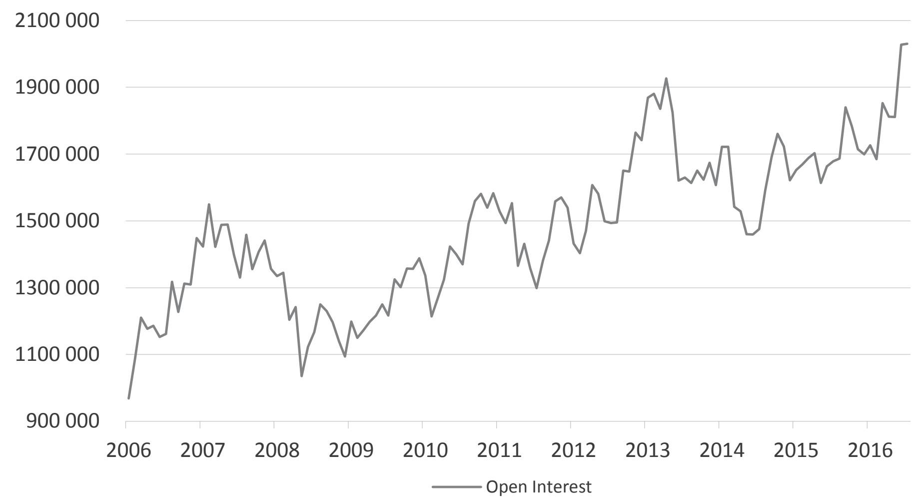


Figure 2: WTI crude oil futures, open interest in number of contracts, monthly observations June 2006 – November 2016.

Figure 3 displays the commitments of long and short hedgers as reported in the weekly COT reports June 2006 – December 2016. There are three distinct features in the graphs. First, we see that the size of hedgers' commitments is substantial. Mean hedging commitments during the 10 years period is some 360 000 contracts on the short side, and 230 000 contracts for long hedgers. Second, short hedgers' commitments have generally been substantially larger than the long commitments. The one exception is fall 2012 – fall 2014, when there was close to what is traditionally called "a balanced market", i.e. a market where the demand for short and long hedges is equal. We will discuss this period in greater detail later.

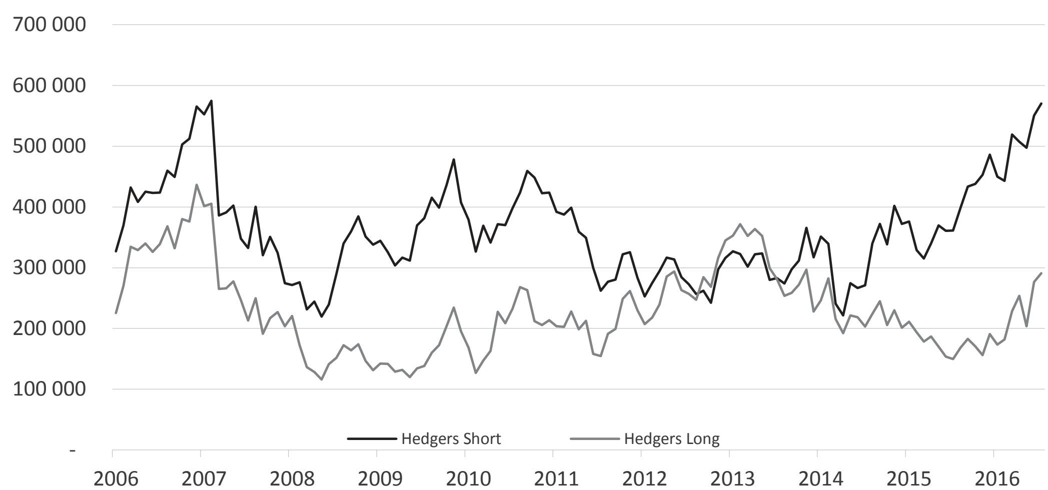


Figure 3: Hedgers long and short commitments in number of contracts, monthly observations, June 2006 – December 2016.

Third, both long and short commitments are very volatile. This is also visualized in figure 4. Aggregated positions can change by as much as +/- 50 000 contracts from one month to the next, occasionally even more. Hedgers clearly adjust their positions frequently, and the changes in commitments are often extensive. This may indicate that hedgers not only seek to minimize risk, but also scale their futures positions according to price expectations. Later we will discuss whether these changes in commitments have been successful, i.e. whether or not changes in commitments have increased the spot-futures portfolio return.

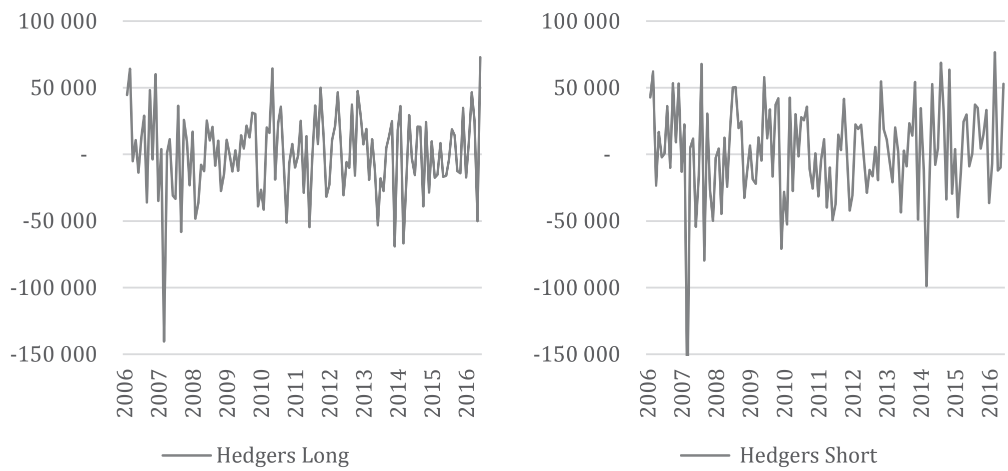


Figure 4: Monthly changes in long and short hedging commitments in number of contracts, monthly observations, June 2006 – December 2016.

Table 1 summarizes trader commitments June 2006 – December 2016. Since hedgers have been predominantly net short in the oil market, speculators are required to balance the market. Here, we define speculators as the combined volume of "Money Manager" and "Other Reportable" positions listed in the COT reports. We exclude the Swap Dealers, i.e. those who deal primarily in swaps and hedge these transactions in the futures market, because even though they are classified as commercial traders by the CFTC, they lack a direct (physical) exposure to the crude oil market[6].

[6] For a thorough and well-written overview on how to interpret the COT reports, we refer to Irwin and Sanders (2012).

Table 1: Descriptive statistics – monthly trader commitments

	Open Interest	Hedgers Long	Hedgers Short	Speculators Long	Speculators Short	Net Short Hedging
Mean	1 479 922	230 062	360 305	342 526	170 540	130 243
St. Dev.	223 589	70 764	79 541	125 330	46 446	86 271
Min	968 619	115 853	219 703	152 971	87 905	- 50 665
Max	2 029 807	436 523	574 794	603 704	358 953	296 685

June 2006 - December 2016, monthly observations

As previously mentioned, short hedgers' commitments have been substantially larger than those of the long side throughout 2006-2016. There has been only one period reminiscent of a balanced market, namely fall 2012 – fall 2014 (figure 3). Normally, short hedgers (i.e. the oil producers) aggregate to substantially more OI relative to the refiners and downstream consumers. On the average, short hedgers make up some 25% of open interest, although declining since 2010. The data do not tell us the producers' average hedge ratio. However, the numbers indicate that producers hedge a substantial share of their production.

During the period we study, open interest in the first nearby contract has averaged 28% of total, while the average for the second nearby has been 27%. In other words, the two contracts closest to maturity make up 55% of open interest on average. The third nearby averages 12% of total. Although these fractions have been relatively stable in the long run, there have been periods when the composition of open interest has changed so that a larger share has been in contracts further out on the curve. This was particularly the case 2013-2014, when the first and second nearby at times were less than 40%.

3.2 Hedgers' commitments, prices and volatility

The WTI light sweet crude oil traded on NYMEX is an important physical market price reference, which serves as a benchmark for the approximately 10 million barrels of daily North American production, as well as for other oil blends. WTI futures (and options) are the most actively traded energy contracts worldwide. From table 2 we see that there has been great variation in the spot price during the last decade. The same is true for futures prices. During the summer of 2008, oil prices reached record highs – trading in the vicinity of USD 145 per barrel. The minimum value of our monthly data is observed on June 15 2008, at close to USD 139 per barrel just prior to the onset of the financial crisis. The lowest price is observed on January 19 2016, at less than USD 29 per barrel.

The mean futures price level increases with time to maturity, which suggest that the futures curve has been in contango for the majority of 2006-2016. This is also reflected in the basis, which is positive on average for both future contracts. We note that the variation in basis is substantial, much larger than for spot and futures prices (and changes). Looking at the coefficient of variation, which is a unitless measure, this feature is even more pronounced.

Table 2: WTI prices, spot, basis, and futures prices 2006-2016

	Spot	ΔS	F^2	ΔF^2	F^3	ΔF^3	BASIS2	BASIS3
Mean	77.45	4.30	78.23	4.31	78.68	4.32	0.78	1.23
St. Dev.	23.65	0.34	23.02	0.32	22.59	0.31	1.24	1.95
Coeff. of Variation	0.31	0.08	0.29	0.08	0.29	0.07	1.59	1.59
Min	28.47	3.35	30.23	3.41	31.28	3.44	- 2.27	- 3.32
Max	138.68	4.93	139.37	4.94	139.83	4.94	5.00	7.73

June 2006 – December 2016, monthly observations
BASIS2 $= F_t^2 - S_t$, where F^2 is the contract with 2 months left to maturity
BASIS3 $= F_t^3 - S_t$, where F^3 is the contract with 3 months left to maturity

Figure 5 displays the crude spot price against net short hedging[7]. As can be seen, the changes in net hedging are characterized by long cycles rather than short-term trends. We see that net short hedging began an upward trend from June 2008, roughly six months before the spot price started to trend in the same direction. In January 2010 net short hedging was at some 250 000 contracts, indicating a strong majority of oil producers in the market. Interestingly, we also see a huge relative increase in short hedging volumes beginning in August 2014, when oil prices were plummeting. The simple correlation between spot price changes and net short hedging volumes is -0.57, while the correlation between short hedging a price changes is -0.43. This is different to the results in Cheng and Xiong (2014), who find that short hedgers' commitments in the agricultural markets are <u>positively</u> correlated with observed price changes.

[7] (Short - long positions)

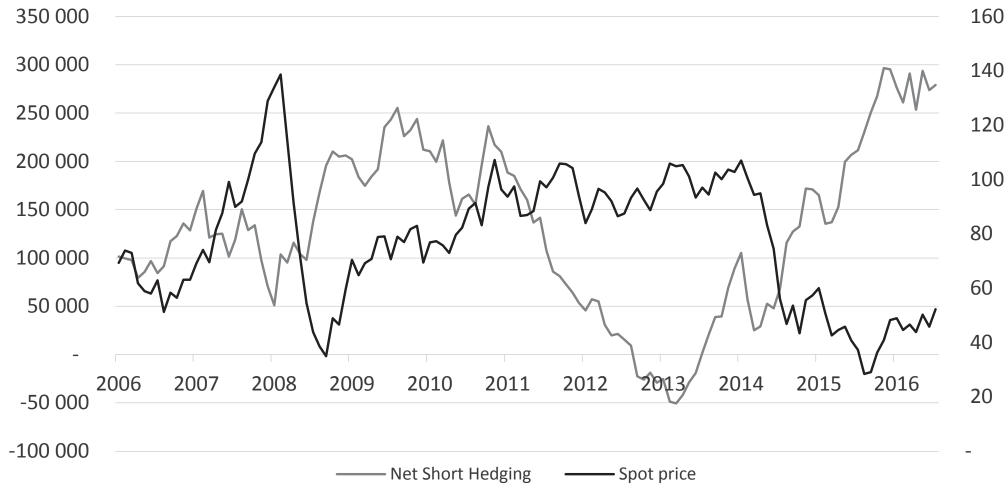


Figure 5: WTI crude oil futures, net short hedging in number of contracts on left axis, spot price in $/barrel on right axis, monthly observations June 2006 – December 2016.

During most of the period short hedging has dominated – with the exception of 2013 when the number of long hedging positions outnumbered the amount of short positions. The declining trend in net short hedging volumes began in March 2011 and suggests that the long hedgers, i.e. downstream refiners and consumers, gradually increased their positions. We note that in 2013, when the hedgers were long on balance, oil prices were at their most stable since 2006. The supply shocks from the Arab Spring and the Libyan production outages had been mitigated, and despite new Libyan outtakes, steady supply from Saudi Arabia managed to smooth out the effects. Rising U.S. oil production and dramatic increases in exploration activities also improved on the expectations regarding global oil supply conditions.

Figure 6 shows net short hedging against the OVX-index. We see that net short hedging demand seems to increase with oil price volatility and the figure also confirms that the period with net long hedging demand in 2013 did indeed occur in a period with expectations of low oil price volatility. That net short hedging demand is substantial during a time of moderate oil price volatility at the end of 2016 is likely due to a depressed market and increasing stocks. In such a situation, it makes sense for oil producers to insure their production against further price declines.

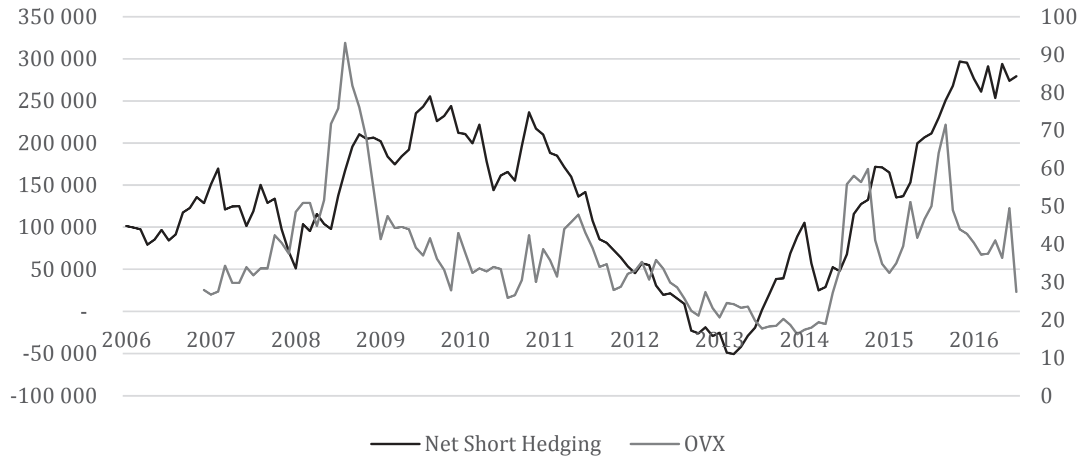
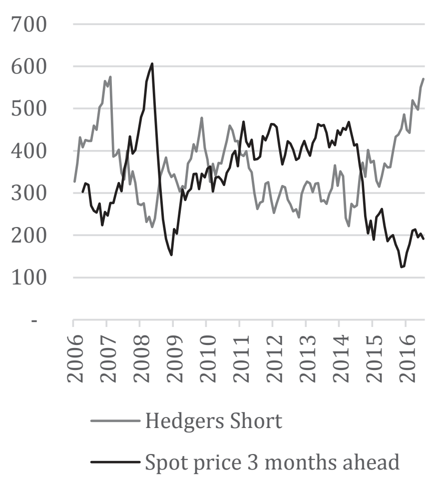


Figure 6: Net short hedging in number of contracts on left axis, the CBEO Crude Oil ETF Volatility index on the right axis, monthly observations June 2006 – December 2016.

Viewing short and long hedging commitments separately (figure 7), we see great variation in hedging volumes throughout the period. Looking at the short side, hedging volumes appear relatively stable 2011-2014. Before surging upwards towards 2016. The latter development occurs in conjunction with plummeting oil prices, and thus seems reasonable as one expect producers to seek insurance against falling prices. A similar inverse relationship between short hedging volumes and oil prices is seen prior to 2009.



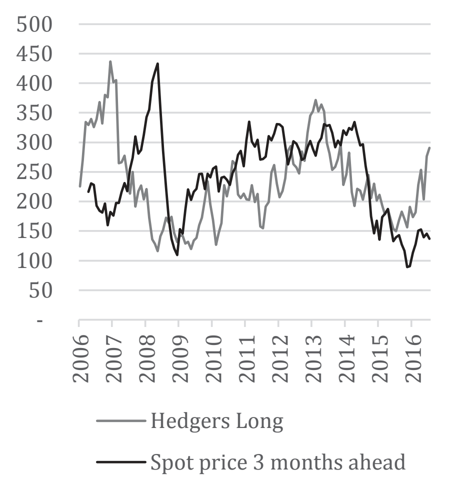


Figure 7: Hedgers' positions in thousands of contracts on left axis, the realized WTI spot price 3 months later in $/barrel on right axis, monthly observations June 2006 – December 2016.

Long hedging demand seems to "mirror" short hedging demand up until October 2008. There is an upward trend in long hedging volumes from the end of 2009 until July 2013. During this period, we also see large short-term variations in hedging activity. Finally, we see that long hedging demand falls with falling oil prices 2014 – as one might expect. From 2013 onwards, there seems to be a stronger relationship between the spot price of oil and long hedging demand, relative to earlier in the period.

3.3 Co-movements in commitments, prices and volatility

To assess possible differences in long and short hedging behavior, we briefly examine how the two entities co-vary with other observable variables. Table 3 presents correlations between hedging commitments and spot and futures prices. The results reveal clear differences in long and short hedging behavior. On the short side, we see that hedging commitments decrease with increasing spot and futures prices. The opposite relation holds for long hedging. These observations indicate that at high prices, short hedgers expect the price level to remain high or even increase further. On the other hand, long hedgers have high commitments at high price levels, and although this relationship is weaker it suggests fear of even higher prices.

Table 3: Correlations 2006-2016 - hedging commitments against basis. spot and futures prices

	Hedge levels		**Hedge changes**	
	Hedgers long	**Hedgers short**	**Hedgers long**	**Hedgers short**
S	0.18	-0.46	-0.08	-0.20
$\boldsymbol{F_2}$	0.18	-0.46	-0.08	-0.19
$\boldsymbol{F_3}$	0.17	-0.46	-0.08	-0.19
Basis2	-0.12	0.30	0.09	0.17
Basis3	-0.18	0.30	0.10	0.19
$\boldsymbol{\Delta S}$	0.12	0.26	0.07	0.10
$\boldsymbol{\Delta F_2}$	0.12	0.26	0.08	0.11
$\boldsymbol{\Delta F_3}$	0.12	0.26	0.08	0.11

June 2006 – December 2016, monthly observations
BASIS2 $= F_t^2 - S_t$, where F^2 is the contract with 2 months left to maturity
BASIS3 $= F_t^3 - S_t$, where F^3 is the contract with 3 months left to maturity

As regards the relationship between hedging commitments and the basis, there is another interesting observation. Short hedging commitments is positively correlated with basis, which suggests that short hedgers are reluctant to believe that high futures prices relative to the spot price means that the spot price will increase. To the extent that a positive basis suggests higher prices in the future, producers (short hedgers) would be expected to abstain from taking futures positions, and vice versa for the long side. However, the correlations (0.30 for short hedgers and -0.12/-0.18 for long hedgers) suggest the opposite. This might be because hedgers expect some degree of mean reversion in prices. In fact. mean reverting models along the lines of Gibson and Schwartz (1990) were the standard way to model oil prices up until 2005, when recent developments in the energy markets made Geman (2005) question whether *"mean-reversion was dead?"* for energy commodities. Further, changes in the basis are generally related to short-term demand and supply conditions, and the price of storage. Thus, it cannot be interpreted solely as a naive forecast of the future spot price. If demand is strong and available supply is small, the spot price typically rises relative to the futures price, which causes a reduction in basis. Conversely, if demand is weak and there is abundant supply, spot prices fall relative to the futures price, causing the basis to increase.

Figure 8 displays the long positions of speculators against short hedging in number of contracts on the left axis, and a 36-month window of rolling correlations between these two series on the right hand side axis. As can be seen, there is an upward trend in speculators long positions (more or less) throughout the entire period, while there is much more variation in short hedging demand. The correlation between the two series varies significantly, and appears to increase with increasing short hedging demand. The correlation between the two series also seems go up with increasing oil price volatility.

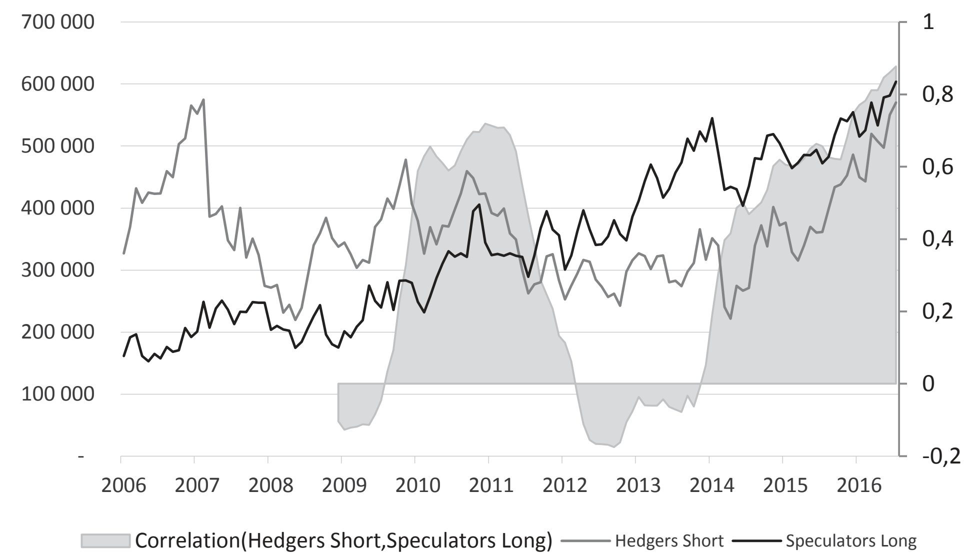


Figure 8: Hedgers short positions and speculators long positions in number of contracts on left axis. 36-month window of rolling correlations between the two series on right axis, monthly observations.

Figure 9 displays net short hedging against the basis of the spot price and a contract with approximately 2 months to maturity. While short hedging commitments and basis share broad trends/cycles, the correlation between the two series is moderate (0.31).

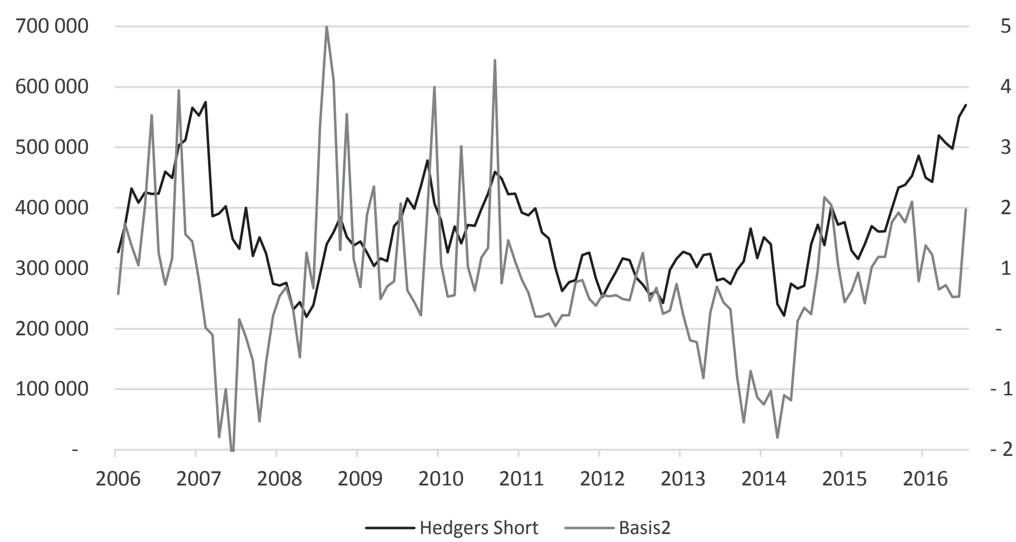


Figure 9: Short hedging in number of contracts on left axis, basis, defined as the difference between the second nearby futures and the spot price on right axis, monthly observations June 2006-2016.

3.4 Risk-minimizing hedge ratios

Going back to Ederington's model on (price) risk minimizing hedging and the optimal hedge ratio, our preliminary exploration of the crude oil futures market does not suggest that hedgers routinely hedge a fixed part of their production. Short hedging commitments have varied substantially between 2006 and 2016. While at the same time there has been moderate variation in global oil production aside from a small long-term growth. Table 4 shows that using the second nearby contract, the price risk minimizing hedge ratio for 2006-2016, as well as two sub periods, is very close to unity. In other words, a hedger focusing on minimizing price risk only would typically offset his entire physical position in the futures market. This strategy would offer substantial risk reduction as measured by R^2, regardless of time period.

Table 4: Risk minimizing hedge ratios

	ΔF^2	**R^2**	**ΔF3**	**R^2**
2006(6)-2016(12)	1.03 (0.01)	0.98	1.05 (0.02)	0.96
2006(6)-2010(12)	1.04 (0.02)	0.98	1.05 (0.03)	0.96
2011(1)-2016(12)	1.02 (0.01)	0.99	1.05 (0.02)	0.97

June 2006 – December 2016, monthly observations
Standard errors in brackets

The estimated hedge ratios in table 4 applies Ederington's model, regressing spot price changes on changes in the futures price. This model is very simple, and may result in sub-optimal hedging decisions since it is based on the unconditional correlation between spot and futures price changes. Miffre (2004) discusses this issue, reviews the literature, and presents an alternative conditional hedge ratio. This approach, assuming that hedgers include additional information in their decisions, opens up for time-varying commitments beyond variations in production.

3.5 Hedging performance

Assuming that spot and futures prices move in parallel (as they are to a large extent doing in the oil market), the hedger can establish what is typically called "a perfect hedge". She is locking in today's futures price, regardless of the direction the spot price. The profit/loss in the physical market is (more or less) exactly offset by the loss/profit in the futures market. Hence, the routine hedger can substitute a certain futures price for an uncertain spot price.

During our period (2006-16), the 2nd and 3rd futures contracts have on average been USD 1.15 and 1.76 per barrel higher than the spot price two and three months later (table 5), or 3.6% and 5.8% higher than the subsequent spot price. In other words, someone who had systematically gone short in two or three months futures would have obtained (*ex post*) a price 3.6-5.8% higher compared to the alternative of not hedging. The opposite would hold for the long hedger. The difference between F_t^i and S_{t+i}, often labeled "forecast error", may be considered a risk premium. In such a context, it is of interest to analyze to what extent hedgers (as a group) have been able to harvest a risk premium, or reduce the risk premium they pay by adjusting their commitments prior to price changes.

Table 5: Forecast error $\left(F_t^i - S_{t+i}\right)$ – 2006-2016

	$F_t^2 - S_{t+2}$	$F_t^3 - S_{t+3}$
Mean	1.15	1.76
St. Dev.	11.97	15.83
Coefficient of variation	10.38	8.97
Kurtosis	2.52	3.64
Skewness	1.12	1.33
Min	-20.89	-30.08
Max	47.88	68.54

June 2006 – December 2016, monthly observations

A successful long hedger is one who scales her commitments up prior to a subsequent price rise, or down prior to a subsequent decrease relative to today's futures price. The opposite applies to a short hedger who should increase her short positions ahead of falling (relative) spot prices. If the short hedger strongly believes in higher future spot prices relative to today's futures price, she would reduce her short positions. In other words, hedgers who are able to make better forecasts than the futures market can improve their results (compared to a routine hedge) by scaling commitments up and down as discussed above.

The COT statistics do not provide information on the maturities of the commitments. However, there is reason to believe that the bulk of the commitments are in the nearest contracts. As we have shown, these are the contracts most heavily traded and many hedgers take advantage of this liquidity and roll their hedge frequently. Making the (unrealistic) assumption that all short hedging commitments are established with a two months horizon, figure 10 demonstrates the success (or rather lack of success) for short hedgers June 2006 – December 2016. The left hand side axis measures the two months forecast error as observed in month $t + 2$. The right hand side axis measures the short hedge commitments in month t.

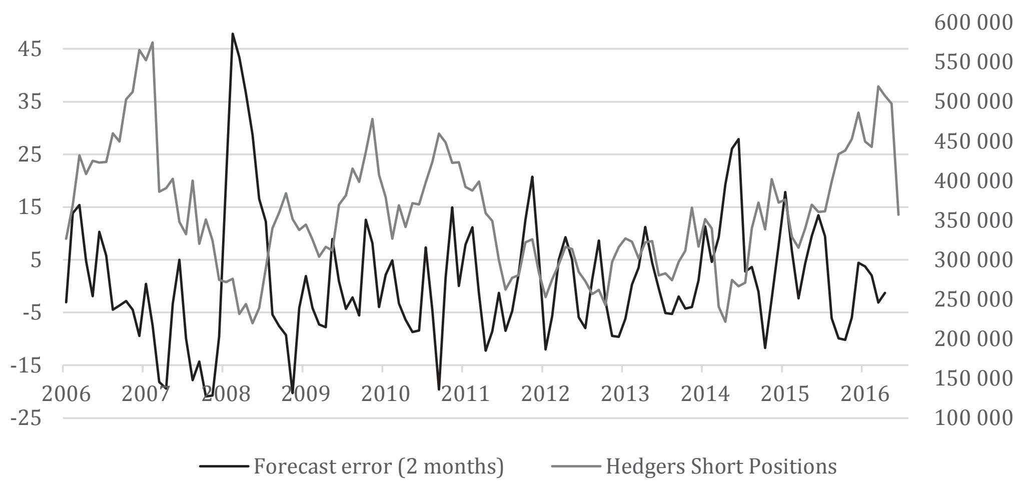


Figure 10: Short hedging commitments in number of contracts on right axis, the forecast error, defined as $F_t^2 - S_{t+2}$ on left axis, monthly observations June 2006-2016.

If short hedgers in aggregate are able to forecast prices better than the futures market, the “profit/loss diagram”, i.e. the forecast error of the 2 months futures contract at time $t + 2$ and the graph showing total short hedge commitments, should move in parallel. When the futures price ex post turns out to be higher than the realized spot price, short hedgers should have up-scaled their positions in front of this event. As can be seen from the graph, this has rarely been so. In 2007, short hedgers increase their positions dramatically while it turns out that the futures price undershot the spot price two months later. Opposite, there are several examples of short hedgers downscaling their commitments prior to the futures price significantly overshooting the subsequent spot price.

The simple correlation between the forecast error at time $t + 2$ and the short commitments at time t is negative. -0.28. Given the assumption that short hedgers are rolling their commitments roughly every two months, they do not seem to have been very successful in scaling their positions. Assuming that commitments are rolled every three months does not change the conclusion. On the contrary, the negative correlation increases to -0.32.

Turning to the long hedgers, a graphical inspection of commitments versus the forecast errors in figure 11 suggests that there is a somewhat stronger correlation between long commitments and forecast errors. At an aggregated level. long hedgers seem to have enjoyed some success in scaling their commitments. When prices increased in 2007. long hedgers had been building up their positions prior to the rise. and when prices fell towards the end of 2008. long hedgers had reduced their commitments. The correlation between $F_t^2 - S_{t+2}$ and long commitments at time t is relatively low. but positive (0.14).

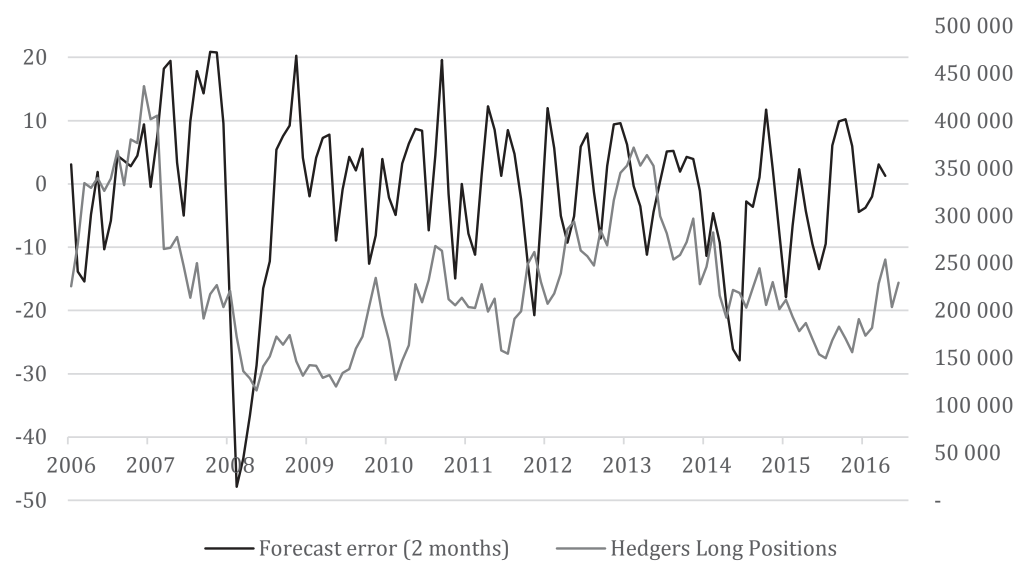


Figure 11: Long hedging commitments in number of contracts on right axis, the forecast error. defined as $S_{t+2} - F_t^2$ on left axis, monthly observations June 2006-2016.

As previously mentioned, the futures price for contracts two and three months ahead overshot the subsequent spot price by USD 1.15 and 1.76 per barrel, on the average

June 2006 – December 2016. This amounts to 3.6 and 5.8% of the spot price. As such, a hedger who consistently took a short position in the third nearby futures contract and reversed the position close to maturity would have made a profit (disregarding transaction costs) of USD 1.76 per barrel. A long hedger performing the opposite transaction every month would have experienced an equivalent loss. (We do not enter into the discussion on whether this is a risk premium). If we pursue the idea that long and short hedgers roll their positions every two and three months and use the reported commitments every month, we find that the long hedgers reduced their loss (or their hedging costs) to USD 0.66-0.95/bbl. The short hedgers, on the other hand, reduce their gain to USD 0.44-0.69/bbl.

Obviously, one can raise critical questions as regards the assumption upon which the above calculations are based. However, we are of the opinion that this may be taken as evidence that long hedgers have been more successful than short hedgers in scaling their positions.

4 State space modeling

Moving on from the descriptive statistics, we test out a series of hypotheses regarding hedging behavior. Because price data on level form, as well as the data from the COT reports, are nonstationary (determined by performing a number of Augmented Dickey-Fuller tests). We formulate these models with a state space representation (SSR). Assuming that the dynamic properties of our variables cannot be observed directly from the data. we specify the models so that the unobserved dynamic process at time t is referred to as the state of the time series (Commandeur and Koopman 2007). The state of a time series may consist of several components, which means a wide range of linear and nonlinear time series models can be expressed through the SSR.

Formally, let $\boldsymbol{y}_t$ denote an $N \times 1$ multivariate time series vector of observations whose evolution across time can be characterized in terms of an unobserved $m \times 1$ state vector $\boldsymbol{\alpha}_t$. A general linear Gaussian state space model that describes the dynamics of this system can be written as:

$$\boldsymbol{\alpha}_{t+1} = \boldsymbol{T}_t\boldsymbol{\alpha}_t + \boldsymbol{R}_t\boldsymbol{\eta}_t. \qquad \boldsymbol{\eta}_t \sim N(\mathbf{0}.\boldsymbol{Q}_t). \qquad (5)$$

$$\boldsymbol{y}_t = \boldsymbol{Z}_t\boldsymbol{\alpha}_t + \boldsymbol{\epsilon}_t. \qquad \boldsymbol{\eta}_t \sim N(\mathbf{0}.\boldsymbol{H}_t). \qquad (6)$$

for $t = 1. \dots . T$. Equation (5) is the state equation (or transition equation), and equation (6) is referred to as the observation (or measurement) equation. The parameter matrices $\boldsymbol{T}_t$, $\boldsymbol{R}_t$ and $\boldsymbol{Z}_t$ are of dimension $m \times m, m \times r$ and $N \times m$, respectively, and unobserved components such as a trend or a cycle can be modeled by an appropriate definition of $\boldsymbol{Z}_t$ and $\boldsymbol{\alpha}_t$. $\boldsymbol{R}_t$ is typically the identity matrix. Unlike with classical regression analysis, the unknown parameters include the observation and state disturbance variances.

The $r \times r$ and $N \times N$ vectors $\boldsymbol{\eta}_t$ and $\boldsymbol{\epsilon}_t$are serially uncorrelated, normally distributed error terms with mean zero and positive definite $r \times r$ and $N \times N$ covariance matrices $\boldsymbol{Q}_t$ and $\boldsymbol{H}_t$, respectively. The disturbances are further assumed to be uncorrelated with each other at all lags, and independent of the initial state vector $\boldsymbol{\alpha}_1$. The $m \times 1$ initial state vector is assumed to be normally distributed with $m \times 1$ mean vector $\boldsymbol{a}_t$ and $m \times m$ covariance matrix $\boldsymbol{P}_t$:

$$\boldsymbol{\alpha}_t \sim N(\boldsymbol{a}_1.\boldsymbol{P}_t) \qquad (7)$$

Generally, the value of the unobserved state at time $t = 1$ is unknown and has to be estimated, through e.g. diffuse initialization. We follow this approach in our study.

The base for our analysis will be a linear structure with only two main components, and as such mirror the classical regression model:

$$Y_t = a + b_k X_{k.t} + \varepsilon_t \qquad (8)$$

where Y_t is the dependent variable at time t. $X_{k.t}$ represents k explanatory variables at time t. b is an estimated parameter. and ε_t is a normally distributed mean zero error term. To cast this model in state space we add the explanatory variables to the observation equation and extend the general state space model through the state equation:

$$\boldsymbol{\alpha}_{t+1} = \boldsymbol{T}_t\boldsymbol{\alpha}_t + \boldsymbol{R}_t\boldsymbol{\eta}_t. \qquad \boldsymbol{\eta}_t \sim N(\mathbf{0}.\boldsymbol{Q}_t). \qquad (9)$$

$$\boldsymbol{y}_t = \boldsymbol{Z}_t\boldsymbol{\alpha}_t + \boldsymbol{x}_t\boldsymbol{\beta}_t + \boldsymbol{\epsilon}_t. \qquad \boldsymbol{\eta}_t \sim N(\boldsymbol{0}.\boldsymbol{H}_t). \tag{10}$$

Where $\boldsymbol{x}_t$ is a $1 \times k$ vector of explanatory variables and the $k \times 1$ vector $\boldsymbol{\beta}_t$ contains the unknown regression coefficients[8]. Please note that for the remainder of this article we will only explicitly state the structure of (8). All models are however estimated by SSR.

The state variable and the unknown parameters have to be estimated from the data. Maximum likelihood estimates of the parameters can be obtained by applying a Kalman filter (Kalman 1960, 1963). The Kalman filter calculates the mean and covariance matrix of the unobserved state at time t, based on the available information at the same date. Because the state is Gaussian the complete distribution is characterized by the mean and variance. The filter is a recursive algorithm, i.e. the current best estimate is updated whenever a new observation is obtained.

5 Econometric results

As shown in table 4, a producer, refiner or consumer of crude oil can obtain a close to perfect hedge by routinely hedging one's total physical exposure, i.e. minimum variance is obtained by a hedge rate close to unity ($\hat{\beta} \approx 1$). Due to high liquidity and a closely integrated spot and futures market there is very little basis risk, and hedgers are able to lock in an almost certain price one to three months into the future. When market data suggests that hedgers refrain from doing so, it is likely because they are reluctant to forego potential profit. A selective long hedger will buy futures when she expects a price increase during the next weeks or months, while a selective short hedger will sell futures when she finds the price acceptable and fears a price fall. In other words, it is rational for a selective long hedger to buy futures whenever $F_t^i < E_t(S_{t+i})$. Conversely, a rational short hedger will sell futures when $F_t^i > E_t(S_{t+i})$.

Building on the assumption that it is rational to seek a profit, we propose that hedgers should increase their long positions prior to price rises, and decrease their short commitments anticipating a price decrease (disregarding risk considerations). We

[8] For more details on the modelling procedure, we refer to e.g. Commandeur and Koopman (2007), who give a detailed overview of state space modelling.

further assume that agents hold rational expectations in the sense that they are right *on average* in forecasting the spot price. i.e. $E_t(S_{t+1}) = S_{t+i}$. As such, we hypothesize that if $F_t^T > E_t(S_{t+i}) = S_{t+i}$, short sellers will increase their positions while long hedgers will reduce theirs.

We test this hypothesis performing the following regressions:

$$Hedging\ commitments_t = \alpha_0 + \alpha_1 \left(F_t^i - E_t(S_{t+i})\right) + \varepsilon_t \qquad (11)$$

If today's futures price of a contract with maturity at time i is higher than our expectation for the spot price at time $t + i$, hedger's long commitments should decrease - i.e. H_0: $\alpha_1 < 0$. On the short side, we expect $\alpha_1 > 0$ when $F_t^i > E_t(S_{t+i})$.

Examining the estimation results from the SSR in table 6, we see that the estimated parameters in the regressions of hedger's long commitments onto the difference between the futures and spot price at time $t+i$ display the expected sign. The estimates are however not significant at the 5% level, and the R^2-values are very low. The regressions involving hedger's short commitments yield significant and negative parameter estimates. In other words, we have been able to establish a relationship between hedger's short commitments and the price difference between a futures contract that expire at time $t+i$ and the realized spot price, but the direction of this connection is not as anticipated. Once more, the R^2 values are low – which implies that changes in hedging commitments are predominantly driven by other factors. Finally, we note that performing the same regressions on changes instead of levels yield no explanatory power at all. These results are excluded for brevity.

Table 6: Hedgers commitments vs the difference between the futures and subsequent spot price – 2006-2016

	α_0	$\alpha_1(F_t^i - S_{t+i})$	R^2
Hedgers long. $i = 2$	230 389 (36.36)	-848 (-1.60)	0.02
Hedgers long. $i = 3$	230 724 (36.19)	-744 (-1.87)	0.03
Hedgers short. $i = 2$	**358 003** **(55.17)**	**-1 759** **(-3.25)**	0.02
Hedgers short. $i = 3$	**358 670** **(55.59)**	**-1 528** **(-3.78)**	0.03

z-values in brackets, parameters marked in bold indicates significance at the 5% level, obs=124

So far, we have examined whether hedgers (on an aggregated level) have adjusted their positions as if they have been able to successfully forecast the direction of the oil price over the next two or three months. In this regard, it is interesting to see that the estimated α_1-parameters in table 6 are all negative. In other words, long and short hedger's tend to increase or decrease their commitments in the same direction prior to a change in $F_t^i - S_{t+i}$. While it is rational for a long hedger to reduce her positions when the spot price falls relative to the futures price, this is not the case for a short hedger.

Following up on this observation, we look at hedging commitments and their relation to the spot price change from today and 3 months ahead. i.e.:

$$Hedging\ commitments_t = \alpha + \beta\Delta^3 S_{t+3} + \varepsilon_t \qquad (12)$$

Table 7 shows that the estimated parameters are small in size compared to the mean hedging levels reported in table 2 (230 062 and 360 305 for long and short hedgers, respectively). In other words, price changes have little influence on hedging commitments. Again, we find that the estimated parameters display the same sign for long and short hedger's, which is surprising as the two sides of a trade are affected differently by price changes. We see no obvious explanation for this finding, and merely note that the coefficient of determination are much higher in value in the regression with short hedging commitments. This indicates asymmetric effects across the two groups.

Table 7: Hedgers commitments vs the future spot price – 2006-2016

	$\boldsymbol{\alpha_0}$	$\boldsymbol{\beta}$	R^2
Hedgers long	**229 514** **(36.07)**	611 (1.55)	0.02
Hedgers short	**355 582** **(57.43)**	**1 712** **(4.45)**	0.14

z-values in brackets, parameters marked in bold indicates significance at the 5% level. obs=123

So far, our results suggests that $\left(F_t^i - S_{t+i}\right)$, i.e. the difference between the futures and subsequent realized spot price is driving changes in hedgers commitments. The descriptive analysis in section 3.2 did however indicate that hedging volumes might vary with volatility. We use the OVX as measure of oil price variability, which tracks the implied volatility of 30-day United States Oil Fund options and as such is forward-looking by construction. Following up on Stulz (1996) on selective hedging, who suggests that hedgers typically try to truncate their tails to avoid severe losses, we also include a measure of tail risk in this step of our analysis. Like Switzer, Lee et al. (2014), we define extreme observations as outliers in the dataset - analogous to how you would construct a box-and-whiskers plot. We consider outliers to be any observation that lies at an abnormal distance from other values in the dataset, and use the lower inner and upper inner fence to identify extreme observations in the tail of the distribution. The lower inner fence is the difference between the lower quartile (Q1) and the value of 1.5 times of the interquartile range (IQR), and the upper inner fence is calculated as the sum of the upper quartile (Q3) and the value of 1.5 times of the interquartile range (IQR). The interquartile range is the difference between the upper quartile and the lower quartile (Q3 – Q1). Extreme values will then be any observations that fall outside these ranges:

$$Extreme\ observation \begin{cases} < Q1 - 1.5 \times IQR \\ > Q3 + 1.5 \times IQR \end{cases} \tag{13}$$

The extreme volatility measure for a given year is defined as the ratio of outliers to trading weeks per year:

$$Ext(\%) = \frac{Annual\ number\ of\ extreme\ observations}{Annual\ number\ of\ trading\ weeks} \times 100 \quad (14)$$

We use weekly data and calculate *Ext* with a rolling window of 52 consecutive observations. To discern how volatility and extreme events influence hedging behavior we regress long and short hedging commitments on both variables. The results are presented in table 8.

Table 8: Hedgers commitments and oil price variability – 2006-2016

	α_0	OVX	Ext	R^2
Hedgers long	**301 113**	**-2 168**	-1 172	0.33
	(46.71)	**(-13.13)**	(-1.77)	
Ln(hedgers long)	**12.64**	**-0.01**	-0.00	0.33
	(422.55)	**(-13.68)**	(-0.71)	
Hedgers short	**332 650**	109	**3 308**	0.03
	(35.50)	(0.45)	**(3.44)**	
Ln(hedgers short)	**12.07**	-0.00	**0.01**	0.04
	(482.36)	(-0.06)	**(4.25)**	

z-values in brackets, parameters marked in bold indicates significance at the 5% level. obs=443

We run the models on both log and level form. Table 8 demonstrates clear differences in how long and short hedging commitments relate to oil price variability. Beginning with the long side, a highly significant parameter estimate for OVX and notable explanatory power as measured by R^2 (0.33) give evidence that long hedging commitments are driven by changes in oil price variability. As can be seen, an 1% increase in volatility is associated with a decrease in long hedging commitments of approximately 2 200 contracts, or 0.01%. As previously mentioned, finding is highly significant, and also somewhat puzzling as it suggests long hedger’s reduce their positions faced with increasing market uncertainty. The OVX is constructed from the implied volatility of 30-day United States Oil Fund options, and is as such and index that measures the market's *expectation* of future price volatility. It seems reasonable to expect hedger's activity to rise with increasing risk, and finding that the opposite holds for long hedging commitments we question whether these market participants are sometimes behaving like speculators, but choose to downsize speculative activities when faced with turbulent market conditions. Unfortunately, we have not found a way to explore this issue further. Examining the relationship between long hedging commitments and the tail risk measure, we find that this is only moderately significant on level form, and the parameter estimate is modest in size. On log-form, it is not significantly different form zero.

Turning to the short side, we find no significant relationship between hedging commitments and the OVX, but there is a positive and significant connection between short hedging and the extreme risk measure. This is consistent with the notion of a short hedger that routinely hedges part of her production, and increase the level of protection in periods with very high price variability. The explanatory power of this regression is however very low, with an R^2 value of 0.04. Regardless, it supports the conjecture made in Stulz (1996), namely that corporate risk management hedge selectively and focus on eliminating the risk associated with extreme and costly outcomes. In other words, the aim of most hedging entities is typically to reduce the expected costs of financial trouble, while still exploiting access to sector-specific information or any comparative advantage in risk bearing they might have.

6 Conclusion

Analyzing crude oil futures hedging commitments, prices and volatility, we have examined whether hedgers' market behavior of hedgers is consistent with a rational hedging strategy. We find that hedgers in the market for crude oil vary their positions substantially from month to month, seemingly inconsistent with a risk minimizing hedging strategy. This suggests that there may be a speculative component to hedgers' trading decisions. Our analysis gives some indication that hedgers scale their positions up or down based on expectations of relative price changes (futures versus spot). However, as far as short hedgers are concerned, the scaling of commitments do not appear successful *ex post*.

We further demonstrate asymmetric effects in how long and short hedging commitments relate to oil prices and oil price variability. Our analysis of the relation between oil price variability and hedging commitments suggests that short hedgers focus on truncating their tails to avoid very costly outcomes, rather than pure variance reduction. This is consistent with the theory of selective hedging presented Stulz (1996). We find no significant relation between short hedging commitments and the OVX.

Long hedging commitments on the other hand, is negatively related to expected future risk, as measured by the OVX. This is a puzzling phenomenon, as one would expect long hedgers to hedge more in an (perceived) increasingly risky market. The observed relationship might be due to long hedgers reducing the speculative component of their futures portfolio face with turbulent market conditions.

Our analysis supports the findings from Cheng and Xiong (2014)'s study on hedging in agricultural futures. However, although we find that hedgers in the oil market trade substantially more than what seems consistent with traditional risk minimizing we do not agree with their main conclusion. Since hedgers are typically speculating in the *physical* market (by adjusting production or leaving their positions exposed to price risk), considering regulations or policy measures geared towards this group appears redundant.

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Commodity market risk from 1995 to 2013: an extreme value theory approach

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Commodity market risk from 1995 to 2013: an extreme value theory approach

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In this article we examine whether extreme risk has increased in the agricultural commodity market during the period 1995–2013. We add to the literature on food price volatility by analysing the tail segment of futures price return distributions. Food price variability is a concern for governments and regulators worldwide, as most nations trade in food. High food price variability can contribute to poverty and malnourishment, in particular for people in less economically developed economies. We find no indications of systematically increasing tail-risk for the commodities in our sample. Analysis of estimated shape-parameters of the Generalized Extreme Value distribution further supports the conclusion that there is no general systematic change in the extreme risk associated with these commodity investments.

Keywords: tail risk; extreme value theory; generalized extreme value distribution; bootstrapping; agricultural commodities

JEL Classification: G1; G13; G15; Q110

I. Introduction

This study is a contribution to the debate on whether commodity prices have become more volatile during recent years. The previous decade has been characterized by significant turbulence in financial markets worldwide, and a lot of attention has been focused on commodities and the adverse effects of increasing food prices. The price volatility of agricultural commodities is a topic that has been under less scrutiny, and the majority of analyses have focused on traditional volatility measures such as variance and SD. Measuring dispersion around the mean can give a good gauge of movements around a trend or a central tendency, but fails to capture the risk associated with the extreme events that manifest themselves as outliers. Our contribution in this respect is an analysis of the tail risk related to commodity investments.

After more than 20 years of stagnant prices, agricultural commodity prices started to increase rapidly in 2006, peaking in July 2008. Soon thereafter prices plummeted, and remained low throughout the financial crisis before recovering in the second half of 2009 (see Fig. 1). By April 2011, prices were again approaching the levels preceding 2008. Both academics and regulators have been

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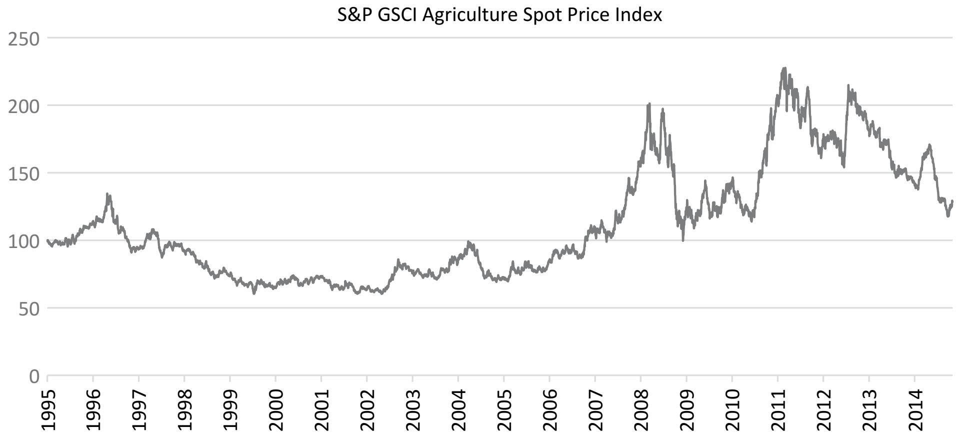

Fig. 1. The S&P GSCI agricultural spot price index, daily prices 02.01.95–31.10.14 (Rebased, 2 January 1995 = 100)

trying to identify the driving forces behind this upsurge in commodity prices.

Food price volatility will affect virtually all economies across the globe, as most nations trade in food (Gilbert and Morgan, 2010). The impact is determined by whether the country is a net importer or exporter of agricultural commodities, and to what degree it is integrated into world markets. Industrial countries are less exposed to volatility risk at the micro level, as households in more economically developed nations spend a lesser proportion of their disposable income on food. Moreover, producers in richer nations have more tools available to accommodate volatility risk, such as futures hedging in commodity markets or crop insurance. Developing countries are clearly more vulnerable to food price volatility because their trade bill is often heavily dependent on primary commodities. The net welfare effects hinge on whether the country is a net importer of food, or whether agricultural commodities are a source for export earnings. For instance, volatility in world soybean prices during the period 2007–2009 contributed to increased poverty in Indonesia, being a net importer of this commodity (Dartanto and Usman, 2011). People in poorer countries generally spend a large portion of the household income on food, and there are often few alternatives for staple food items (Gilbert and Morgan, 2010).

In this article we expand the existing body of literature on commodity price volatility by examining extreme price deviations, as opposed to deviations defined in terms of the normal distribution. This topic should be of both academic and practical interest as price variability influences a variety of financial decisions such as asset allocation, risk transfer and derivative pricing. It is well established that commodity price returns exhibit high peaks and excess kurtosis (Geman, 2005), which means that extreme deviations from the mean are more likely than what models and risk metrics based on the normal distribution imply.

Extreme events have been widely discussed in the aftermath of the financial crisis. Some argue that not only are such events much more common than predicted by modern financial theory, the consequences of extreme market moves are also largely underestimated. A problem with many tools in finance is that they attempt to capture the entire density of a distribution typically using SD, skewness and kurtosis. In practice, this means that we get a good description of the mean and central area where we have an abundance of data, but this approach fails in the tails where we have very few observations to go on. For these reasons, we choose to focus solely on the tail behaviour of commodity price returns in order to provide more information on price volatility in these markets, and whether price volatility changes during the period 1995–2013. Our theoretical approach is the extreme value theory (EVT), which has the advantage of utilizing the benefit of asymptotic results that hold for a wide range of parametric distributions. Further, EVT provides the possibility of focusing on the two tails of the distribution separately, which is appropriate when faced with skewed distributions.

In the next section, we discuss the rationale and theoretical foundation for this article. Section III presents data and descriptive statistics for nine agricultural commodities, observed daily from January 1995 through December 2013. In Section IV, we outline a methodological framework for risk assessment based on EVT. Section V gives an overview of our empirical findings, and Section VI contains concluding remarks.

II. Related Literature

Equities and bonds are valued by discounting expected future cash flows, and exist for the sole purpose of being investment vehicles. Commodities are different in that they exist to be consumed, and not to generate future returns. In that sense, they are not financial assets. A defining feature of commodities as an asset class is that they should not be valued by net present analysis (Greer, 1997; Geman, 2005). Instead, long-term commodity prices are determined by a combination of fundamental factors and the interaction of supply and demand. In the short run, price changes are driven by inflow of information to the market place, forming expectations and speculation regarding future supply and demand dynamics.

Fundamental factors

Typically, agricultural price booms and periods of high volatility are caused by shocks to the supply side. Weather events or animal diseases that disturb the normal pattern of variation that is expected in agricultural production are examples of such supply-side shocks. High and unexpected demand can also cause high prices and volatility spikes. During the crop year 1972–1973, Chicago wheat prices gyrated when the Soviet regime abandoned their policy of not trading with the capitalist world and instead bought 30 million metric tons of grain. This was more than half the commercially exported grain worldwide that season (Kub, 2012). The impact of supply and demand shocks on price volatility depends on the corresponding supply and demand elasticities. While it is difficult to get accurate elasticity estimates, it is generally agreed that commodity supply and demand are relatively inelastic, particularly within a crop season. Farmers cannot reap what they have not sown, and consumers are generally slow in terms of changing habitual food patterns. As previously mentioned, it can also be difficult to find alternative food staples in less developed economies.

Another key factor that affects agricultural prices and volatility is available inventory, worldwide or in a given region. In contrast to financial markets, volume risk is as crucial as price risk in commodity markets, because the quantity produced is not known with certainty *ex ante*. The theory of storage applies to all commodities that can be physically stored, and was brought forward by scholars like Keynes (1930), Working (1927, 1933, 1948, 1949), Kaldor (1939) and Brennan (1958). The theory makes two main predictions, where the first is that when the quantity held in inventory is low, spot prices will exceed futures prices, and spot price volatility will exceed futures price volatility. Conversely, when inventories are abundant, spot prices can become depressed with respect to futures prices, and volatility will be low.

Both 2007–2008 and 2010–2011 were characterized by adversely affected crops in several important regions for agricultural production (Trostle *et al.,* 2011). However, Gilbert (2010) argues that agricultural price booms are better explained by common factors, rather than market-specific factors like supply shocks. He highlights that demand growth, monetary expansion and exchange rate movements have been central explanatory factors of price movements since 1971. Monetary expansion and depreciation of the US dollar is also emphasized in Abbott *et al.* (2008) as driving the increase in agricultural prices. A good overview of macroeconomic factors that likely contributed to the price spike in 2008, is given in Pies *et al.* (2013). Here demand for food increased more rapidly than supply, together with subsequently declining stocks listed at the forefront.

Kilian (2009) demonstrates that rapid economic growth and industrialization in emerging Asia caused unexpected demand pressure that made energy prices gyrate around 2007–2008. Hamilton (2009) concludes that low demand price elasticity and strong growth in world demand were contributing factors to the increase in crude oil prices from 2006 through 2008. Both results are interesting, as a growing literature suggests that the correlation between energy and food prices is increasing – see, for instance, Gilbert (2010), Dorfman and Karali (2012), and Tang and Xiong (2012). Some authors attribute the strengthening of this linkage to the production of biofuel using corn as an input. Mitchell (2008) claims that the increase in biofuel production in the United States and the European Union was responsible for a large part of the build-up in food prices prior to the 2008 price spike. Rosegrant (2008) presents a similar conclusion in a testimony for the US Senate Committee on Homeland Security and Governmental Affairs. Likewise, Baffes (2011) discusses biofuel production, but downplays its role as a determinant of food prices during the last decade. His article highlights that biofuels only account for about 1.5% of the areas allocated to grains and oilseed crops worldwide, and shows that the correlation between biofuel production volume and maize/oilseed prices is very low. Nevertheless, the role of biofuels as a determinant of agricultural commodity prices and volatility remains controversial.

A thorough review of how biofuel policies might influence corn price volatility and price levels is given in Abbott (2013). The author concludes that increasing ethanol production has brought about a large, persistent and new demand for corn resulting in higher corn prices. He identifies a tighter linkage between energy and agricultural markets in some periods, but this effect is not constant. Finally, Abbott identifies switching regimes in terms of volatility levels, with short periods of surging volatility. This has led to a misperception of a permanent change in commodity price volatility levels, when in reality it was the big moves, especially around 2007–2008, which formed a false impression of lasting higher volatility levels. Baumeister and Kilian (2014) use impulse response analysis to disentangle the channels of transmission from the real price of oil to raw agricultural product prices, but find no evidence that the change in US biofuel policies in May 2006 have created a tighter link between oil and agricultural markets. Their analysis further shows that there is no systematic increase in food price volatility.

The role of speculation

Another widespread belief is that speculative influences, especially the growth of long-only index commodity funds, are driving commodity prices away from their fundamental levels. The debate on speculation and commodity price (in)stability has a long history (Jacks, 2007). For almost as long as we have had modern futures exchanges, a central issue has been whether futures trading stabilizes or destabilizes markets, where, in the latter case, it undermines the main reason for having such markets (Tomek and Gray, 1970; Peck, 1976). In a much debated paper, Pindyck and Rotemberg (1990) claimed some 20 years ago that commodity prices moved too much in parallel, indicating that herd behaviour rather than fundamentals was driving commodity prices.[1] This debate resurfaced during the commodity price boom in the period 2007–2008. A number of academic papers concluded that financial investors and speculators had turned commodities into financial assets decoupled from the fundamentals in, for instance, agricultural production. The increasing number of long-only commodity index trackers and the influx of large institutional investors and highly leveraged hedge funds in the commodity markets were said to cause excessive price surges (‘bubbles’) and dysfunctional markets. Two well-known papers in this category are Singleton (2011) – which found a statistically significant relationship between oil prices and investor activities in the market for oil futures[2] – and Tang and Xiong (2012), which found that commodity prices have become increasingly inter-correlated after 2005 and particularly so for commodities carrying weight in the most popular indices for index trackers. The authors argue that this means commodities have become ‘financialized’.

Irwin and Sanders dispute both the theoretical and empirical ground that futures market speculation is driving physical commodity prices (e.g. Irwin *et al.,* 2009; Irwin and Sanders, 2011, 2012). Likewise, Stoll and Whaley (2011) conclude that commodity index flows, whether due to rolling over existing futures positions or establishing new ones, have little impact on futures prices. The authors argue that owing to the passive and long-only nature of commodity index investments, these are unlikely culprits of inflated commodity prices. Steen and Gjølberg (2013) revisit Pindyck’s herding hypothesis applying principal component analysis on a basket of 20 commodities. Examining monthly prices for the period 1986–2010, they find evidence of increased co-movements across commodities, and between commodities and the stock market after 2004. The

[1] This paper was later criticized for model misspecifications such as arbitrarily selected variables and failure to account for conditional heteroscedasticity; see, for instance, Deb *et al.* (1996) and Le Pen and Sévi (2013).
[2] This article has later been criticized for issues related to the data used in the analysis, as well as the interpretation of the results; see, for instance, Fattouh *et al.* (2012).

authors do, however, show that this result is mainly driven by the extreme price movements after 2008, and find no strong evidence of 'financialization', or contamination from the market activities of financial investors, prior to 2008.

There is also a growing body of literature that addresses the issue of increasing commodity market volatility. McPhail *et al.* (2012) study corn futures traded on the Chicago Board of Trade and use a structural vector autoregressive model and variance decomposition to analyse corn price volatility. The authors find that second to market-specific shocks for corn, speculation is the most important factor for explaining corn price variability in the short run. The other factors considered are global demand, energy prices and fuel policies. After six months, global demand becomes a more important explanatory factor relative to speculation, and after 12 months the influence of speculation on corn price volatility becomes negligible compared with the effects of global demand and energy prices. Algieri (2012) finds that (excess) speculation Granger causes changes in volatility for several agricultural commodities, but also notes that whether or not this finding is statistically significant depends on the selection of time windows. That the lead–lag dynamics of the two variables varies depending on the time period under consideration begs the question of whether or not the relationship is spurious. Tang and Xiong (2012) identify increasing co-movement in volatility returns for commodities by separating into yearly sub-periods using a regression-based approach. They find that commodities that are part of an index exhibit larger volatility increases relative to nonindex commodities in the years 2004, 2006–2009 and 2011. They argue that this is evidence that commodity prices no longer are determined solely by fundamental factors like supply and demand. The authors conclude that commodity markets are 'financialized', i.e. that commodity prices are affected by the investment behaviour of commodity index investors.

Several papers are unable to confirm that speculation has caused increasing commodity market volatility. Bastianin *et al.* (2012) examine energy and agricultural commodity futures markets and find that excess speculation is not relevant in explaining commodity return variability, with the exception of crude oil. Sanders and Irwin (2011) analyse the entire range of agricultural, energy, metal and soft commodity futures prices alongside index trader-position data. Cross-sectional Fama–McBeth regression tests reveal little evidence that index trader-positions influence commodity market return or volatility. While most studies of commodity price volatility focus on futures markets, Bohl and Stephan (2013) focus on how index investments might influence spot price volatility. Their study of six major agricultural and energy commodities fails to confirm a relationship between the share of non-commercial traders and commodity price variability. A similar conclusion is reached for futures prices in Bohl *et al.* (2013). The authors conclude that 'with respect to twelve increasingly financialized grain, livestock, and soft commodities, we do not find robust evidence that CITs[3] can be held responsible for making their futures prices more volatile' (Bohl *et al.,* 2013, p. 15).

A more detailed literature survey of how financial speculation influences agricultural commodity prices can be found in Will *et al.* (2012). They conclude that there is little empirical evidence for the point of view that futures trading was the driving force behind the price spike in 2008, or that futures trading has caused increased commodity market volatility. Cheng and Xiong (2013) review academic studies of speculation in commodity markets, including energy and metals. They investigate how financial investors affect commodity prices through economic mechanisms, with emphasis on risk sharing and information discovery. The authors conclude that the influx of index investors has changed commodity markets through these channels.

III. Data

Because food price volatility is the main focus of this article, we have chosen to examine a broad range of agricultural commodities, namely corn, wheat, soybeans, soya oil, sugar, cocoa, orange juice, lean hogs and feeder cattle. The data cover front month futures prices from the Chicago Mercantile Exchange (CME) Group and the Intercontinental Exchange (ICE). The CME group is the largest commodity options and futures exchange in the world, also providing markets for interest rates, equity indexes, foreign exchange, weather and real estate, in addition to a large number of commodities. It forms a trading

[3] Commodity index traders.

Table 1. Descriptive statistics

	Corn	Wheat	Soybean	Soyaoil	Sugar	Cocoa	Orange juice	Lean hogs	Feeder cattle
1995–2000									
St. Dev	0.22	0.25	0.21	0.19	0.29	0.25	0.34	0.26	0.12
Kurtosis	1.99	2.26	3.35	1.95	3.06	3.39	17.08	2.01	1.44
Skewness	−0.01	−0.24	−0.12	0.20	−0.18	0.52	1.30	−0.28	0.18
2000–2005									
St. Dev.	0.23	0.26	0.24	0.24	0.36	0.36	0.26	0.25	0.12
Kurtosis	1.35	1.62	2.29	1.20	6.53	1.45	6.28	0.92	8.25
Skewness	0.26	0.33	−0.20	0.15	−1.10	−0.18	0.32	−0.19	−0.88
2005–2010									
St. Dev.	0.34	0.37	0.30	0.29	0.34	0.32	0.35	0.22	0.13
Kurtosis	1.00	1.25	1.88	2.16	1.97	2.99	4.08	1.31	1.92
Skewness	−0.07	−0.08	−0.42	0.02	−0.20	−0.50	0.16	−0.22	−0.21
2010–2013									
St. Dev.	0.31	0.34	0.22	0.20	0.35	0.27	0.33	0.17	0.10
Kurtosis	2.33	1.99	1.58	1.18	2.71	1.10	3.37	0.90	1.33
Skewness	−0.09	0.06	−0.17	0.06	−0.50	−0.14	−0.37	−0.02	−0.13

Notes: Kurtoses are reported as excess kurtosis. SDs are annualized. The number of observations in each period is ≈ 1200, except in the last period where the number of daily observations is 991.

platform that includes the Chicago Mercantile Exchange, Chicago Board of Trade, Kansas City Board of Trade, New York Mercantile Exchange and New York Cotton Exchange (see www.cmegroup.com for more information regarding markets, product specifications, etc.). ICE consists of a global network of exchanges and clearing houses including amongst others the New York Cotton Exchange and the Coffee, Sugar and Cocoa exchange. ICE provides futures contracts on financial, commodity and energy markets. Additionally, ICE offers equities, equity indexes, exchange-traded products, fixed-income instruments and equity options. More details about the different contracts and where they are traded can be found in the Appendix. We choose to examine prices of nearby futures contracts since this market is forward looking by construction and respond rapidly to news and changes in expectations. Our analysis is based on continuous series of front month futures prices obtained from Datastream. The data is given as an index, which starts with base 100 representing the first price or the nearest contract month. Daily price returns from the front month contract is applied to the index until the contract reaches its expiry date. At this point the price returns from the next contract month is used. As the daily return from the index is consistent with the contract month, this effectively adjusts the index for rolling yield making this an excess return index. All return series are calculated as logs, and augmented Dickey–Fuller tests confirm that these series are stationary.

In Table 1, we have divided 18 years of daily observations into time periods of 5 years (the most recent period contains 3 years). The mean level of returns averages to zero over all periods and across all commodities, which is why we refrain from reporting these values here. All return distributions display moderate amount of skewness, which is natural as the commodity sector traditionally consists of both producers and consumers. As a consequence, the market is made up of participants that are concerned about both price rises and declines.

There has been a lot of focus on the period from 2006 onwards in terms of increasing commodity prices and price volatility. Table 1 shows that the period 2005–2009 does indeed exhibit high volatility levels. This phenomenon is, however, not without exceptions. The volatility of lean hogs has actually decreased compared to the previous time periods.

We see that there is great variation in SDs and kurtosis, both across commodities and time periods. Corn is a commodity with a variety of uses and a product that is heavily traded on exchanges. We see that this commodity had an upsurge in volatility levels after 2005. For the period 2005–2010 this could in part be explained by large price movements that came with the 2008 price spike and the

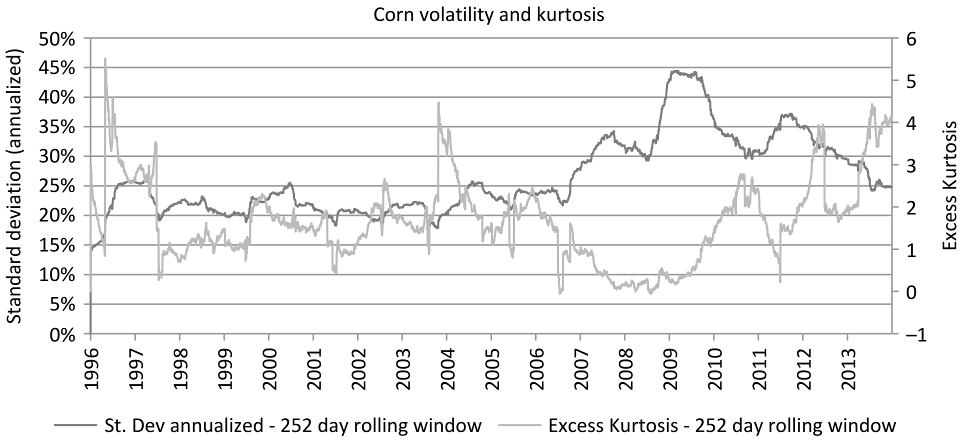

Fig. 2. Corn continuous settlement price – Uc/Bc, rolling window estimates of SD and excess kurtosis based on daily log-returns, 2 January 1995 to 31 December 2013

subsequent financial crisis, but it is less obvious as to what is causing the high volatility levels after 2010. Increased demand for corn for the production of biofuel in the United States, as well as adverse weather conditions in the US Corn Belt, are possible culprits. While the risk is increasing in terms of volatility, we see no evidence of increasing tail risk. We see that the return series exhibit fat tails relative to the normal distribution, but the amount of excess kurtosis is moderate.

Like corn, wheat prices have been characterized by increasing volatility levels after 2000 as measured by SD. We also see that wheat prices are more volatile than corn prices for all time periods. The latter phenomenon is puzzling for two reasons. First, we note that corn exports are dominated by one major player, the United States. Wheat benefits from having a number of exporters, and while the United States is still the largest, their export competes with those of Canada, Russia, Ukraine, Argentina and Australia, among others. Some argue that there should be substantial diversification benefits from producing in different regions, as production shortfall in one region can be made up by other regions. However, these data tell another story – wheat prices have been significantly more volatile relative to corn prices since the late 1990s.

The second puzzle relates specifically to the premise that speculation might drive commodity prices. The amount of corn traded on exchanges is much larger than that of wheat. If it is true that speculation is driving price volatility, one should expect relatively more volatile corn prices. A counterargument would be that the large number of trades in corn makes this market more robust against speculative influences.

Figure 2 displays the evolution of volatility and kurtosis for corn front month futures contracts from 1995 through 2013. We use rolling window estimation to illustrate how descriptive statistics sometimes fail to capture all the subtleties of a probability distribution. The problematic areas occur when volatility levels are low while kurtosis is high, like we see around the year-end of 2003 and also in the latter part of 2013. It is common to associate low volatility levels with small amounts of risk. However, several of the risk models in modern finance assume a normal distribution, which implies that these models will misjudge the probability of observing large price changes in the presence of heavy tails. When the return distribution exhibits fat tails, i.e. when kurtosis is high, the estimated SD severely understates the true degree of observations far away from the mean. It follows that thinking solely in terms of normally distributed returns will seriously underestimate risk when kurtosis levels are high.

IV. Method

Tail-related risk is today an integrated part of modern risk management. The branch of statistics that deals with probability distributions and extreme deviations from the mean are generally referred to as EVT. In this article we use a variation of the block maxima estimation method. This approach considers the maximum or minimum a variable takes in sequential periods. Formally, the limit law for the maxima M_n, where n is the size of the subsample (block), is given by the Fisher–Tippett–Gnedenko theorem (Fisher and Tippett, 1928; Gnedenko, 1943):

Let (X_n) be a sequence of i.i.d. random variables. If there exist norming constants $c_n > 0\, d_n \in \mathbb{R}$ and some nondegenerate distribution function H such that

$$c_n^{-1}(M_n - d_n) \xrightarrow{d} H \quad (1)$$

then H belongs to one of the three following distribution functions:

$$\textit{Fréchet}: \Phi_\alpha(x) = \begin{cases} 0, x \le 0 \\ \exp[-x^{-\alpha}], x > 0 \end{cases} \quad \alpha > 0$$

$$\textit{Weibull}: \Psi_\alpha(x) = \begin{cases} \exp[-(-x)^{-\alpha}], x \le 0 \\ 1, x > 0 \end{cases} \quad \alpha > 0$$

$$\textit{Gumbel}: \Lambda(x) = \exp[-e^{-x}], x \in \mathbb{R}$$

The theorem above is one of the fundamental results in EVT, and can be thought of as analogous to the central limit problem in standard probability theory (Embrechts *et al.*, 1997). The key insight is that the asymptotic distribution of the maximum values belongs to one of the three distributions, regardless of the original data. The existence of a sequence of norming constants is not always guaranteed, though for virtually any textbook distribution it has been proven that location and scale parameters are defined (Embrechts *et al.*, 1997; Rocco, 2014). The generalized extreme value (GEV) distribution introduced by Jenkinson (1955) combines these three distributions into a single function with the following cumulative distribution function:

$$H(x; k, \alpha, \xi) = \begin{cases} \exp\left[-\{1 - k(x-\xi)/\alpha\}^{1/k}\right], \ k \ne 0 \\ \exp[-\exp\{-(x-\xi)/\alpha\}], \ k = 0 \end{cases} \quad (2)$$

where k, α and ξ are the shape, scale and location parameter, respectively. When $k > 0$, we have the Fréchet distribution family with heavy tails. For $k < 0$, we get the Weibull distribution with a short tail and finite right end-point, and for $k = 0$ the GEV distribution reduces to the Gumbel that encompasses several distributions with tails ranging from light to moderately heavy.

To assess whether the extreme risk profile of agricultural commodities has changed systematically during the period 1995–2013, we define the first and ninety-ninth percentiles as block minima and maxima, respectively. The percentiles are calculated as medians. Because the tail distributions are highly asymmetrical, the mean no longer represents a good measure of central tendency. As for the block size, we choose to divide by calendar years to avoid any seasonal effects. This gives 18 nonoverlapping subsamples containing daily log-returns of the successive calendar years.

One inherent difficulty in assessing tail-related risk is the fact that extreme events are, by definition, rare. This means that it is challenging to make statistical inference about changes in extreme risk from one period to the next. To make assessment about inference, we use the bootstrapping technique to estimate confidence intervals around the annual distributions of extremes. The bootstrap creates a large number of datasets from the original data using resampling, and then computes all statistical measures from these datasets (see Efron, 1979, for details). We produce 2000 bootstrapped distributions per year for each commodity in order to create bias-corrected confidence intervals (Poi, 2004). This correction is found to have better asymptotic properties than the normal approximation (Efron, 1987). In order to avoid inflating Type I error when comparing the actual percentiles and their respective confidence intervals over multiple years, we employ the strict Bonferroni adjustment to the 5% significance level by assuming three comparisons across the time period 1995–2013 (i.e. significance level/3 = 1.67%, yielding a confidence interval of 100% – 1.67% = 98.33%). The choice of number of comparisons is arbitrary, but informed by the fact that the Bonferroni method is overcompensating for the risk of Type I error. A visual comparison of the 2013 percentile (ninety-ninth or first) with these confidence intervals over time sheds light on whether tail-related risk is changing. This visual method is informative since the reader can choose which time periods are most interesting to compare across.

As a rudimentary robustness check, we calculate nonparametric confidence intervals for the median based on the binominal distribution. Upper and lower confidence intervals are calculated according to the following approximation, analogous to Campbell and Gardner (1988):

$$CI = nq \pm Z\sqrt{nq(1-q)}$$

where n is the sample size and q denotes which quantile we examine. In our case, $q = 1/2$, because we are interested in the median. The value of Z depends on the confidence level required, and is given by the standard normal distribution. The nonparametric confidence intervals overlap the bias-corrected ones with high proximity, and we thus refrain from reporting them in the results section of this article.

We also assess the change to the probability-weighted moments estimator for the shape parameter of the GEV distribution, $\hat{k}$, through the same subsequent periods of one year. Probability-weighted moments (PWMs) estimators compare favourably with estimators obtained by maximum likelihood as shown in Hosking *et al.* (1985). By using the method of PWM, we were able to utilize a simple yet powerful test of whether the tail belongs to the domain of a Fréchet, Weibull or Gumbel distribution. If the shape parameter $\hat{k} = 0$, the estimator is asymptotically distributed as $N(0, 0.5633/n)$. By calculating $Z = k\sqrt{(n/0.5633)}$, we could compare this statistic with the critical values of a standard normal distribution (Hosking *et al.*, 1985). Significant positive values of Z imply the rejection of the null hypothesis in favour of $\hat{k} > 0$, while significant negative values of Z imply rejection in favour of $\hat{k} < 0$. All estimates were calculated using the bootstrapping technique.

V. Results

In this section, we give an overview of our empirical findings. Figure 3 displays the evolution of the first percentile for corn futures contracts from 1995 through 2013. The straight, horizontal line represents the actual percentile value in 2013. Examining the first percentile, we see that this line for the most part falls outside the bias-corrected bootstrapped confidence intervals prior to 2006. This can be interpreted as an indication of increased extreme risk after 2006, although the evidence is not conclusive. We note that the large 'dip' to the right of the annual distribution of minima coincides with the onset of the financial crisis. Considering extreme risk to the upside in Fig. 4, we see a similar pattern with a breaking point in 2006. The annual distribution of maxima suggests that there was a relatively larger amount of tail risk in the time period 2006–2012, with large price deviations. In 2013, extreme risk reverts to the post-2006 level.

In sum, we find some indications of corn price changes being more extreme after 2006, with upside risk normalizing in 2013. A similar pattern is detected in the price series for wheat. In Fig. 5, we see that both extreme outliers, as well as the confidence intervals around them, are shifting upwards

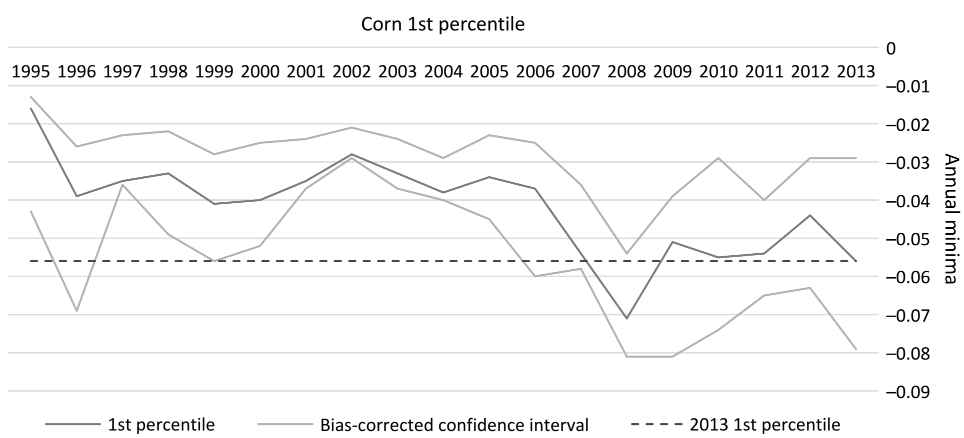

Fig. 3. Corn continuous settlement price – Uc/Bc, first percentile with bootstrap confidence intervals, 1995–2013. The horizontal dashed line represents the actual percentile value in 2013

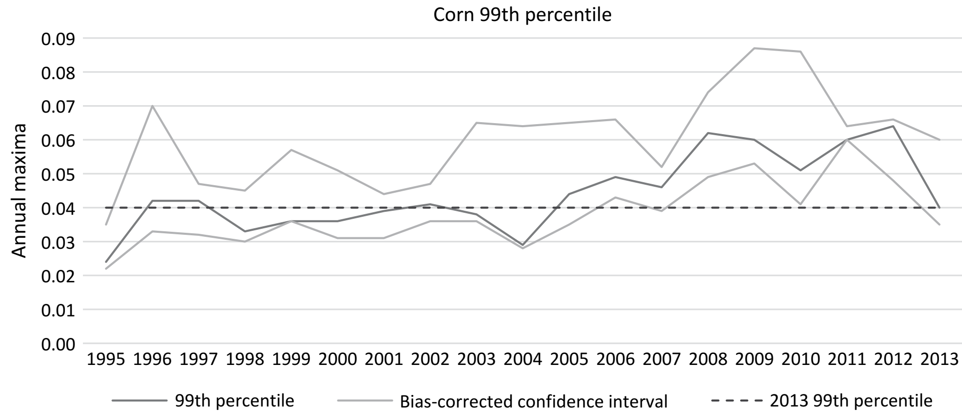

Fig. 4. Corn continuous settlement price – Uc/Bc, second percentile with bootstrap confidence intervals, 1995–2013. The horizontal dashed line represents the actual percentile value in 2013

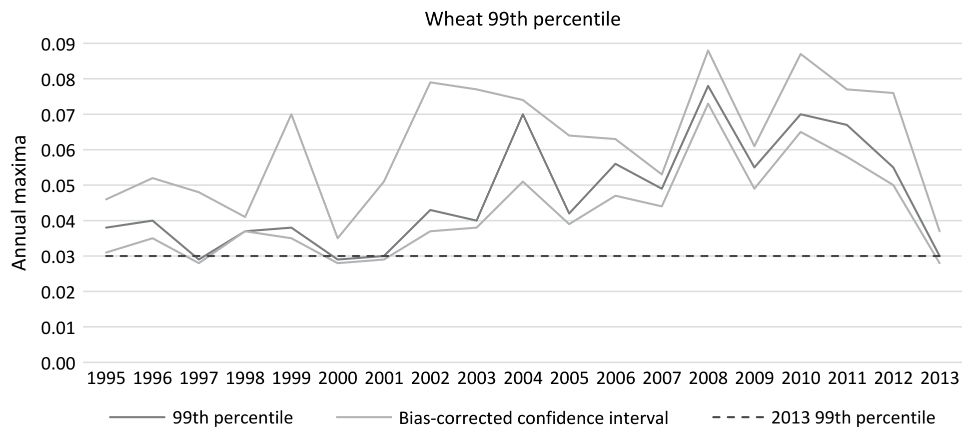

Fig. 5. Wheat continuous settlement price – Uc/Bw, ninety-ninth percentile with bootstrap confidence intervals, 1995–2013. The horizontal dashed line represents the actual percentile value in 2013

after 2002. The actual block maxima percentile value in 2013 falls below the bootstrapped confidence interval on all but three occasions during the time period we examine. If we consider the fundamentals, we find that a large part of the build-up in wheat prices prior to the year 2006–2007 can be explained by unfavourable weather conditions; most notably the drought conditions in Ukraine had a severe impact on wheat prices in this period. Ukraine also experienced drought and a large reduction in yields in 2012, which coincided with unfavourable weather conditions in the US Corn Belt. In other words, adverse weather conditions are a likely culprit for increasing prices and price variability.

The results for corn and wheat are somewhat atypical across the return series we have investigated. We did not find any evidence of increasing tail risk in the return series for the other commodities. Figure 6 depicts the tail risk profile of soybean futures contracts, and as before the straight line crossing the diagram horizontally represents the actual ninety-ninth percentile value in 2013. We see that this value mainly falls inside the estimated confidence interval for the entire time period, and there is no upward trend in the distribution of annual extremes. Hence, there is nothing here that suggests that extreme risk to the upside has increased since the late 1990s for this commodity. Further, the width of the confidence band is fairly uniform for the period.

That we only find evidence of increasing extreme risk in the tail distributions for corn and wheat suggests that the aforementioned weather events, and/or new and persistent demand for corn as an input in biofuel production, could be driving the increase in tail-related risk after 2006. Taken together with the analysis done by Gilbert and Morgan (2010) where

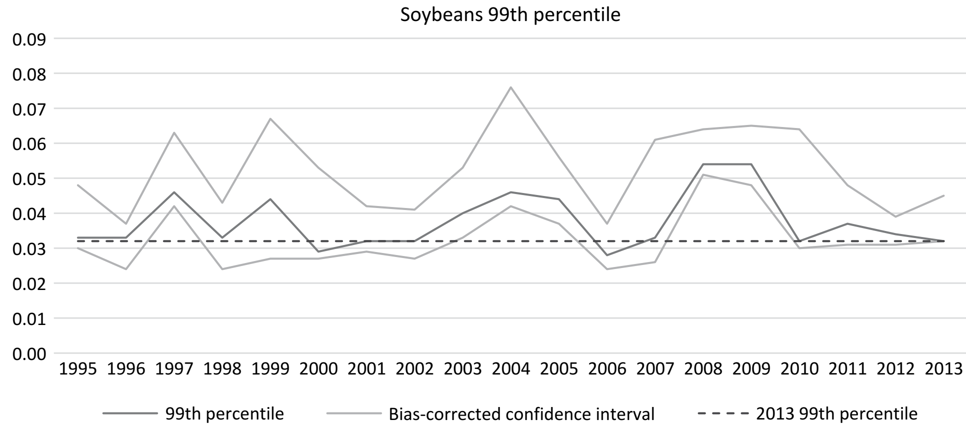

Fig. 6. Soybeans continuous settlement price – Uc/Bs, ninety-ninth percentile with bootstrap confidence intervals, 1995–2013. The horizontal dashed line represents the actual percentile value in 2013

the hypothesis of increased food price volatility is contested, this raises doubts regarding the claim that index tracking and speculation uniformly have generated increased and excessive price volatility.

An analysis of the estimated shape-parameters of the GEV-distribution further supports the hypothesis that there is no systematic change in the extreme risk associated with commodity investments. Block sizes of one year should be of sufficient size for the asymptotic properties of the Fisher–Tippett–Gnedenko theorem to hold, and also provide enough information to get robust estimates of the distribution parameters.

Table 2 summarizes the parameter estimates for the right tail of the distributions of the return series. We see that most of the tails belong in the Fréchet domain, while a few follow the Weibull or Gumbel

Table 2. Estimated *k*-parameters – right tail

	Corn	Wheat	Soybean	Soyaoil	Sugar	Cocoa	Orange juice	Lean hogs	Feeder cattle
Year									
1995	−0.01	**0.39**	**0.30**	**1.09**	**0.65**	**0.76**	**0.58**	**0.64**	**−0.15**
1996	**−0.08**	**0.05**	**0.63**	**0.23**	**0.99**	**−0.41**	**0.97**	**1.06**	**0.74**
1997	**0.78**	**−0.20**	**0.05**	**0.30**	**1.22**	0.03	**0.05**	**1.05**	**0.38**
1998	0.02	**0.59**	**0.23**	**1.01**	**1.23**	**0.20**	**−0.16**	**1.63**	**1.21**
1999	**−0.13**	**−0.16**	**0.09**	**0.22**	**0.40**	**0.45**	**−0.62**	**0.31**	**0.30**
2000	**0.10**	0.00	**−0.41**	**−0.14**	**0.60**	−0.03	**−0.22**	**−0.16**	**0.58**
2001	**0.74**	**−0.46**	**0.32**	**−0.34**	**0.33**	**0.05**	**0.45**	**0.35**	**1.12**
2002	**0.53**	**−0.30**	**0.14**	**0.12**	**0.52**	**−0.25**	**0.21**	**0.80**	**2.65**
2003	**−0.08**	**−0.42**	**0.15**	**0.26**	**−0.41**	**0.41**	**0.43**	**0.42**	**0.30**
2004	**−0.21**	**0.78**	**−0.21**	**0.25**	**−0.11**	**0.04**	**−0.26**	**−0.09**	**0.59**
2005	**0.07**	**−0.17**	**0.26**	**0.02**	0.05	**0.23**	**−0.09**	**−0.19**	**0.25**
2006	**0.05**	**0.64**	**0.06**	**−0.47**	**0.36**	**0.22**	**−0.47**	**−0.36**	**0.13**
2007	**0.60**	**0.35**	**−0.11**	**−0.14**	−0.01	**0.49**	**0.96**	**0.12**	**0.11**
2008	**0.42**	**0.29**	**0.16**	**0.39**	**0.42**	**−0.13**	**−0.12**	**0.47**	**0.08**
2009	**−0.06**	**0.27**	**0.47**	**0.28**	**0.35**	**−0.17**	**−0.20**	**0.63**	**0.08**
2010	**−0.13**	**0.35**	**−0.38**	**−0.08**	**0.80**	**0.34**	**0.27**	**0.38**	**0.10**
2011	**0.99**	**0.57**	**0.22**	**−0.06**	**0.05**	**−0.23**	**0.34**	**0.68**	**0.72**
2012	**0.81**	**0.13**	**0.40**	**0.52**	**0.49**	**0.49**	**−0.12**	**0.79**	**0.08**
2013	**0.13**	**0.21**	0.00	**0.10**	**0.74**	**0.48**	−0.02	**0.16**	**0.52**

Notes: This panel presents bootstrap-estimated k-parameters for 10 different commodities. Figures marked in bold indicate that these estimates are significantly different from zero at a 5% level, based on a test on the PWM estimator of k. Under the null of $\hat{k} = 0$, the estimator is asymptotically distributed as $N(0, 0.5633)/n)$, and the test is performed by comparing the statistic $Z = k\sqrt{(n/0.5633)}$ with the critical values of a standard normal distribution (Hosking *et al.*, 1985). Significant positive values of Z imply rejection of H_0 in favour of $k > 0$, and significant negative values of Z imply rejection in favour of $k < 0$.

distributions. Since the latter two comprise of lighter-tail distributions (to be specific, the Gumbel domain features a variety of tail distribution functions ranging from light to moderately heavy), we confine our discussion to the Fréchet domain of attraction. The first observation we make is that all but 10 of these parameters are confined within the interval [0,1]. In fact, only 42 out of the 162 estimated parameters are above 0.5. There is no form of clustering among these values, and we see no systematic increase in tail fatness that coincides with increasing commodity prices. On an individual commodity level, we see that the shape-parameters for sugar, lean hogs and feeder cattle indicate a large number of dramatic price changes. However, we find no commodity that shows systematically increasing tail indexes, which suggests that extreme risk to the upside has not increased during the time period we examine.

Examining the left side of the distributions in Table 3, we see that the risk of large deviations to the downside is much greater than the risk of dramatic price increases. The estimated parameters suggest that the majority of the left tails of commodity return distributions belong to the Fréchet domain. The bulk of the parameters are estimated to be in the area of 0.5, and many are as high as 1 indicating very heavy tails. But this result merely confirms a well-known fact about commodity returns, namely that their distributions are fat-tailed relative to the normal distribution. It seems not to be any discernible pattern of increasing commodity market risk in the left tail of the distribution, regardless of which individual commodity we are looking at. While certain commodity returns such as lean hogs display distributions with heavy left tails, this characteristic is uniform across the entire time period we analyse.

VI. Concluding Remarks

Our analysis confirms a well-established fact, namely that the distribution of commodity price returns is fat-tailed relative to the Gaussian. Beyond this, examining annual distributions of extremes with their bootstrapped confidence intervals gives no evidence of

Table 3. Estimated *k*-parameters – left tail

	Corn	Wheat	Soybean	Soyaoil	Sugar	Cocoa	Orange juice	Lean hogs	Feeder cattle
Year									
1995	**0.99**	**0.61**	**0.17**	**0.11**	**0.20**	**0.93**	**0.46**	**0.08**	**−0.10**
1996	**0.76**	**0.13**	**−0.06**	**0.90**	**0.71**	**0.42**	**0.32**	**0.10**	**−0.34**
1997	**−0.35**	**0.39**	**0.70**	**0.78**	0.03	**0.36**	**0.47**	**−0.15**	**−0.47**
1998	**0.65**	**1.02**	**0.83**	**0.96**	**−0.13**	**0.58**	**0.72**	**−0.07**	**−0.40**
1999	**0.60**	**0.26**	**0.83**	**0.49**	**0.53**	**−0.07**	**0.41**	**0.99**	**0.52**
2000	**0.23**	**0.83**	**0.17**	**0.93**	**0.79**	**1.08**	**−0.04**	**0.47**	**0.47**
2001	**−0.08**	**0.06**	**0.39**	**0.07**	**0.74**	**0.60**	**0.64**	**−0.14**	**1.12**
2002	**1.40**	**0.40**	**−0.43**	**0.31**	**0.93**	**0.81**	**0.24**	**0.26**	0.00
2003	0.00	**0.65**	**0.18**	**0.62**	**0.24**	**0.33**	**0.83**	**0.34**	**0.49**
2004	**0.06**	**0.44**	**0.52**	**0.32**	**0.34**	0.02	**−0.33**	**0.23**	**−0.13**
2005	**0.92**	**0.30**	**0.63**	**0.44**	**−0.23**	**0.96**	**0.54**	**0.65**	**0.51**
2006	**0.60**	**0.47**	**−0.11**	**−0.12**	**0.32**	**1.45**	**0.42**	**−0.10**	**0.24**
2007	**−0.07**	**0.22**	**−0.15**	**0.79**	**0.28**	**0.31**	**0.16**	**0.19**	**0.53**
2008	**0.16**	−0.01	**−0.16**	**0.20**	**0.73**	**0.62**	**0.74**	**0.17**	**−0.27**
2009	**0.70**	**0.96**	0.02	**0.70**	**0.18**	**0.69**	**0.29**	**0.28**	**−0.17**
2010	**0.18**	**0.12**	**0.24**	**0.33**	**0.26**	**0.18**	**1.52**	**−0.15**	**0.67**
2011	**1.05**	**−0.01**	**0.29**	**0.51**	**0.31**	**0.76**	**0.11**	**0.11**	**0.34**
2012	**0.62**	**0.13**	**0.55**	**0.51**	**0.28**	**0.31**	**0.44**	**0.19**	**−0.48**
2013	**0.38**	**1.62**	**0.60**	**0.20**	0.02	**0.33**	**0.11**	**1.05**	**0.50**

Notes: This panel presents bootstrap-estimated k-parameters for 10 different commodities. Figures marked in bold indicate that these estimates are significantly different from zero at a 5% level, based on a test on the PWM estimator of k. Under the null of $\hat{k} = 0$, the estimator is asymptotically distributed as $N(0, 0.5633)/n)$, and the test is performed by comparing the statistic $Z = k\sqrt{(n/0.5633)}$ with the critical values of a standard normal distribution (Hosking *et al.*, 1985). Significant positive values of Z imply rejection of H_0 in favour of $k > 0$, and significant negative values of Z imply rejection in favour of $k < 0$.

increasing tail-related risk, with a possible exception for corn and wheat. An analysis of estimated shape-parameters of the GEV-distribution further substantiates that there is no systematic change in the extreme risk associated with commodity investments. We find that the return distributions of a majority of the commodities we have examined belong in the Frechét domain of attraction. This suggests commodity return distributions with heavy tails throughout the period 1995–2013.

Our findings do not support the hypothesis of increasingly extreme commodity market risk. This is in line with the results obtained by Gilbert and Morgan (2010), who use their conclusion to highlight that volatility has been high in the past before reverting to normal levels. The results in our analysis further cast doubt on the claim that the substantial growth in index tracking and speculation during the last 10 years has generated increased (and excessive) price volatility. Our results support the traditional view that agricultural price volatility is mainly driven by demand- and supply-side shocks, typically caused by adverse weather or dramatic political decisions and events. This is an important finding, because volatility driven by fundamentals cannot be tamed by regulation. To the contrary, one needs to look for good ways to manage this risk.

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No potential conflict of interest was reported by the authors.

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Appendix

Commodity	Contract specifications	Mnemonic
Corn	CBOT Contracts of 5000 bushels	CC.CS04
Wheat	CBOT Contracts of 5000 bushels	CW.CS04
Soybeans	CBOT Contracts of 5000 bushels	CS.CS04
Soyaoil	CBOT Contracts of 60 000 pounds	CBOCS04
Lean Hogs	CME Contracts of 40 000 pounds	CLHCS04
Sugar	CSCE No 11, Contracts of 112 000 pounds	NSBCS04
Feeder cattle	CME Contracts of 50 000 pounds	CFDCS04
Cocoa	CSCE Contracts of 10 metric tons	NCCCS04
Orange juice	NYCE Contracts of 15 000 pounds, frozen concentrated	NJOCS04

Note: CBOT, Chicago Board of Trade; CME, Chicago Mercantile Exchange; CSCE, Coffee, Sugar and Cocoa Exchange; NYCE, New York Cotton Exchange.