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Individual decisions and outside influences affecting U.S. commodity markets and cropland used for grain production

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Individual decisions and outside influences affecting U.S. commodity markets and cropland used for grain production

by

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DEDICATION

I dedicate this work to my wife Jennifer and three (soon to be four) children: Logan, Emma, and Leia. Jen, I am tremendously grateful for your support, patience, and contented sacrifice throughout this pursuit. We have achieved this together. Kids, thank you for loving me in spite of this work and for teaching me about perspective.

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CHAPTER 1. GENERAL INTRODUCTION

1.1. Overview

This dissertation is composed of four essays broadly focusing on U.S. commodity markets with an emphasis on grains and cropland used to produce grains. Recent years have witnessed unprecedented swings in agricultural commodity prices and volatility. Some of the factors affecting commodity prices and volatility have been market induced, such as increased demand from China, business cycle dynamics, and specific weather or geopolitical events acting as market supply shocks. Other factors may be policy related. While monetary and fiscal policies are important considerations, U.S. biofuel policies have also played a particularly significant role in grain markets and land use. The essays within this dissertation each individually address specific factors surrounding commodity markets and agricultural land use which have been relevant in individual decision-making processes or policy debates during this period of heightened uncertainty. Each essay has been written as a stand-alone paper. Accordingly, each essay comprises a unique chapter to this dissertation, each with a unique motivation or methodology.

The first essay, “The Impact of Price-Induced Hedging Behavior on Commodity Market Volatility” is motivated by data which reveal that grain producers’ hedging decisions have changed over time, and have been strongly correlated with futures price levels. That a producer’s hedge ratio, the share of expected output hedged in derivative markets, changes with the level of futures prices is a result that expected utility theory does not generate. This inconsistency is addressed by proposing an alternative mechanism that draws on prospect theory as the behavioral framework that utility-maximizing producers adhere to when making their hedging decisions. Using prospect theory as the underlying behavioral framework, there are two main goals of this essay. The first is to outline a mechanism that allows for correlation between the level of futures prices and a producer’s hedge ratio. The second is to emphasize the effect that an increase in futures prices may have on cash prices and volatility at harvest.

The results of this essay show that an increase in futures prices may result in larger price and volatility swings when prospect theory is the underlying decision-making framework as compared to expected utility theory. The implication of this result is that hedging strategies may play a role in exacerbating commodity price and volatility fluctuations as opposed to speculative trading which is often blamed for such effects.

The second essay, "Speculative Trading and Commodity Futures Markets: An Examination of Causality in the Time and Frequency Domains," uses an empirical approach to determine the extent to which speculative trading has influenced commodity futures prices and volatility. Claims that speculators are responsible for driving commodity prices and volatility, particularly as prices spiked in 2008 and 2010-2011, have fueled significant political debate in recent years focusing on whether to tighten the regulation of speculative trading in commodity derivatives. The goal of this essay is to test whether speculative trading has been a factor in these markets. Tests of causality, specifically Granger causality, are conducted in the time domain for each of 19 actively-traded commodities individually as well as in aggregate using seemingly unrelated regression analysis. The same tests of causality are then conducted in the frequency domain to distinguish between long-run causality and short-run causality.

The results of this essay suggest there is little empirical evidence to support the hypothesis that speculators have played a significant role in influencing commodity futures prices or volatility, particularly in the long run. On the contrary, there is evidence that speculative trading is influenced by futures prices, particularly in the long run. Whereas speculator positions are found to be generally unaffected by changes in volatility, there is slight evidence suggesting that speculators may contribute to changes in volatility.

The third essay, "A Bounds-Testing Empirical Analysis of Granger Causality in Commodity Futures Speculation," in an extension to the previous essay, offers an alternative measure of speculation to provide clarity to the debate on the role of speculation in commodity derivative markets. This essay recognizes that there may be more than one form, and thus more than one measure, of speculation. A "stock effect" results from the general size of speculative activity in a given market. A much different effect, a "flow effect," results from changes in speculative trading.

Encompassing both measures of speculation, an error correction model is proposed to test for a long-run level relationship among the variables of interest. With this alternative methodology, long-run causality may be determined when there is evidence of a level relationship. Short-run causality is determined by applying the error-correction model to account for this relationship. As in the previous essay, little evidence is found to suggest that speculative trading has affected futures price levels in either the long-run or short-run. There is some evidence, however, that speculation has impacted volatility, particularly in the long-run. We also find strong evidence that speculation has been influenced by futures price levels.

The final essay, "The Trade-off Between Bioenergy and Emissions with Land Constraints," addresses a shortcoming of conventional agricultural life cycle analysis (LCA) when used to determine optimal land-use for biofuel production. Conventional LCAs measure greenhouse gas emissions per unit of energy (or, equivalently, per gallon). However, a land-use optimization model taking into account a given land constraint suggests that emissions be measured per acre. The relative rankings of biofuel pathways with respect to greenhouse gas emissions may be different when using LCAs measuring emissions per acre. With this in mind, the goal of this essay is to explore the implications of conventional LCAs that fail to account for the opportunity cost associated with land scarcity. A model to represent the interests associated with biofuel production in the United States is constructed that minimizes environmental damages and accounts for the external benefits to production by choosing acreage optimally. Corn and switchgrass are modeled as crops competing for land-use.

The results indicate that switchgrass is optimal for biofuel production only under relatively high carbon prices or when there is very little external value ascribed to biofuel production and use. When there is no external value, corn is found to be the optimal crop within the Corn Belt. Switchgrass becomes the optimal crop in scattered regions of the southern United States and western Plains states using an external value of $0.45 per gallon and a carbon price of $30/t.

1.2. Dissertation Organization

The remainder of the dissertation is organized as follows. Each of the next four chapters presents the essays described above in sequence. Each essay begins with an individual abstract and introduction. Each essay also contains its own conclusion. Appendices, when used, are provided following the conclusion of each chapter. References are provided individually for each essay at the end of the chapter in which they are cited. All figures and tables are presented within the essays as they are presented in the text. Chapter 6, the final chapter of this dissertation, presents a general conclusion with respect to the essays comprising chapters 2 through 5.

CHAPTER 2. THE IMPACT OF PRICE-INDUCED HEDGING BEHAVIOR ON COMMODITY MARKET VOLATILITY

A modified version of the paper to be submitted to a peer-reviewed journal

2.1. Abstract

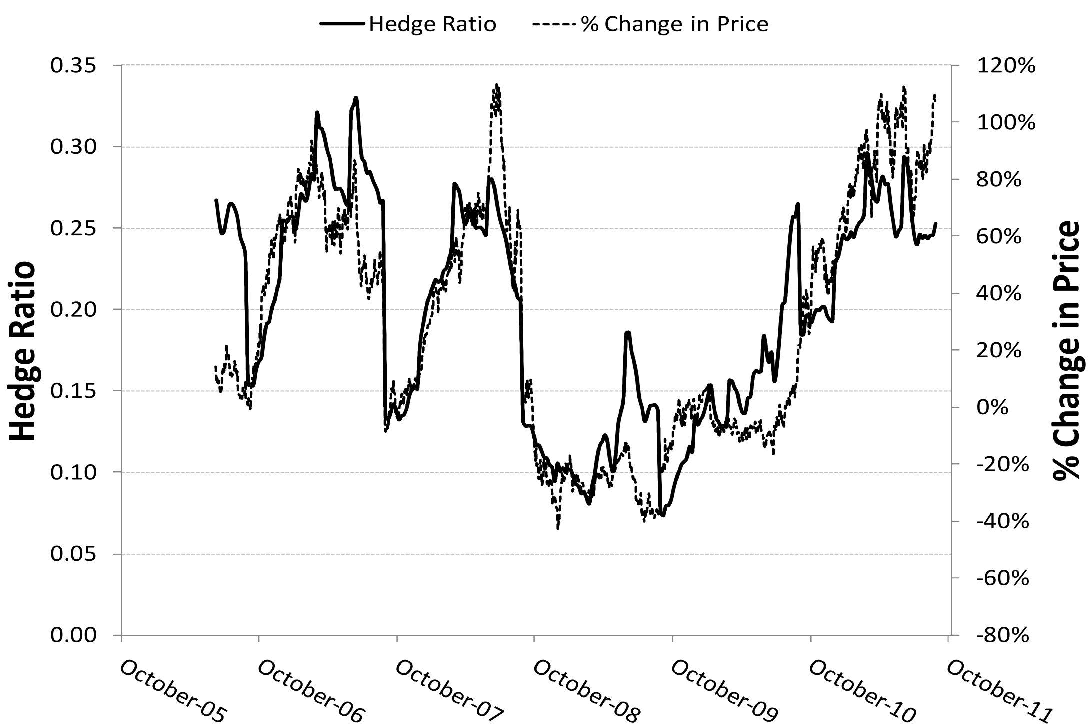
Conventional theory posits that the optimal hedging position of a producer should not increase solely due to increases in the level of futures prices. However, a strong degree of positive correlation is apparent in the data. Our results show that with prospect theory serving as the underlying behavioral framework, the optimal hedge of a producer is affected by changes in futures price levels. The implications of this price-induced hedging behavior on spot prices and volatility are subsequently considered. The results suggest that hedging behavior can exaggerate price volatility in years when there is more than one positive price shock.

2.2. Introduction

It is generally accepted that futures markets are beneficial to agents with a physical position in the underlying commodity, serving as an invaluable risk management tool. With futures markets, a producer who is naturally long a given commodity can hedge a portion of his future output by taking a short position in the futures market and subsequently offset his position as harvest approaches. In the case of grains, a common scenario is one in which a producer sells his future output through a forward contract with a local elevator. The elevator then manages its corresponding risk by taking a (possibly equivalent) short position in the futures market. This hedging approach allows a producer to effectively lock in a price for his crop well in advance of harvest. The producer is then obligated to deliver his grain to the elevator at harvest or be forced to pay a significant penalty should he fail to do so.

The application of expected utility (EU) theory to the production of agricultural commodities assumes that producers make their production and hedging decisions in a manner consistent with the Von Neumann-Morgenstern (VNM) utility axioms. This assumption does not allow for reference-dependent utility, leading producers to care only about absolute wealth, not relative wealth in any sense. The corresponding implication is that producers seeking to determine the optimal amount of output to hedge within a crop year, after initial production and hedging decisions have been made, do not deviate from their initial hedging decision when futures prices change. With futures prices serving as a producer's best predictor of the price expected to prevail at harvest, an increase in futures prices results in an equivalent increase in the harvest price expectation. Thus, all else equal, a producer has no reason to change his hedging behavior as a result of the price increase under EU theory. However, the data suggest that producers' hedging activity and futures price levels are very closely related as illustrated in Figure 2.1.

Figure 2.1. Aggregate Producers' Hedge Ratio for Corn and Nearby Futures Prices.



The dashed line in Figure 2.1, read from the left vertical axis, shows the aggregate producer hedge ratio for corn from June 2006 to September 2011. This ratio is determined as the aggregate quantity of grain held by producers in short futures contracts divided by the sum of expected production and inventories. The solid line indicates the percentage change in nearby futures prices, relative to the previous year's average, and is read from the right vertical axis. Immediately apparent in the figure is the strong degree of correlation between the two series, particularly during price increases observed in 2006, 2008, and late 2010.[1]

The implication here is that increases in futures prices may cause a corresponding increase in price volatility as producers are "induced" to sell a larger share of output in advance of harvest. Contractually obligated to deliver a specified amount of output at harvest, the flexibility of producers to respond to, and absorb, potential market shocks is reduced. Severe unfavorable weather near harvest, representative of a negative supply shock, would result in higher spot prices and higher volatility. Connecting these strands, an increase in futures prices at some intermediate point within a crop year, possibly the result of increased demand for grain, may cause increases in real cash prices and volatility at harvest by inducing producers to increase their hedged position.

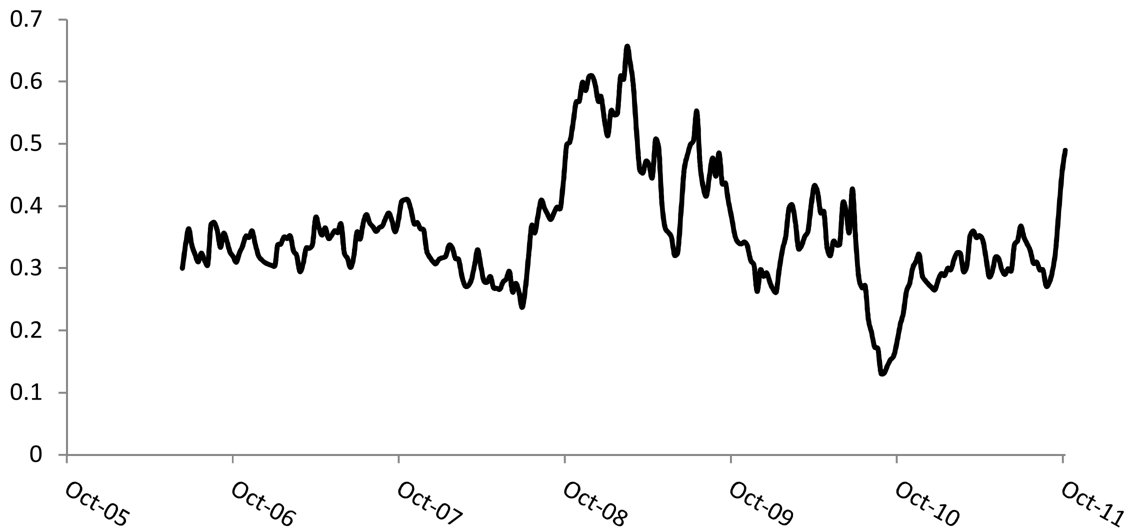
Figure 2.1 provides motivation for considering a non-expected utility theory model that more adequately explains why producers might respond to an increase in futures prices by changing their hedging behavior, and what the implications would be for spot prices and volatility. Prior to October 2009, generating this figure was not possible because the Commodity Futures Trading Commission (CFTC) included swap dealers together with producers in its Commitment of Traders (COT) reports. Since then, in an effort to increase transparency, the aggregate positions specifically for producers have been published weekly in Disaggregated Commitment of Traders (DCOT) reports. These reports have allowed us to identify, for the first time, the extent to which producers' hedging behavior is correlated with futures prices on an aggregate level.

There are two main contributions of this paper. The first is to outline a mechanism drawing on prospect theory as an alternative to EU theory, whereby grain producers'

[1] It should be noted that forward contracts and options are not included in this figure, which could cause the amount of crop committed in advance, the hedge ratio, to be substantially higher.

hedging positions in short futures contracts are dependent upon the level of futures prices at a given point in time. As indicated, this is a behavior that deviates from what conventional EU theory would predict. The second main contribution of the paper is to illustrate the effect the price-level-dependent futures hedge has on spot prices and price volatility at harvest. Specifically, a scenario will be presented in which prices and volatility at harvest increase as the amount of output hedged in futures markets increases during a crop year due to rising futures prices. It should be emphasized here that this result would not be obtained if speculators, not intending to take delivery, were the only group of traders taking the opposing futures trade. As illustrated in Figure 2.2, however, grain purchasers who are naturally short the underlying commodity typically account for between 30% and 60% of futures contracts sold by producers.

Figure 2.2. Ratio of Long to Short Producer Futures Contracts for Corn.



Conventional EU theory posits that the existence of an unbiased futures market allows a risk-averse farmer to determine his optimal level of production as a function of only his marginal cost and the current futures price, referred to as the "separation result" (Sandmo, 1971; Holthausen, 1979; Feder, Just, and Schmitz, 1980). This result holds when there is price uncertainty and no production uncertainty. Moreover, with only price uncertainty (and no basis risk), the optimal hedge is the complete hedge, effectively removing all exposure to risk. Allowing for output uncertainty complicates the determination of this optimal hedge somewhat by requiring knowledge of the interaction between revenue and prices (Rolfo, 1980; Grant, 1985). Allowing for basis risk adds another dimension of complexity (Lapan and Moschini, 1994; Myers and Hanson, 1996).

In an EU framework where there is no basis risk and futures markets are unbiased, the optimal amount of grain hedged through futures contracts is determined by two factors: yield variability and the correlation between prices and yields. The presence of yield variability causes the optimal hedge to be less than the complete hedge observed when there is only price uncertainty.[2] This is because the "natural hedge," due to negative correlation between prices and yields, partially replaces the need for a futures hedge. As the price-yield correlation becomes more strongly negative, the natural hedge becomes relatively more effective and the amount hedged in futures markets decreases. Therefore, when prices and yields are uncorrelated and yield variability is held fixed, EU theory predicts that the optimal hedge does not increase as the level of futures prices increases. Prospect theory shows that even when prices and yields are uncorrelated and yield variability is constant, an increase in futures prices will cause the amount hedged to increase.

As time progresses toward harvest, it is reasonable to assume that the degree of yield uncertainty diminishes. As shown by Lapan and Moschini (1994), this time decay is the only factor which would cause the optimal hedge to adjust under EU theory when prices and yields are uncorrelated. Given that hedging all of expected production is optimal when there is only price uncertainty, time decay causes the optimal hedge to increase as output uncertainty is resolved during a crop year. This aspect, however, is unrelated to a change in futures prices. Thus, the conclusion that changes in futures price levels do not affect the optimal hedge under EU theory is still maintained.

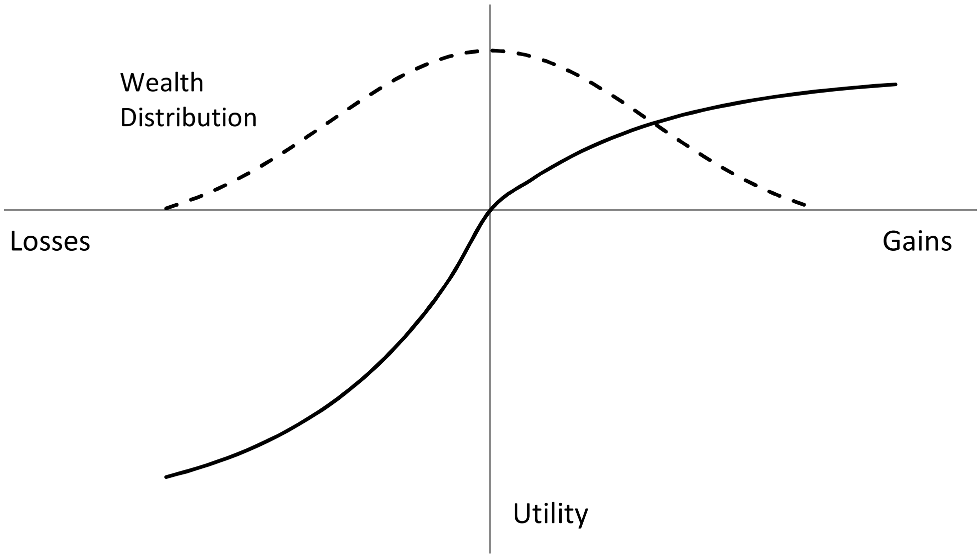
[2] It is possible that the presence of yield variability could cause the optimal amount hedged to be more than the complete hedge, but this would require a positive correlation between prices and yields which is not realistic.

In order to allow for a non-expected utility theory outcome in which futures price levels affect the optimal hedge ratio determination, this paper draws on a rapidly growing body of literature in behavioral finance referred to as prospect theory. Prospect theory was originally conceptualized in a seminal paper by Kahneman and Tversky (1979) and has become an empirically grounded alternative frequently used in behavioral economic models. At its core, prospect theory suggests that agents exhibit behavior that is inconsistent with the efficient markets hypothesis of expected utility under rational expectations. Specifically, it posits that agents tend to be risk-averse over gains and risk-seeking over losses as illustrated by the solid curve in Figure 2.3.

Whereas traditional EU theory suggests a utility function that is not reference-dependent, the function based on prospect theory in Figure 2.3 is convex in the domain of losses (negative changes in wealth) and concave in the domain of gains. A secondary component of prospect theory, referred to as loss aversion, also recognizes that agents are more sensitive to losses than to gains, seen by the differing slopes of the utility function in the figure for changes in wealth of equal magnitude on either side of the vertical axis.

Intuitively, we would expect that an agent who is risk-averse over some domain and risk-seeking over some other domain would behave differently than an agent who is everywhere risk-averse. Within the context of this paper, a grain producer under prospect theory seeking to determine how much of the expected output to hedge in the futures market would take a different action than the same producer in an EU framework. By definition, risk seeking means to prefer a gamble relative to a certain outcome. A gamble in this context would involve a producer compounding his risk by taking a long position in the futures market in addition to his natural long position in the physical market. A risk-averse agent, on the other hand, would take a short position in the futures market to mitigate his exposure to risk. Thus, if the representative producer's probability distribution of wealth contains mass on both sides of the vertical axis as in Figure 2.3, the producer will exhibit both risk-seeking and risk-aversion tendencies.

Figure 2.3. Utility Function Under Prospect Theory.



The producer's wealth distribution is determined by price and output distributions. For a wealth distribution initially centered at the vertical axis as shown in Figure 2.3, a rightward shift in the distribution of prices will consequently shift the wealth distribution rightward causing the agent to exhibit relatively more risk-averse tendencies than risk-seeking tendencies. Recalling the fact that a risk-seeking producer would choose to take a long futures position and a risk-averse producer a short position, this rightward shift in the price distribution causes the producer to take a larger short futures position. An increase in demand that shifts the wealth distribution rightward, then, causes the optimal futures hedge to increase.

To our knowledge, this is the first paper to propose a mechanism by which producers' optimal hedge ratio increases due solely to changes in the level of futures prices. The implication of this result is the corresponding effect of increased price levels and volatility at harvest in the event of a subsequent supply shock. Whereas much debate has been focused on the capability of speculators to affect commodity prices or volatility with little evidence of causation (Sanders, Irwin, and Merrin, 2010; Irwin, Sanders, and Merrin, 2009), this paper suggests the possibility that producers may affect prices and volatility through hedging practices.

The remainder of the paper is organized as follows. In section 2.3, we provide a review of the relevant literature regarding futures hedging in an agricultural context and a brief review of literature on prospect theory. In section 2.4, we present a simple model that incorporates prospect theory into a producer's hedging decision. In section 2.5, we present numerical simulations to show the effect of prospect theory on the determination of the optimal hedge and ultimately its impact on spot prices and volatility. Section 2.6 provides concluding remarks.

2.3. Literature Review

In this section, we provide a review of two areas of literature relevant to this paper. First, we review literature that has sought to characterize the determination of a producer's optimal hedge ratio under varying conditions. Second, we provide a brief review of prospect theory, which will be used as the behavioral framework in our model.

2.3.1. Optimal Producer Futures Hedging

Some of the first studies developing the theory of hedging in commodity markets in an EU framework are those of Sandmo (1971), Holthausen (1979), and Feder, Just and Schmitz (1980). Considering only price uncertainty, these papers present implications associated with hedging in futures markets and the effect of futures markets on the production decision. These papers propose a two-period model in which a producer makes his production and hedging decision in the first period by maximizing a given utility function of second-period profit. In addition to the result that a producer's output decision is made separate from the evolution of cash prices, it is also shown that the optimal hedge is to hedge all output, which is considered to be known with certainty. Turnovsky (1983) and Kawai (1983) seek to expand on this by determining market clearing spot and futures prices in a rational expectations framework. The two-period model of these early papers is subsequently generalized by Anderson and Danthine (1983) into three periods and also by Ho (1984) in an intertemporal context.

Rolfo (1980), Grant (1985), and Losq (1982) generalize these models which consider only price uncertainty to allow for output uncertainty as well. Assuming a mean-variance representation of utility, Rolfo, Grant, and Losq, respectively, show that the optimal hedge consists of two components, a pure hedging component and a pure speculative component.[3] In unbiased futures markets, the speculative component vanishes, leaving only the hedging component. The hedge is determined as the ratio between the covariance of revenue with futures prices and the variance of futures prices. In most other utility representations, such analytically appealing results are often difficult to obtain.

Adding another dimension of risk, Lapan and Moschini (1994) construct a model to allow for the determination of the optimal hedge under joint price, output, and basis risk. In their model, Lapan and Moschini assume a constant absolute risk aversion (CARA) utility function to obtain analytical results characterizing the optimal hedge ratio. Myers and Hanson (1996) also consider the additional effects of basis risk in their study.

Various functional forms for utility are employed in the literature. Whereas some representations are more tractable, others may be more capable of capturing empirical realities. Perhaps the simplest form used to derive the optimal futures hedge is the minimum-variance utility representation (Johnson, 1960; Ederington, 1979). Mean-variance utility provides another widely used form through which analytical results are easily obtained (Turnovsky, 1983; Rolfo, 1980). Constant absolute risk aversion (CARA) represents a unique form of utility that is often used in the literature due to its tractability in generating closed form analytical solutions (Lapan and Moschini, 1994; Lence, 1995; Lien, 2001; Mattos, Garcia, and Pennings, 2008). When closed form expressions are unattainable, one must employ numerical estimation procedures to determine the optimal futures hedge (Cecchetti, Cumby, and Figlewski, 1988; Baillie and Myers, 1991).

[3] Speculative here refers to taking a position in the futures market in an attempt to gain from changes in futures price movements.

While there have been many studies that have focused on commodity futures market hedging behavior within an expected utility framework, very few have considered the implications in a non-expected utility environment. Three papers that have attempted to do so are those of Albuquerque (1999), Lien (2001) , and Mattos *et al*. (2008).

Albuquerque (1999) applies prospect theory in the context of a loss-averse firm seeking to determine an optimal currency hedge, specifically the implications of managing downside risk, compared with a conventional firm that is not loss-averse. Lien (2001) uses a two-period model of grain production to show how the optimal hedge of a commodity producer differs under loss aversion as opposed to a producer who maximizes mean-variance utility. One of the main results is that loss aversion has no effect when futures markets are unbiased. If markets are in either backwardation or contango, this is not true. Lien (2001) goes on to show how, and in which direction, the optimal hedge is influenced in these generalized cases. Mattos *et al*. (2008) expand on this result by also allowing for subjective probability weighting together with loss aversion. Employing numerical simulations, Mattos *et al*. (2008) show that the optimal hedge ratio decreases as the degree of loss aversion increases, as risk-seeking behavior increases, or as the parameter of subjective probability weighting decreases.

2.3.2. Prospect Theory

Prospect theory was introduced by Kahneman and Tversky (1979) as an attempt to better explain observed psychological behavior, with the violation of Allais' paradox serving as a well known example. There have been numerous other theories proposed to explain deviations from traditional expected utility theory such as weighted-utility theory (Hong, 1983), disappointment aversion (Gul, 1991), regret theory (Bell, 1982; Loomes and Sugden, 1982), and rank-dependent utility (Quiggin, 1982). Prospect theory is often espoused as the most promising due to its ability to capture observed behavior by relaxing only the independence axiom within the set of VNM utility axioms. The other theories cited here require the weakening of additional axioms beyond independence.

Maintaining much of the structure of the standard VNM axioms has allowed prospect theory to become a relatively accepted alternative to the efficient markets hypothesis in behavioral economics. For this reason, prospect theory with loss aversion is chosen as the behavioral framework in this paper although a brief mention will be made of how regret theory, another seemingly plausible alternative in our context, could also be applied to obtain similar results.

2.4. The Model

Consider a three-period model of grain production. In the context of this model, period 1 can be thought of as a pre-planting period (March), period 2 as an intermediate (July) period, and period 3 as harvest (October). A grain consumer makes a utility-maximizing demand decision facing expected spot market prices in period 3. All consumption is assumed to occur in this terminal period. Aggregate demand will be specified by the following isoelastic demand function:

$$q_3 = \delta\left(p_3^s\right)^{-\gamma}\varepsilon_2 \tag{2.1}$$

In equation (2.1), δ and γ are exogenously specified parameters, q_3 is the quantity of grain demanded in period 3, p_3^s is the terminal spot price, and ε_2 is taken to be a demand shock variable such that $E_1[\varepsilon_2]=1$. This formulation explicitly allows for the possibility of a demand shock occurring in period 2, which will affect both the period-2 futures price as well as the period-2 conditional expectation of the period-3 spot price.

In period 1, a representative grain producer must determine how much output to produce and how much of this output to hedge in the futures market. The producer faces both price and output risk. It is assumed that there is no basis risk. Futures markets are assumed to be unbiased and for simplicity this model does not allow for inventory holdings. The producer determines his optimal output and optimal futures hedge by maximizing the following utility as a function of terminal wealth:

$$U\left(\tilde{W}\right) = U\left(\tilde{p}_3{}^s\tilde{y}a + x_1\left(p_1{}^f - \tilde{p}_2{}^f\right) + x_2\left(\tilde{p}_2{}^f - \tilde{p}_3{}^f\right) - ca\right) \tag{2.2}$$

In the above, $\tilde{p}_i^f$ denotes the futures price in period i, $\tilde{y}$ denotes the crop yield at harvest, and c represents the marginal cost of an acre of land, assumed to be constant. Tildes indicate random variables unknown to the producer in period 1 for which there is a known distribution. In period 1, decision variables include a, the amount of acreage the producer chooses to allocate to crop production and x_1, the quantity of grain hedged in futures contracts (where short positions are represented by positive values). In period 2, acreage is fixed and only the quantity hedged, x_2, may be adjusted.

In a 3-period model, maximization of equation (2.2) is solved recursively. In period 2, the representative producer, taking a and x_1 as fixed, chooses x_2 optimally according to:

$$\max_{x_2} E_2 U\left(\tilde{p}_3\tilde{y}a + x_1\left(p_1 - p_2\right) + x_2\left(p_2 - \tilde{p}_3\right) - ca\right) \tag{2.3}$$

In equation (2.3), E_2 represents the expectations operator in period 2. Given the assumptions of unbiasedness, no basis risk, and no inventory holdings, the futures price will be equal to the spot price in each period, allowing us to drop the s and f superscripts. With x_2 optimally chosen (denoted as x_2^*), the producer faces a similar maximization problem in period 1 with a and x_1 as choice variables. Solving equation (2.4) results in solutions to each of the decision variables, a, x_1, and x_2 from the perspective of period 1.

$$\begin{aligned} &\max_{a,x_1} E_1 U\left(\tilde{p}_3\tilde{y}a + x_1\left(p_1 - \tilde{p}_2\right) + x_2^*\left(\tilde{p}_2 - \tilde{p}_3\right) - ca\right) \\ &= \max_{a,x_1} E_1 U\left(\tilde{p}_3\tilde{y}a + x_1\left(p_1 - \tilde{p}_2\right) - ca\right) \end{aligned} \tag{2.4}$$

2.4.1. Hedging Under Expected Utility Theory

In an EU framework, $U(\cdot)$ is typically taken to be some increasing and concave function, $U' > 0$ and $U'' < 0$, stemming from risk aversion. If this were the case, equation (2.4) would be solved as the following integral:

$$\max_{a,x_1} \iint U\left(\tilde{p}_3\tilde{y}a + x_1\left(p_1 - \tilde{p}_3\right) - ca\right) f\left(\tilde{p}_3, \tilde{y}\right) d\tilde{p}_3 d\tilde{y} \tag{2.5}$$

Here $f(\tilde{p}_3, \tilde{y})$ represents the joint distribution of prices and yields. Equation (2.5) also makes use of the fact that from the perspective of period 1, the expectation of period-3 prices is the same as the expectation of period-2 prices, i.e., $\tilde{p}_2 = \tilde{p}_3$. As shown by Grant (1985), first order conditions would be specified as:

$$\frac{dE\left[U(\cdot)\right]}{da} = \iint U'(\cdot)\left(\tilde{p}_3\tilde{y} - c\right) f\left(\tilde{p}_3, \tilde{y}\right) d\tilde{p}_3 d\tilde{y} = 0 \tag{2.6}$$

$$\frac{dE\left[U(\cdot)\right]}{dx_1} = \iint U'(\cdot)\left(p_1 - \tilde{p}_3\right) f\left(\tilde{p}_3, \tilde{y}\right) d\tilde{p}_3 d\tilde{y} = 0 \tag{2.7}$$

It is assumed that the presence of risk neutral speculators ensures that futures markets clear and are unbiased, where speculators' futures positions are denoted as z_1^*. Additionally, following from grain consumer utility maximization that gives rise to equation (2.1), consumers also choose an optimal futures position denoted by v_1^*. Assuming N producers and optimal solutions to equations (2.6) and (2.7) denoted by a^* and x_1^*, first-period market clearing conditions are specified as:

$$q_3 = N\bar{y}a^* \tag{2.8}$$

$$x_1^* + v_1^* + z_1^* = 0 \tag{2.9}$$

Equation (2.8) represents spot market clearing, with $E[\tilde{y}] = \bar{y}$, and equation (2.9) represents the futures market clearing condition. It should be emphasized here that due to consistent, unchanging risk preferences on the part of the producer (and consumer by assumption), period-2 market clearing conditions can be expected to take precisely the form of equation (2.8) and equation (2.9) in the absence of any new information revealed in period 2.

Upon choosing the optimal production, a^*, this amount cannot be changed in period 2. From the perspective of a producer, only x_2^* could potentially differ from x_1^*. In an attempt to further characterize the optimal hedging decision, equation (2.7) can be rewritten as:

$$E\left[U'(\cdot)\left(p_1 - \tilde{p}_3\right)\right] = E\left[U'(\cdot)\right]E\left[\left(p_1 - \tilde{p}_3\right)\right] - \operatorname{cov}\left[U'(\cdot), \tilde{p}_3\right] \tag{2.10}$$

Given that futures markets are unbiased, equation (2.10) reduces to:

$$E\left[U'(\cdot)\left(p_1-\tilde{p}_3\right)\right]=-\operatorname{cov}\left[U'(\cdot),\tilde{p}_3\right]=0 \tag{2.11}$$

In general, a closed-form expression for the optimal hedge, x_i^* is unobtainable. However, it can be seen from equation (2.11) that determining x_i^* amounts to the determination of $\operatorname{cov}(U', \tilde{p}_3)$. This covariance term is dependent upon the correlation between prices and output (or yields) as well as output (or yield) variability as explained earlier. When prices and yields are uncorrelated, an increase in the level of futures prices has no effect on this covariance term and thus no effect on the optimal hedge, x_i^*.

Moving from period 1 to period 2, a portion of uncertainty surrounding crop yields at harvest is resolved. Assuming that prices and yields are uncorrelated, this is the only factor which will cause the optimal hedge to change from period 1 to period 2 under EU theory. Allowing for negative correlation between prices and yields does not change the key result of this paper. An increase in the level of futures prices still causes the optimal hedge to increase initially before declining somewhat.[4] For this reason, we make the simplifying assumption that prices and yields are uncorrelated, but model both cases and illustrate how the results change when allowing for correlation. As this assumption is not crucial to our main results, the exposition from this point forward considers only the case when prices and yields are uncorrelated. This is done to isolate and accentuate the effects of the underlying behavioral framework.

A demand shock realized in period 2, which causes futures prices to rise, will not cause the optimal hedge to change. Intuitively, this is because producers expect this same (higher) price to prevail in the next period as well, and risk preferences, embodied in the utility function, have not changed due to the shock. In this paper, we show that the optimal hedge is affected by a change in the level of futures prices due to changing risk preferences

[4] As with price-yield correlation, the presence of yield variability may also cause the optimal hedge to decline slightly under expected utility. However, yield variability must be rather high for the magnitude of this effect to be non-trivial. Moreover, this also does not affect the main results of this paper and will be ignored for expositional purposes but included in the numerical results.

inherent under prospect theory. In conventional EU theory, a change in the level of futures prices would have no impact on the change in the volatility of spot prices, or prices themselves, at harvest. Under prospect theory, this is not so. A change in futures prices will result in a change in volatility of spot prices as well as a change in price levels at harvest.

2.4.2. Hedging Under Prospect Theory

The approach to modeling market conditions under prospect theory is quite similar to the approach shown above under traditional EU theory which posits $U'>0$ and $U''<0$ everywhere. In prospect theory, however, we have $U'>0$, $U''>0$ for $\tilde{W}<0$ and $U'>0$, $U''<0$ for $\tilde{W}>0$ where $\tilde{W}=\tilde{p}_3\tilde{y}a+x_1(p_1-\tilde{p}_2)+x_2(\tilde{p}_2-\tilde{p}_3)-ca$, or the change in wealth from period 1 to period 3. Thus, in our model, equation (2.5) must be written as:

$$\max_{a,x_1}\int_{-\infty}^{0}U_1\left(\tilde{W}\right)f\left(\tilde{W}\right)d\tilde{W}+\int_{0}^{\infty}U_2\left(\tilde{W}\right)f\left(\tilde{W}\right)d\tilde{W} \tag{2.12}$$

In equation (2.12), U_1 is a convex function reflecting risk-seeking behavior in the domain of losses and U_2 is a concave function indicating risk-averse behavior in the domain of gains. The distribution of $\tilde{W}$ is determined by the distributions of $\tilde{p}$ and $\tilde{y}$.

If the distribution of $\tilde{W}$ were known, equation (2.12) could be solved separately for the optimal period-1 futures position with x_1^L corresponding to the solution for the term on the left and x_1^G the solution for the term on the right. The optimal hedge could then be determined as $x_1^*=\alpha x_1^G+(1-\alpha)x_1^L$ where α equals the fraction of $\tilde{W}$ such that $W\geq 0$. The optimal hedge would be a weighted average of risk-seeking behavior and risk-averse behavior where the weights are determined by the area under the probability density function for random variable $\tilde{W}$ as shown in Figure 2.3.

Now suppose that equation (2.12) was solved first by assuming that the producer was everywhere risk-seeking, i.e., $U_1=U_2, U'>0, U''>0$. This would be the case if the entire distribution of $\tilde{W}$ were to reside to the left of the vertical axis in Figure 2.3. For a producer who is naturally long the underlying physical commodity, this would imply taking a long position in the futures market, clearly a more risky proposition. The solution to this problem would be $x_1^L* = -\infty$. A strictly risk-seeking producer would prefer the largest gamble possible. As a practical matter, a producer would clearly face some wealth constraint preventing him from taking such a long position. Therefore, let the solution to this problem be given by $x_1^L* = L$ where L is a real, negative number arising due to the wealth constraint.

Likewise, suppose that equation (2.12) were solved with the producer everywhere risk-averse, i.e., $U_1 = U_2, U' > 0, U'' < 0$. This would correspond to the case in which the entire distribution of $\tilde{W}$ lies to the right of the vertical axis in Figure 2.3. The solution in this case would correspond to the standard EU outcome presented earlier, where the producer takes a short position in the futures market to mitigate exposure to risk. Let this solution be denoted by $x_1^G* = G$, where $G > 0$. Thus, in the case where $\alpha = 1$, we have $x_1^* = x_1^G* = G$ and for $\alpha = 0$, we have $x_1^* = x_1^L* = L$. The general solution to this approach can be represented as the following:

$$\begin{cases} x_1^* = x_1^{L*} \quad \text{for } \alpha = 0 \\ x_1^* = x_1^{G*} \quad \text{for } \alpha = 1 \\ x_1^* = \alpha x_1^{G*} + (1-\alpha) x_1^{L*} \quad \text{for } 0 < \alpha < 1 \end{cases} \tag{2.13}$$

It should be clear that since $L < G$, there is increasing weight placed on the risk-averse solution and decreasing weight placed on the risk-seeking solution as the distribution of $\tilde{W}$ shifts from left to right. This would occur with a period-2 demand shock such that $\varepsilon_2 > 1$. Thus, we have the result that $x_2^* > x_1^*$ whenever $p_2 > p_1$ and $0 < \alpha < 1$. It is important to emphasize here that the only change required to cause an increase in the optimal hedge is an increase in the price level. As of period 1, the producer has sold in advance an amount of output equal to x_1^*. In the absence of hedging, the amount of unsold output is $a^* N(\bar{y} - x_1^*)$.[5]

[5] Again for expositional purposes, this supposes that only commercial end-users take the opposing trade to producers' short positions. The presence of speculators would reduce the amount of committed production in that speculators do not typically intend to take delivery of the underlying commodity.

Once period-1 decisions have been made, the producer faces an optimization problem similar to equation (2.12) in period 2 as follows:

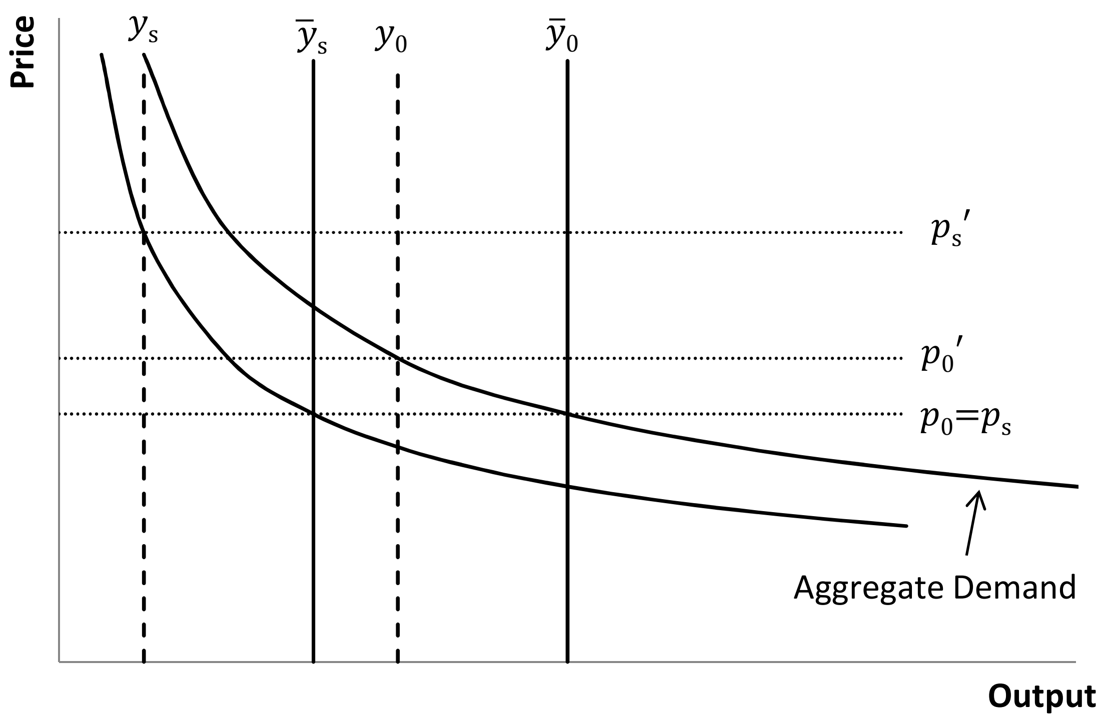
$$\max_{x_2} \int_{-\infty}^{0} U_1\left(\tilde{W}\right) f\left(\tilde{W}\right) d\tilde{W} + \int_{0}^{\infty} U_2\left(\tilde{W}\right) f\left(\tilde{W}\right) d\tilde{W} \qquad (2.14)$$

In this case, $\tilde{W} = \tilde{p}_3 \tilde{y} a^* + x_1^*(p_1 - p_2) + x_2(p_2 - \tilde{p}_3) - ca^*$ as before, with x_1^* and a^* fixed at values optimally chosen in period 1, and period-2 prices no longer uncertain. As acreage is no longer a choice variable in period 2, the only decision variable that a producer can adjust is the amount of output hedged in futures contracts. Assuming for the moment that there is no output uncertainty resolved from period 1 to period 2, the producer would choose his period-2 hedge, x_2^* such that $x_2^* = x_1^*$. Consider, however, the case in which $\varepsilon_2 > 1$. An increase in demand will cause $p_2 > p_1$ and $x_2^* > x_1^*$ as more weight is placed on the risk-averse solution and less weight on the risk-seeking solution. In this case, the amount of unsold output available at harvest will be $a^* N(\bar{y} - x_2^*)$, which is less than the amount previously available in period 1, $a^* N(\bar{y} - x_1^*)$.

Moving forward to the terminal period, consider the effect of a negative supply shock, possibly unfavorable weather near harvest, such that $y < \bar{y}$. The negative supply shock affects the entire harvest. However, a portion of this harvest has already been sold in advance. As the supply curve shifts leftward, there is a larger increase in the spot price in the presence of futures market hedging than if there had not been any crop sold in advance. Moreover, the increase in the level of futures prices in period 2, which caused the amount hedged to increase, will exacerbate this price increase even further. Figure 2.4 provides the intuition behind this result.

In Figure 2.4, aggregate demand is taken to be the sum of two (equal) individual grain consumer demand curves, shown here to be each equal to half of the aggregate demand. Group 1 is interpreted as consumers purchasing grain through forward (futures) markets, intending to take delivery at harvest. Group 2 purchases only in the spot market at harvest. In the absence of any supply shocks at harvest, realized aggregate supply is equal to expected aggregate supply $\bar{y}_0$. In this case, the price paid by group 1, p_0 is equal to the price paid by group 2, p_s. In equilibrium, both groups purchase grain in the amount of $\bar{y}_s$ since they are equal in size.

Figure 2.4. Effect of Terminal Period Supply Shock on Spot Prices and Volatility.



Now consider the effect of a terminal period supply shock in which realized aggregate supply is reduced to y_0. In this case, grain producers have committed to supplying grain to group 1 in the amount contractually agreed upon, $\bar{y}_s$. Subtracting this amount from aggregate realized supply gives $y_0 - \bar{y}_s = y_s$, the amount of uncommitted grain remaining in the spot market available to respond to the negative shock at harvest. Now the equilibrium price at harvest, based upon the demand curve of group 2, still in need of grain, is p_s'. As illustrated in the figure, this price is greater than what the equilibrium price would have been if there had been no futures trading, p_0'. This simple illustration shows that an increase in the amount of output hedged by producers in the futures market reduces the amount of output available at harvest to respond to negative (or positive) supply shocks. As a result, cash prices and volatility at harvest are necessarily higher. Thus, in the context of our paper, any factor that increases futures prices (such as an increase in demand) within a crop year will cause spot prices and the volatility of prices at harvest to increase. In the case of isoelastic demand, this effect increases dramatically as the severity of the supply shock at harvest increases, or as the amount of crop sold in advance increases.

2.5. Numerical Results

This section provides numerical results to support the theory presented in the previous section to help provide a better understanding of two key points: the extent to which producers' optimal hedge is affected by upward price movements under prospect theory and the ensuing impact on spot prices and volatility.

For the purposes of the numerical simulations, a CARA utility representation is used to obtain results due to its ability to be parameterized to encompass prospect theory as well as its general prevalence in the hedging literature alluded to in section 2.3. Utility is thus specified as follows:

$$U = \begin{cases} -\varphi\left[1-\exp\left(\theta_L \tilde{W}\right)\right] & \text{for } W < 0 \\ 1-\exp\left(-\theta_G \tilde{W}\right) & \text{for } W \geq 0 \end{cases} \tag{2.15}$$

In equation (2.15), $\tilde{W} = \tilde{p}_3 \tilde{y} a + x_1(p_1 - \tilde{p}_2) + x_2(\tilde{p}_2 - \tilde{p}_3) - ca$ as before, θ_G (θ_L) defines the measure of risk-averse (risk-seeking) behavior over gains (losses), and φ allows for the possibility of a higher sensitivity to losses than gains (loss aversion). This would be the case when $\varphi > 1$. Estimates for φ are found to be between 2.25 and 2.5 (Kahneman and Tversky, 1992; Pennings and Smidts, 2003). Given the specification of utility in equation (2.15), the producer's first-period maximization problem can be written as:

$$\max \int_{-\infty}^{0} -\varphi\left[1-\exp\left(\theta_L\left(\tilde{p}_3\tilde{y}a + x_1\left(p_1-\tilde{p}_3\right)\right)\right)\right] f\left(\tilde{W}\right) d\tilde{W} + \int_{0}^{\infty}\left[1-\exp\left(-\theta_G\left(\tilde{p}_3\tilde{y}a + x_1\left(p_1-\tilde{p}_3\right)\right)\right)\right] f\left(\tilde{W}\right) d\tilde{W} \tag{2.16}$$

Prices, $\tilde{p}_3$, are drawn from a lognormal distribution with a (period 1) mean and standard deviation of 4.19 and 1.28 respectively. As explained previously, yields are assumed to be uncorrelated with prices and are drawn from a four-parameter beta distribution. For robustness, results will also be presented for a case in which prices and yields are negatively correlated with a correlation coefficient of -0.47. The mean and variance of the yield distribution in period 1 is 150 and 15.4 respectively. From these distributions, a distribution for revenue per acre, $\tilde{p}_3\tilde{y}$ is constructed. For simplicity, and without loss of generality, the demand equation given by (2.1) is calibrated by adjusting δ so as to generate a market clearing price equal to the mean of the given price distribution for $a=1$. The elasticity of demand, γ, is set equal to 0.5. The cost parameter c, is set to ensure that there is an approximately equal probability of realizing a loss as a gain in the first period.

For the purposes of simulations, φ is set equal to 2.25 as cited in the literature, but the value of this parameter is not crucial to the key results. Likewise, values of risk aversion and risk-seeking parameters, θ_G and θ_L are set equal to each other at 0.01. The values for these parameters were chosen so as to allow for sufficient non-degenerate curvature over the range of the distribution of $\tilde{W}$. The relatively arbitrary values chosen for these parameters are also not crucial to the key results, but provide some ease in numerical simulations by preventing extremely large or small numbers, given the range of $\tilde{W}$.

In most circumstances, as discussed earlier, it can be expected that a producer who has a natural long position in an underlying commodity will take a short position in the futures market to manage price and production risk. Recalling the fact that a risk-seeking producer will choose a long futures position as large as possible without a wealth constraint, a lower bound was placed on the size of the long position taken. This bound can be interpreted as a wealth constraint which ensures that the amount hedged by the producer will be nonnegative, thereby conforming to empirically observed data. Ultimately, we are interested in how the optimal hedge changes due to an increase in the level of prices, so the exact magnitude of this bound is of little importance.

2.5.1. Hedge Ratio Effect

As mentioned in section 2.4, after period-1 decisions on production (acreage) and hedging have been made, the only choice variable in period 2 is the hedging decision. Moreover, there is an assumed stickiness in the hedging decision. Once a portion of output is sold in short futures contracts, it cannot be "unsold." Thus, the only real decision is whether to hedge additional output in the second period beyond what was hedged in the first period. In the second period, we allow for a demand shock of varying intensity (i.e. $\varepsilon_2 > 1$) that causes producers to hedge additional output under prospect theory due to a price level increase.

Figure 2.5 illustrates this result for two scenarios. The solid curve represents the scenario in which no uncertainty is resolved moving from period 1 to period 2. The dashed curve represents the scenario in which the variance of prices and yields is reduced by 25%. In the figure, the period-2 conditional expectation of the period-3 spot price is displayed on the horizontal axis. This is the mean of the price distribution as of period 2. The curves then represent the optimal hedge ratio read from the vertical axis. As prices increase, risk-averse behavior takes over and a larger short position is maintained. The optimal hedge ratio eventually flattens out at a level corresponding to the solution in which the producer is strictly risk-averse.

Figure 2.6 presents the case in which there is negative correlation between prices and yields. As can be seen from the figure, the result that the optimal hedge initially increases as the weight on risk-averse behavior increases is still maintained. In contrast to Figure 2.5, however, the optimal hedge reaches a peak before subsequently declining as the effectiveness of a natural hedge relative to a futures hedge is increased.

Figure 2.5. Hedge Ratio as a Function of Price Levels (No Price-Yield Correlation).

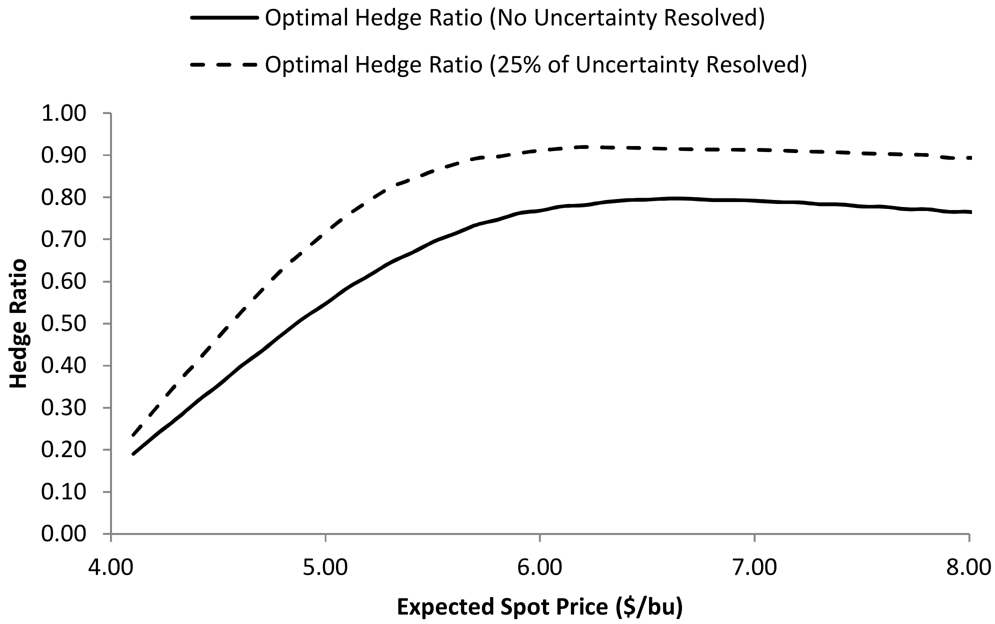
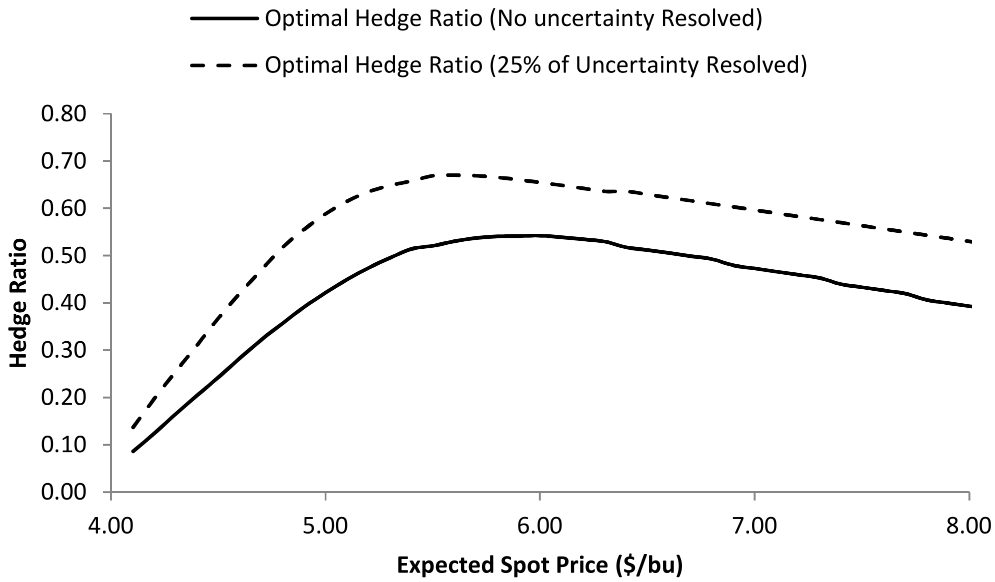


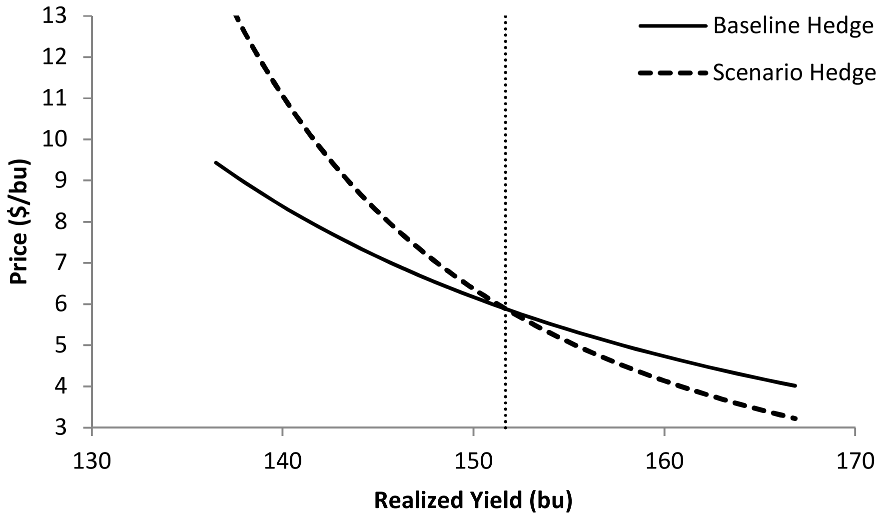
Figure 2.6. Hedge Ratio as a Function of Price Levels (Neg. Price-Yield Correlation).



2.5.2. Volatility Effect

Finally, in period 3 we consider the effect of a supply shock in order to emphasize the pronounced effect on volatility and spot prices at harvest due to producers having sold a greater amount in the futures market between periods 1 and 2. Intuitively we would expect that as producers sell a larger share in advance, the effect of the supply shock in the terminal period will become amplified. This is illustrated in Figure 2.7 for supply shocks ranging from -10% to 10%. In this figure, the solid curve represents the case in which the hedge ratio remains unchanged from period 1 to period 2 (baseline hedge). The dashed curve represents the case in which there is a period-2 demand shock of 30 bu/acre.

Figure 2.7. Effect on Spot Price Levels and Volatility Due to Increased Hedging.



With period-2 expected yields of approximately 152 bu/acre (assuming the 25% uncertainty resolution case), a -10% supply shock corresponds to a realized yield of 137 bu/acre. As expected, increased hedging activity results in a higher variation of equilibrium prices. This effect increases non-linearly as the magnitude of the period-3 supply shock increases. As illustrated, changes in price volatility are minimized when the amount of output hedged in period 2 remains unchanged from the amount hedged in period 1, i.e. the baseline hedge. It is also apparent in Figure 2.7 that observed spot prices in the “scenario hedge” case increase due to a negative period-3 supply shock above those price levels that would have been observed in the “baseline hedge” case. It should be clear from Figure 2.7, and intuitively so, that less unsold grain available at harvest (due to higher period-2 hedge ratios) directly translates to a higher conditional variance in spot prices.

2.6. Conclusion

Using prospect theory as an alternative to conventional expected utility theory, this paper considers the corresponding utility maximization problem of a representative grain producer. There are two key findings. First, under prospect theory futures price level increases can lead to a higher share of output being hedged in futures markets. This is a result that conventional expected utility theory does not generate, but is observed empirically. Second, as more output is sold in advance, there is less available at harvest to respond to a potential supply shock, resulting in greater spot price volatility as well as higher spot price levels.

In connection with these findings, there are several qualifications and limitations that should be addressed. The first qualification is the degree to which output sold in advance in futures markets is considered unavailable in the terminal period. The numerical results of this paper present a case in which grain consumers, intending to take delivery at harvest, take the opposing positions for all of the output hedged by producers in short futures contracts. As was mentioned in the paper, the ratio of commercial long contracts to commercial short contracts typically lies within a range of 0.3 and 0.6 with non-commercial traders (speculators) accounting for the remainder of opposing positions. Thus, the numerical results on price level effects and volatility effects at harvest due to increased short hedging are biased upward somewhat. These effects should be scaled by the ratio of commercial long-to-short contracts to better capture the extent to which future output is sold to a buyer intending to take delivery, thereby rendering this output unavailable at harvest.

A second point that deserves mention is the extent to which the optimal hedge under expected utility theory differs from the optimal hedge under prospect theory in magnitude. Since expected utility theory typically assumes producers are everywhere risk-averse, the corresponding optimal hedge will be an upper bound for the hedge under prospect theory. This is because prospect theory incorporates some degree of risk-seeking behavior, which would imply taking a long position in futures markets rather than a short position. It might seem then that the effects under expected utility theory at harvest would always dominate the effects under prospect theory if more output is hedged under the former. The focus of this paper, however, is not necessarily on the magnitude of the optimal hedge ratio in any given period, which is somewhat arbitrary, but rather the direction and magnitude of the change in this hedge ratio from one period to the next.

A final comment to be made concerning the results of this paper is in regards to the specific behavioral assumption being made: that grain producers are risk-averse over gains and risk-seeking over losses. A limitation of this paper is that this is not necessarily the only behavioral assumption that would give rise to increased short hedging activity due to an increase in futures prices. Regret theory would also generate similar results. In this case, as the distribution of prices rises above some reference, a producer would experience regret if prices subsequently fall below this level. This would induce the producer to sell more when prices are above the reference in order to avoid regret later. Modeling this or other behavioral assumptions could be done as a possible extension to the current paper.

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CHAPTER 3. SPECULATIVE TRADING AND COMMODITY FUTURES MARKETS: AN EXAMINATION OF CAUSALITY IN THE TIME AND FREQUENCY DOMAINS

A modified version of the paper to be submitted to a peer-reviewed journal

3.1. Abstract

Commodity market speculation is often criticized for allegedly driving futures prices and volatility higher. In this paper, bivariate Granger causality tests on futures prices and speculation and on volatility and speculation are conducted for 19 actively-traded commodity markets. Hypothesis testing is done first in the time domain, then in the frequency domain to identify potential causality in the short run as distinct from the long run. Our results show that speculators do not generally influence futures prices in either the long run or short run. Conversely, futures prices are shown to be a causal factor for speculator positions in the long run, but less so in the short run. Speculator positions are generally unaffected by volatility, but some evidence exists that suggests speculator positions may contribute to fluctuations in volatility.

3.2. Introduction

Often accompanying commodity price spikes, or persistent increases above historical norms, is an appeal for further regulation in commodity markets, specifically in derivatives trading. Regulation proponents are frequently known for directing the blame for these price increases at speculative buying behavior in commodity futures markets. The blame comes with the assertion that speculators, with their increasing net long positions in futures markets, distort cash markets in various ways, one of which is an artificially created hoarding of physical commodities. By withholding supply of these commodities, prices are said to be driven upward, ultimately harming the final consumer who has to pay for the increase, while speculators are rewarded for their bets. Speculators are also often accused of injecting additional volatility into commodity markets to the detriment of producers wanting to mitigate exposure to price fluctuations.

An extreme example sometimes used to emphasize the harmful effects of these allegations is the massive rioting that was observed in a number of developing countries which were forced to pay prices never before seen for staple foods during, and immediately following, the surge in commodity prices in 2008. To illustrate the extent to which prices rose during this period, the futures price for crude oil with nearby maturity was trading at about $51 per barrel in January 2007. By July 2008, the price had rocketed to its peak of $147 per barrel. Oil prices, and commodity prices in general, subsequently plummeted and, once again, began an upward ascent toward the end of 2010. Volatility has seen similar fluctuations across other commodity markets. Figure 3.1 and Figure 3.2 illustrate the degree of price and volatility movements in the oil and corn futures markets from 1992-2011.

Figure 3.1. Nearby Futures Prices and T-Index Values for Crude Oil 1992-2010.

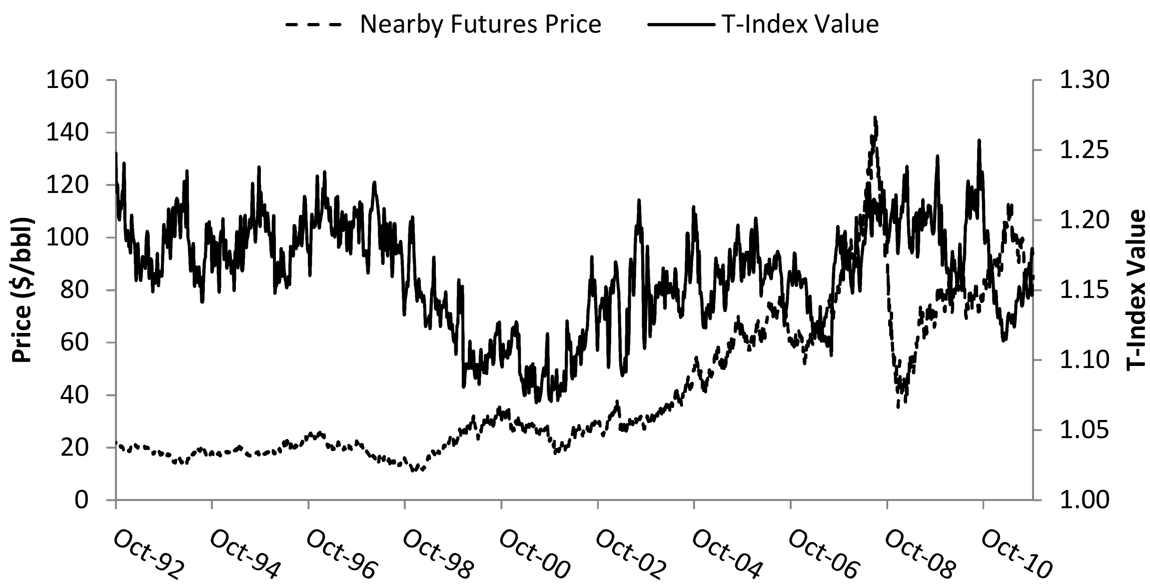
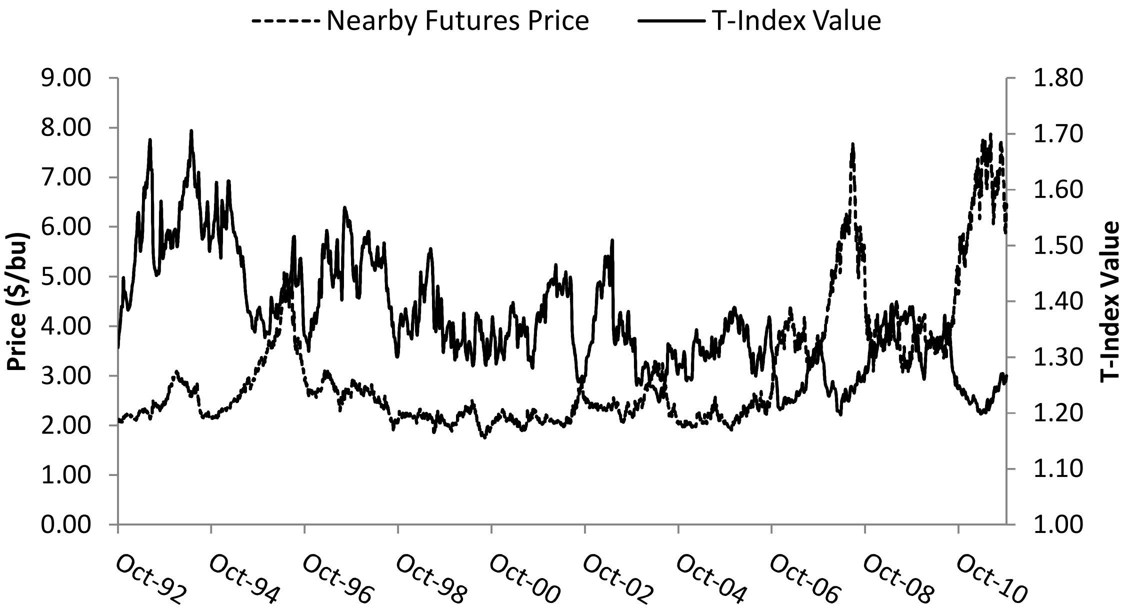


Figure 3.2. Nearby Futures Prices and T-Index Values for Corn 1992-2010.



During, and immediately following these price and volatility spikes, numerous allegations were made that speculators and long-only commodity index traders were the culprit, some of which reached the floor of Congress. In his testimony to the U.S. Senate in May 2008, as prices were on the rise, hedge fund manager Michael Masters was unequivocal in his accusation that institutional investors, speculators, were to blame for food and energy price inflation (Masters, 2008).

Shortly after reaching their peak prices in the summer of 2008, prices fell back to levels similar to where they had been trading in January 2007. Nonetheless, there has been a continued push for further regulation and oversight in commodity markets, specifically regarding the extent to which speculators should be allowed to participate in futures markets. In May 2011, the Commodity Futures Trading Commission (CFTC) filed a lawsuit against three individuals for alleged market manipulation who purportedly drove oil prices higher during the 2008 spikes. In what may be a precedent, the lawsuit is the biggest case of oil market manipulation in history. In recent years, the CFTC has been occasionally criticized for its inability to prevent commodity price spikes and "unlawful" profit generation. In the wake of the Dodd-Frank Act, these events could reignite a debate calling for new speculative trading limits.

Blaming speculators for increasing commodity prices and volatility is not a new phenomenon. In what is perhaps the most well known case of federal intervention, responding to mounting criticism of speculative buying, the U.S. Congress banned trading in onion futures in 1958. The ban remains in effect today. The U.S. Senate continues to push for further regulation with the belief that regulations and restrictions on speculative buying will alleviate the pressure on commodity prices. The push for regulation has gathered steam globally as well, with French President Nicolas Sarkozy frequently advocating for additional restrictions, specifically in energy and grain markets (Tait, 2011; Ruitenberg, 2011).

There have been numerous papers written to address the notion of “excessive speculation” and its potential to influence prices. More recent studies have taken a statistical approach to test for causality between trader positions and futures prices. The motivation behind such studies is to address a cited weakness in Masters’ argument, that correlation implies causation. The studies have made use of publicly available CFTC data. The CFTC began reporting large traders’ positions in individual commodities in 1992 in its Commitment of Traders (COT) report, where traders have been classified as either commercial, non-commercial, or non-reporting entities. More recently, the CFTC has further disaggregated these reports, and concurrently publishes its Disaggregated Commitment of Traders (DCOT) with historical data available beginning in June 2006.

The goal of this paper is to assess the extent to which speculators have in fact contributed to price movements or volatility fluctuations by their trading practices, or whether the reverse is true.[1] These tests are often referred to as tests of Granger Causality, used interchangeably with causality in this paper (Granger, 1969). There are three key contributions of this paper to the existing literature. First, whereas other studies have often considered only one market, our analysis considers 19 commodities possessing actively traded futures markets. We perform causality tests both at the individual commodity level

[1] From this point forward, the term “speculators” refers to non-commercial and non-reporting traders as classified by the CFTC in its COT reports.

and on an aggregate basis by means of a seemingly unrelated regression (SUR) framework. Second, we seek to expand a discussion that has frequently targeted speculators' contribution, or lack thereof, to price movements by also considering the possibility of effects on volatility. Finally, our tests of causality are conducted both in the time domain and in the frequency domain. In empirical applications, the vast majority of the economics literature considers only the time domain.

The benefit of conducting tests of causality in the frequency domain, the background of which will be presented later, is that it allows us to draw conclusions about causality in the short run as distinct from the long run. Tests conducted only in the time domain that reject the hypothesis that speculators cause price changes may provide an incomplete picture if frequency-domain tests show evidence of causality within one time horizon but not another. This would have important policy implications as regulations may be approached differently if it is found, for instance, that speculators do not cause changes in the long run but possibly do so in the short run.

The remainder of the paper is organized as follows. Section 3.3 reviews the relevant literature regarding speculation in commodity markets and tests for causality between prices and positions. Studies making specific use of frequency-domain analysis, particularly in economic applications, are also presented. Section 3.4 describes the nature of the data used in our analysis in greater detail. Section 3.5 outlines the statistical methods used to test for causality. Section 3.6 presents the results of the statistical tests applied to the data at hand, and section 3.7 provides concluding statements.

3.3. Literature Review

In this section, we review three strands of literature significant to this paper. First, we discuss literature that has addressed the debate of speculation in commodity markets. We then review recent literature that has adopted a time-series approach to test for causality. Finally, we briefly outline the scope and theory of frequency-domain causality which relies on spectral analysis.

3.3.1. Commodity Market Speculation

One of the earliest studies frequently cited addressing the notion of "excess" speculation is Working (1960). A major motivation behind Working's paper was the ban on onion futures trading, which had been imposed just two years earlier. Working believed that the U.S. Congress was mistakenly persuaded that there was excess speculation in onion futures trading. His paper was written so as to make clear the relationship that speculation and hedging have in commodity markets.

Working is perhaps best known for introducing what has become known as Working's speculative *T*-index as a rough benchmark of the extent of excess speculation in a market. Working's *T*-index is defined as follows:

$$T = \begin{cases} 1 + \dfrac{SS}{HS + HL} \text{ if } HS \geq HL \\ 1 + \dfrac{SL}{HS + HL} \text{ if } HS < HL \end{cases} \tag{3.1}$$

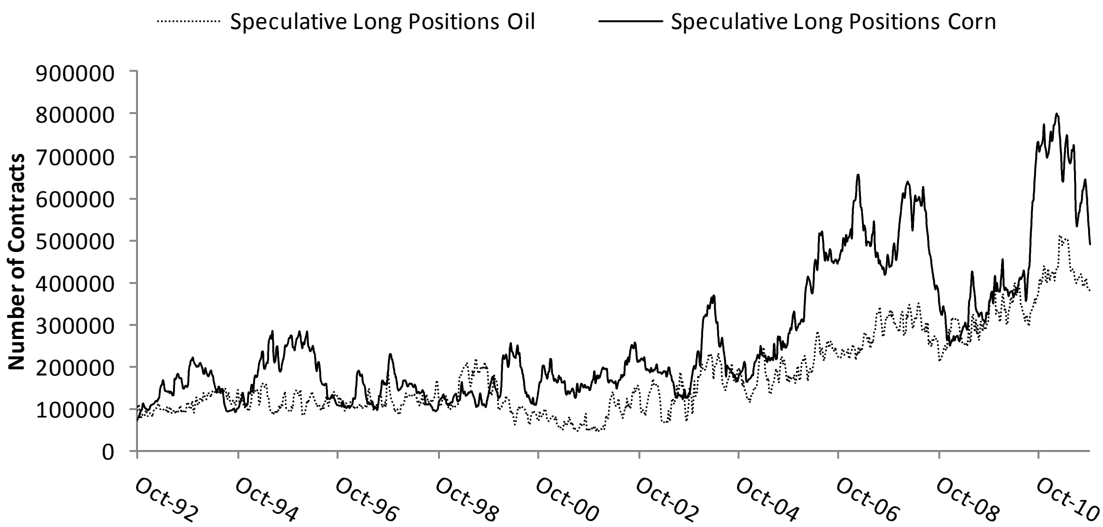
In equation (3.1), SS (SL) is the open interest held by short (long) speculators and HS (HL) is the open interest held by short (long) hedgers. The intuition behind the index is as follows. The total amount of open interest as contracts held by hedgers is in the denominator of the second term. If there are more short hedgers than long hedgers, then speculative long positions are needed to balance the market. (For every short position, there must be a corresponding long position, and vice versa.) Thus, any amount of speculative short positions are not "needed" in the sense that they serve no purpose to balance the market as arising from the needs of hedgers. Equation (3.1) then represents a measure of excess speculation, where speculative short (or long) positions are not required by hedgers in order to balance the market. A *T*-index value of unity would imply there is no excess speculation in the given market.

Working's *T*-index, although falling short of being a statistically rigorous approach to address the question of causality between traders' positions and futures prices, has been cited as a general benchmark as to whether the amount of speculative trading is excessive. It seeks to quantify an otherwise arbitrary notion of what constitutes excess speculation.

Figure 3.1 illustrates the relationship observed between crude oil futures prices (with nearby maturity) and Working's *T*-index over the relevant time period covered in the COT reports. Figure 3.2 illustrates the same relationship for corn futures.

Till (2009) applies Working's *T*-index and the notion of excess speculation to the CFTC's DCOT reports. By treating swap dealers as speculators, Till seeks to put an upper bound on the *T*-index. Even treating all swap dealers as speculators, the *T*-index values that Till obtains are still roughly comparable to historical *T*-index values that have been obtained where speculation was not said to be "excessive." For the time period considered in this paper, futures prices and corresponding *T*-index values are graphically provided in Figure 3.1 and Figure 3.2 for crude oil and corn respectively. While it is true that speculative buying has increased in magnitude, as shown in Figure 3.3 for oil and corn, the *T*-index values illustrated in Figure 3.1 and Figure 3.2 lend some non-rigorous support to the conclusion that futures prices appear to depict no immediately discernible causality running from positions to prices.

Figure 3.3. Speculative Long Positions for Crude Oil and Corn.



3.3.2. Time-Domain Causality

Whether or not there is excess speculation in a particular market is only one concern. The main issue is whether speculative positions are driving prices. In an effort to explore the relationship between futures prices and trader positions more rigorously, Sanders, Boris, and Manfredo (2004) tested for Granger causality using data from weekly COT reports for trader positions. Their analysis specifically focused on the energy sector: crude oil, gasoline, heating oil, and natural gas. Their results showed very little evidence that trader positions led futures prices (returns) in the sense of Granger causality, but showed much stronger evidence that futures prices led trader (percent net long) positions.

Similar results were obtained by the CFTC in its report on crude oil, making use of non-public daily data on trader positions (CFTC, 2008a). In this case, the results were even more conclusive that there appeared to be no evidence of trader positions leading futures prices in the crude oil market. One important difference between this report and that of Sanders *et al*., however, is that no trader position of any group in the CFTC report was found to lead futures prices, whereas Sanders *et al*. found that hedgers' (referred to as commercial users in earlier COT reports) positions were significantly affecting futures prices. The CFTC report was more comprehensive than Sanders *et al*., in that it included delta-weighted options contracts in addition to futures. Robles, Torero, and von Braun (2009) also conducted similar Granger causality tests using COT reports, but came to a different conclusion, stating that speculative activities might in fact have been influential in the commodity price spikes of 2008.

Irwin, Sanders, and Merrin (2009) provide an intuitive refutation of allegations that speculators have manipulated futures prices, drawing on some of their previous work of a more rigorous statistical nature to support the intuition. Irwin *et al*. present a number of conceptual errors made by what they term "bubble proponents," who claim that speculative buying, specifically by index funds in commodity futures, have inflated commodity prices. Sanders and Irwin (2010) expand on their previous studies by examining the presence of causality using cross-sectional regressions over alternative horizons. Other studies have also focused explicitly on the role of commodity index traders and their potential to influence commodity prices (Stoll and Whaley, 2010; CFTC, 2008b).

3.3.3. Frequency-Domain Causality

Although Granger causality is most often tested within the framework of the time domain in economic applications, the frequency domain provides an alternative approach, sometimes referred to as spectral analysis (or cross-spectral analysis, depending on the objective). Granger (1969) also provides an introduction to this approach in his original work along with a motivation for economic applications. Spectral analysis, however, is most often utilized in the natural sciences (e.g., physics, neurophysiology, and chemistry) or engineering applications, where frequency serves as a more intuitively relevant metric than time. As will be shown in section 3.5, though, the data that are specified within the time domain can be transformed into the frequency domain by means of a relatively simple Fourier transform. The data can be transformed back to the time domain by using an inverse Fourier transform.

Whereas Granger (1969) provided a general approach to frequency-domain causation, Geweke (1982) and Hosoya (1991) developed the theory into a measure of causality encompassing both linear dependence between two series and the possibility of instantaneous feedback. Assuming a vector autoregression (VAR) structural framework for two series specified in the time domain, the measure of causality in the frequency domain is specific to an individual frequency. This measure is shown to be additively separable in terms of linear feedback from one series to another, the converse, and instantaneous feedback.

Breitung and Candelon (2006) expand upon the formulation developed by Geweke and Hosoya and provide an approach to hypothesis testing in empirical applications. Breitung and Candelon propose a testing procedure based upon this formulation and show that testing for causality at a specific frequency is equivalent to a set of derived linear restrictions, providing an ordinary *F*-statistic to test the null hypothesis of no causality. This approach serves as the basis for the frequency-domain causality tests in our paper.

Pierce (1979) outlines another measure of causality within the frequency domain that is appealing because its interpretation is analogous to that of a standard *R*-squared measure in conventional econometrics. This measure is referred to as a coherency value and illustrates the degree of connectedness between two series at a given frequency. As with the *R*-squared measure, coherency values are defined on the interval [0, 1], with a value of 1 indicating a perfect relationship and a value of 0 indicating no relationship. A shortcoming of this measure, however, is its inability to provide an indication of the direction of causality.

Despite its relative obscurity in tests of Granger causality, the use of spectral analysis is not entirely new in the economics literature. Riezman, Whiteman, and Summers (1996) apply spectral analysis to draw conclusions about whether specific countries' export-led growth is a long- or short-run phenomenon. Nachane, Nadkarni, and Karnik (1988) use the Geweke framework to explore causal linkages between energy prices and GDP. In an application more closely related to the premise of our paper, Gronwald (2009) seeks to determine whether there is short- or long-run causality between the price of oil and certain macroeconomic variables in Germany.

Our underlying motivating factor in adopting spectral analysis, consistent with the studies referenced above, is to test for causal linkages between two series with the short run tested separately from the long run. Spectral analysis, by allowing causality to be tested on a frequency-specific basis, allows us to do this in addition to the more conventional time-domain tests referenced earlier.

3.4. Data

In this study, we seek to explore the causal linkages between speculators' positions in the futures market and futures prices as well as between positions and futures price volatility. Therefore, there are four separate tests requiring three unique data series. The null hypothesis for each case is the following:

$$\begin{array}{l} \text{Case A - } H_0 \text{ : Speculator positions do not explain futures price changes.} \\ \text{Case B - } H_0 \text{ : Changes in futures prices do not explain speculator positions.} \\ \text{Case C - } H_0 \text{ : Speculator positions do not explain futures price volatility.} \\ \text{Case D - } H_0 \text{ : Futures price volatility does not explain speculator positions.} \end{array} \quad (3.2)$$

The three data series required for the above tests are i) a measure of speculator positions, ii) futures prices, and iii) a measure of futures price volatility.

Data for speculator positions are obtained from the CFTC's COT reports, which provide a breakdown of trader positions by open interest for markets in which at least 20 traders maintain positions at or above the reporting levels established by the CFTC. The COT reports are generated through the collection of data in the CFTC large-trader reporting program with positions reported at the end of each Tuesday. The reports are provided for both futures-only open interest as well as futures-and-options-combined formats. The open interest that is reported consists of the aggregate of all outstanding contracts covering the time period from October 1992 through October 2011.

In the COT reports, traders are categorized as either commercial, non-commercial, or non-reporting entities.[2] For practical purposes, commercial entities are typically interpreted as producers, merchants, and users (hedgers) with a physical stake in the underlying asset. These traders seek to hedge production, trading commitments, and consumption by employing futures market strategies to mitigate risk. Non-commercial entities are investors with no physical stake in the underlying asset, typically identified as large speculators. Likewise, non-reporting entities are typically interpreted as small speculators. Thus, the latter two groups, when combined, represent speculators in the aggregate.[3]

We use the same measure for speculator positions that was used by Sanders, Boris, and Manfredo (2004), referred to as percent net long (PNL):

[2] In an effort to increase transparency, the CFTC began making DCOT reports available beginning in June 2006. This could serve as a better data set than the original COT reports, by allowing speculators to be more narrowly defined. However, the fact that data are only available beginning in 2006 would significantly limit the number of observations to conduct hypothesis testing.
[3] It should be noted that the COT reports do not, and cannot, identify traders explicitly as hedgers or speculators. Some commercial traders may take speculative positions. However, it is less likely that non-commercial entities would unnecessarily classify themselves as such, thereby subjecting themselves to speculative limits, if their primary business activity is in fact commercial hedging.

$$PNL_t = \frac{L_t - S_t}{L_t + S_t + 2SP_t} \tag{3.3}$$

In (3.3), L_t, S_t, and SP_t represent, respectively, the number of speculative long, short, and spread positions in open interest at time t. PNL serves as a measure of the extent to which speculators maintain a net long position, with the possibility of driving prices higher due to their buying position.

For each time period, t, a corresponding set of Tuesday's closing futures price for the nearby contract, P_t is obtained for each of the 19 commodities considered in our study. So as to ensure stationarity, we use returns from Tuesday-to-Tuesday closing prices, defined as $R_t \equiv \ln(P_t / P_{t-1})$. In the event that there is a change in contract between periods $t-1$ and t we use the futures price corresponding to the new contract for both periods, so as to avoid the possibility of "spurious" price changes resulting merely from the use of two different contracts.

Given that price volatility is unobserved, various estimates have been cited and used in the literature (Parkinson, 1980; Garman and Klass, 1980; Rogers and Satchell, 1991; Yang and Zhang, 2000). Despite these alternative estimates, Alizadeh, Brandt, and Diebold (2002) provide a theoretical, numerical, and empirical justification for the use of the range as an efficient proxy for volatility. Accordingly, the estimate of price volatility we use is the (mean of the) log-range estimate, defined as:

$$V_t = \frac{1}{T}\sum_{\tau=1}^{T} \ln\left(\ln\left(H_\tau\right) - \ln\left(L_\tau\right)\right) \tag{3.4}$$

In (3.4), H_τ and L_τ respectively denote the daily high and low futures prices observed. Values of $\tau = 1, 2, \ldots, T$ correspond to days of the week between successive Tuesdays, with $\tau = T$ corresponding to each Tuesday, the day for which position data is available. For weeks in which a "limit-movement" day is observed (i.e. $H_\tau = L_\tau$), we use the median instead of the mean to avoid a resulting measure of $-\infty$. As with the return series R_t if there is a change in contracts between $\tau = 1$ and $\tau = T$, we draw the corresponding high and low prices from the new contract only.

As presented, PNL_t, R_t, and V_t provide us with the three series necessary to conduct the hypothesis tests specified in (3.2). Each series is tested for stationarity using Dickey-Fuller tests and found to be stationary in each case. These series then form the basis for the time- and frequency-domain causality tests, the methodology of which will be presented in the following section.

3.5. Methods

In this section, we begin by outlining the methodology used to test the hypotheses specified in (3.2) for causality in the time domain. We then outline the methodology used to test for causality in the frequency domain.

3.5.1. Time-Domain Causality

Given the time-series data described in the previous section, the model for each case (A, B, C, and D) and each commodity is specified as follows:

Case A: $$R_t = \alpha_A + \sum_{i=1}^{m} \beta_{i,A} R_{t-i} + \sum_{j=1}^{n} \gamma_{j,A} PNL_{t-j} + \varepsilon_{t,A} \quad (3.5)$$

Case B: $$PNL_t = \alpha_B + \sum_{i=1}^{m} \beta_{i,B} PNL_{t-i} + \sum_{j=1}^{n} \gamma_{j,B} R_{t-j} + \varepsilon_{t,B} \quad (3.6)$$

Case C: $$V_t = \alpha_C + \sum_{i=1}^{m} \beta_{i,C} V_{t-i} + \sum_{j=1}^{n} \gamma_{j,C} PNL_{t-j} + \varepsilon_{t,C} \quad (3.7)$$

Case D: $$PNL_t = \alpha_D + \sum_{i=1}^{m} \beta_{i,D} PNL_{t-i} + \sum_{j=1}^{n} \gamma_{j,D} V_{t-j} + \varepsilon_{t,D} \quad (3.8)$$

In equations (3.5) through (3.8), m and n represent the number of lags of the dependent and independent variables, respectively. Lags are chosen in each case, for each commodity, by minimizing the Akaike Information Criteria (AIC). In (3.5) through (3.8), the null hypothesis is formally stated as $H_0 : \gamma_{j,k} = 0 \ \forall j, k \in A, B, C, D$. Rejection of the null hypothesis implies that the exogenous series of regressors provides explanatory power for the dependent series on the left hand side of each at some specified level of significance. In each case, $k \in A, B, C, D$, an *F*-statistic is generated as:

$$F_k = \frac{\left(RSS_{r,k} - RSS_{u,k}\right)/m}{\left(RSS_{u,k}\right)\left(Obs - m - n - 1\right)} \tag{3.9}$$

In equation (3.9), $RSS_{r,k}$ is the residual sum of squares for case k with the restriction $\gamma_{j,k} = 0\ \forall j$ imposed, $RSS_{u,k}$ is the residual sum of squares for the unrestricted model for case k, and Obs is the number of observations. If F_k is sufficiently large, the null hypothesis of no significance is rejected in favor of the alternative, that there is explanatory power.

Equations (3.5) through (3.8) form a model for testing the different null hypotheses for each commodity. However, the individual commodities can also be stacked to form a seemingly unrelated regression (SUR) to test each hypothesis as a system of equations. The motivation behind this procedure lies in the fact that there tends to be a strong level of correlation across futures prices of different commodities. This framework allows us to consider the possibility that the error terms for each commodity are correlated in each of equations (3.5) through (3.8), and also increases the power of each of the tests.

The SUR model corresponding to equation (3.5), for example, would be written as:

$$\begin{aligned} \begin{bmatrix} R_{t,1} \\ \vdots \\ R_{t,Z} \end{bmatrix} &= \begin{bmatrix} \beta_{1,1} & \cdots & \beta_{M,1} \\ \vdots & \ddots & \vdots \\ \beta_{1,Z} & \cdots & \beta_{M,Z} \end{bmatrix} \begin{bmatrix} R_{t-1,1} & \cdots & R_{t-1,Z} \\ \vdots & \ddots & \vdots \\ R_{t-M,1} & \cdots & R_{t-M,Z} \end{bmatrix} \\ &+ \begin{bmatrix} \gamma_{1,1} & \cdots & \gamma_{N,1} \\ \vdots & \ddots & \vdots \\ \gamma_{1,Z} & \cdots & \gamma_{N,Z} \end{bmatrix} \begin{bmatrix} PNL_{t-1,1} & \cdots & PNL_{t-1,Z} \\ \vdots & \ddots & \vdots \\ PNL_{t-N,1} & \cdots & PNL_{t-N,Z} \end{bmatrix} + \begin{bmatrix} \varepsilon_{t,1} \\ \vdots \\ \varepsilon_{t,Z} \end{bmatrix} \end{aligned} \tag{3.10}$$

In equation (3.10), Z represents the number of commodities for which data are available (19 in our study), M denotes the maximum number of lags of R_t, and N the maximum number of lags of PNL_t. In the SUR case, the null hypothesis is $\gamma_{i,j} = 0,\ i = 1,\ldots,N$, and $j = 1,\ldots,Z$.

3.5.2. Frequency-Domain Causality

There is a crucial difference of interpretation between tests of causality in the time domain as opposed to tests of causality in the frequency domain (spectral analysis). Time-domain causality tests seek to determine the extent to which past values of a variable X are significant in explaining the current values of another variable Y. Tests of causality in the frequency domain seek to determine the extent to which the fraction of the total power of Y at a given frequency is significantly contributed by X (either past or current values). Readers who are unfamiliar with the intuition and theory behind spectral analysis should refer to the appendix for an overview.

Consistent with Geweke (1982) and Breitung and Candelon (2006), we assume a VAR model specification as follows:[4]

$$\Theta(L) z_t = \varepsilon_t \tag{3.11}$$

where $z_t \equiv [R_t, PNL_t]'$, $\Theta(L) = I - \Theta_1 L - \ldots \Theta_p L^p$ is a 2 × 2 lag polynomial with lags indexed by *k* (i.e., $L^k z_t = z_{t-k}$), the maximum number of lags is given by p, and ε_t is Gaussian white noise with $E[\varepsilon_t] = 0$ and $E[\varepsilon_t \varepsilon_t'] = \Sigma$. Given stationary series, this system can be represented in moving average (MA) form as:

$$\begin{aligned} z_t = \Phi(L)\varepsilon_t &= \begin{bmatrix} \Phi_{1,1}(L) & \Phi_{1,2}(L) \\ \Phi_{2,1}(L) & \Phi_{2,2}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \\ = \Psi(L)\eta_t &= \begin{bmatrix} \Psi_{1,1}(L) & \Psi_{1,2}(L) \\ \Psi_{2,1}(L) & \Psi_{2,2}(L) \end{bmatrix} \begin{bmatrix} \eta_{1,t} \\ \eta_{2,t} \end{bmatrix} \end{aligned} \tag{3.12}$$

where $\Phi(L) \equiv \Theta(L)^{-1}$, $\Psi(L) \equiv \Phi(L) G^{-1}$ and G is the lower triangular matrix of the Cholesky decomposition $G'G = \Sigma^{-1}$, such that $\eta_t \equiv G\varepsilon_t'$ and $E[\eta_t \eta_t'] = I$. From this formulation, the spectral density matrix S takes the following form after applying a Fourier transform to the corresponding MA coefficients given in (3.12):

[4] To conserve space and notation, the model specification is presented here, simultaneously, for Cases A and B described in (3.2). The remaining specification for Cases C and D is entirely analogous.

$$S(\omega)=\begin{bmatrix} S_{R,R} & S_{R,PNL} \\ S_{PNL,R} & S_{PNL,PNL} \end{bmatrix}$$
$$=\frac{1}{2\pi}\begin{bmatrix} \left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2+\left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2 & \left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2+\left|\Psi_{21}\left(e^{-i\omega}\right)\right|^2 \\ \left|\Psi_{21}\left(e^{-i\omega}\right)\right|^2+\left|\Psi_{22}\left(e^{-i\omega}\right)\right|^2 & \left|\Psi_{21}\left(e^{-i\omega}\right)\right|^2+\left|\Psi_{22}\left(e^{-i\omega}\right)\right|^2 \end{bmatrix} \tag{3.13}$$

In equation (3.13), $S(\omega)$ is a symmetric matrix with off-diagonal elements representing the cross-spectral density functions and the diagonal elements representing the autospectral density functions of R_t and PNL_t, respectively. Each element of S is a function of angular frequency ω, where $\omega \in (0,\pi)$ is measured in radians.[5]

Geweke (1982) and Hosoya (1991) derive a measure of causality from PNL to R as:

$$H_{PNL\to R}(\omega)=\ln\left[1+\frac{\left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2}{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2}\right] \tag{3.14}$$

From (3.14), it can be seen that $H_{PNL\to R}(\omega)=0$ whenever $\Psi_{12}(e^{-i\omega})^2=0$, which means that PNL does not significantly explain R at frequency ω. Breitung and Candelon show that this is equivalent to:

$$\left|\Theta_{12}\left(e^{-i\omega}\right)\right|=\left|\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega)-\sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)i\right|=0 \tag{3.15}$$

Correspondingly, the following serves as a set of necessary and sufficient conditions for (3.15) to hold:

$$\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega)=0 \tag{3.16}$$

$$\sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)=0 \tag{3.17}$$

The VAR equation for R_t given by equation (3.11) can be written explicitly as:

$$R_t=\alpha_1 R_{t-1}+\ldots+\alpha_p R_{t-p}+\beta_1 PNL_{t-1}+\ldots+\beta_p PNL_{t-p}+\varepsilon_{1,t} \tag{3.18}$$

[5] Angular frequency (ω) is restricted to the interval (0, π) because the interval (π, 2 π) gives symmetric results, with π corresponding to the Nyquist frequency.

where $\alpha_j = \theta_{11,j}$ and $\beta_j = \theta_{12,j}$. The set of conditions given in (3.16) and (3.17) are therefore equivalent to the linear restriction $H_0 : Q(\omega)\beta = 0$ with $\beta \equiv [\beta_1, \ldots, \beta_p]'$ and

$$Q(\omega) \equiv \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \cdots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \cdots & \sin(p\omega) \end{bmatrix}, \tag{3.19}$$

and the resulting F-statistic distributed as $F \sim (2, N-2p)$.

3.6. Results

The results of the hypothesis tests described in (3.2) are presented in this section. As in the previous section, these results are presented first in the time domain and then in the frequency domain.

3.6.1. Time-Domain Causality

Table 3.1 presents the first set of results for tests of Granger causality in the time domain for Cases A through D. *P*-values are provided for each test, with asterisks denoting the level of significance at which the null hypothesis can be rejected. Tests of Granger causality are determined first for each commodity individually and finally for the stacked SUR model given in the last line of the table. Correspondingly, Table 3.2 displays the optimal number of lags chosen for each series by minimizing the AIC. In the SUR model, the number of lags chosen is 7. This corresponds to the maximum number of lags optimally chosen for any commodity individually.[6]

There are several key results that are apparent in Table 3.1. First, of the 19 commodities analyzed, the null hypothesis that PNL does not cause R (i.e., Case A) is only rejected 4 times at the 5% level of significance. Collectively, then, there is very little evidence that speculator positions are a factor in causing increases in futures prices. Moreover, the *p*-

[6] There are potentially two approaches to choosing the number of lags for the SUR model. One could simply use the same number of lags for each commodity as was optimally chosen in the individual OLS regressions. However, this assumes that equation-by-equation OLS is the correct approach. Alternatively, one could assign the same number of lags for each commodity in an effort to be consistent. We chose the latter approach and adopted 7 lags to be conservative in the ability to reject the null hypotheses.

value in the SUR model is 0.50, which provides more support to the refutation that speculators have been driving prices higher. One notable exception in this analysis is gold, for which the null hypothesis is rejected at the 1% significance level.

Table 3.1. Time-Domain Granger Causality Tests.

	Case A: *PNL* does not cause *R*		Case B: *R* does not cause *PNL*		Case C: *PNL* does not cause *V*		Case D: *V* does not cause *PNL*	
	p-value[a]	Signific.[b]	*p*-value[a]	Signific.[b]	*p*-value[a]	Signific.[b]	*p*-value[a]	Signific.[b]
Cocoa	0.07	*	0.00	***	0.02	**	0.31	
Coffee	0.03	**	0.00	***	0.49		0.61	
Copper	0.84		0.00	***	0.00	***	0.76	
Corn	0.89		0.00	***	0.02	**	0.38	
Cotton	0.70		0.00	***	0.12		0.59	
Feeder Cattle	0.01	**	0.00	***	0.88		0.10	*
Gold	0.01	***	0.00	***	0.00	***	0.89	
Heating Oil	0.90		0.00	***	0.55		0.68	
Lean Hogs	0.46		0.00	***	0.00	***	0.91	
Live Cattle	0.10	*	0.00	***	0.28		0.04	**
Natural Gas	0.12		0.00	***	0.00	***	0.54	
Oil	0.63		0.00	***	0.89		0.70	
Silver	0.03	**	0.00	***	0.84		0.58	
Soy Meal	0.89		0.00	***	0.04	**	0.54	
Soy Oil	0.47		0.00	***	0.01	***	0.57	
Soybeans	0.88		0.00	***	0.83		0.04	**
Sugar	0.45		0.00	***	0.18		0.60	
Wheat (CME)	0.18		0.00	***	0.01	***	0.80	
Wheat (KC)	0.76		0.00	***	0.02	**	0.10	*
SUR	0.50		0.00	***	0.25		0.48	

[a] Low *p*-values suggest rejection of the null hypothesis. For example, in Case A this would imply that speculator positions (*PNL*) are significant in explaining returns (*R*).
[b] *, **, and *** denote rejection of the null hypothesis at a significance level of 10%, 5%, and 1% respectively.

Table 3.2. Optimal Number of Lags for Time-Domain Causality Tests.

	Case A: *PNL* does not cause *R*		Case B: *R* does not cause *PNL*		Case C: *PNL* does not cause *V*		Case D: *V* does not cause *PNL*	
	PNL Lags	*R* Lags	*PNL* Lags	*R* Lags	*PNL* Lags	*R* Lags	*PNL* Lags	*R* Lags
Cocoa	2	1	1	1	1	1	1	1
Coffee	3	1	1	1	1	1	1	3
Copper	1	7	1	2	1	1	1	3
Corn	7	1	1	7	1	1	1	4
Cotton	2	6	1	1	1	1	1	1
Feeder Cattle	7	1	1	1	1	1	1	2
Gold	7	1	1	1	1	1	1	7
Heating Oil	2	7	1	1	1	1	1	1
Lean Hogs	4	1	1	1	1	1	1	2
Live Cattle	1	6	1	1	1	1	1	7
Natural Gas	1	4	1	3	1	1	1	3
Oil	2	7	1	1	1	1	1	1
Silver	4	1	1	1	1	1	1	7
Soy Meal	7	1	1	3	1	1	1	3
Soy Oil	7	1	1	1	1	1	1	2
Soybeans	7	1	1	7	1	1	1	1
Sugar	5	1	1	1	1	1	1	1
Wheat (CME)	3	1	1	5	1	1	1	1
Wheat (KC)	3	1	1	6	1	1	1	6
SUR	7	7	7	7	7	7	7	7

Conversely, the null hypothesis that R does not cause PNL (Case B) is strongly rejected both on a commodity-by-commodity basis as well as in the SUR model. This result provides an even more compelling argument against the notion that speculators have been driving futures prices by suggesting the opposite: that speculators are actually responding to changes in futures prices by changing their positions. This is a result that is consistent with those obtained elsewhere and in reference to commodity index traders (Sanders, Boris, and Manfredo, 2004; Stoll and Whaley, 2010; Sanders and Irwin, 2010; Sanders and Irwin, 2011).

Pairwise, the existence of causality between speculator positions (PNL) and volatility (V) is somewhat less conclusive than between speculator positions and returns (R). However, results for Case C suggest slight evidence that speculator positions contribute to fluctuations in volatility. In Case C, the null hypothesis is rejected for 10 out of 19 commodities at the 5% significance level. Conversely, the null hypothesis is only rejected for two commodities in Case D. These results provide some evidence that volatility is in fact affected by speculator positions, but clearly show that speculators do not in general respond to changes in volatility.

3.6.2. Frequency-Domain Causality

As explained earlier, conducting tests of causality in the frequency domain is relevant to gain insight into the possibility that conclusions of directional causality differ in the long run as opposed to the short run. Causality is tested for each commodity at individual (angular) frequencies. Since frequency is the inverse of period length, a low frequency corresponds to a long period length or cycle. Therefore, frequencies approaching 0 are indicative of a long-run scenario (long cycles), whereas frequencies approaching π are indicative of a short-run scenario (short cycles). To be consistent with the SUR model, the VAR model specification here consists of 7 lags for each commodity.

Figure 3.4 through Figure 3.7 present the collective results of the frequency-domain causality tests in quantile plots. *P*-values are read from the vertical axis for a given angular frequency measured on the horizontal axis. As before, a high *p*-value suggests rejection of the null hypothesis for the particular case in question. The solid vertical lines within the figure represent reference period lengths, from left to right, of 1 year, 3 months, and 1 month.[7] The horizontal dotted line provides a reference of 5% significance. Thus, a quantile plot that lies below the dotted line suggests that we should reject the null hypothesis of no significance.

[7] It should be noted that the vertical reference lines representing period length are not equidistant because period length is inversely related to frequency. The figure is constructed with points equidistant in frequencies.

From these frequency-domain causality tests, there are several key pieces of information that provide additional insight beyond the conventional time-series tests presented above. First, it can be seen from Figure 3.4 that there is very little evidence that speculator positions affect futures prices, whether the long run (left side of the plot) or short run (right side of the plot).

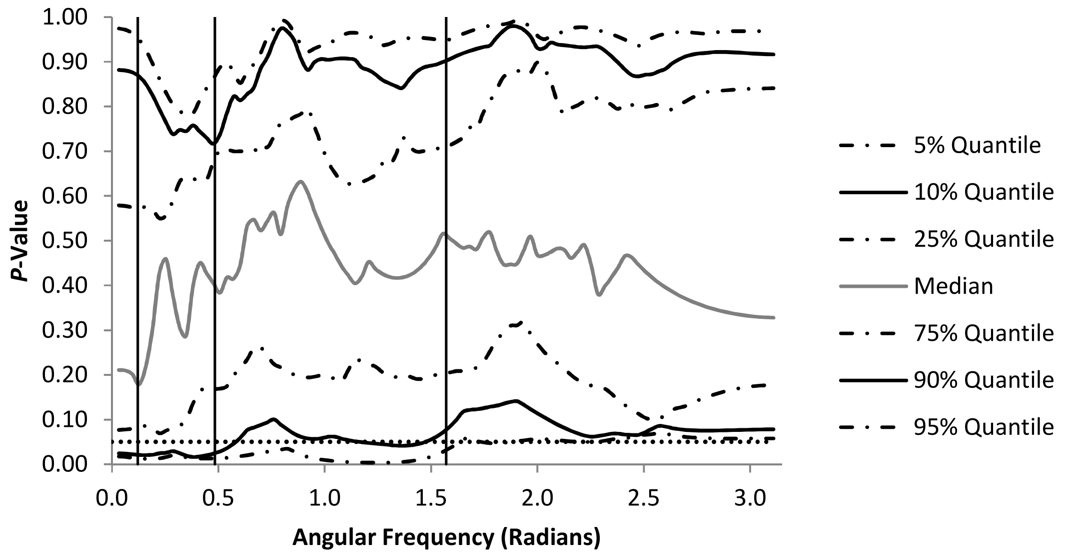
The second main result of this spectral analysis is an entirely opposite result for Case B seen in Figure 3.5. Here, it is apparent that speculators seem to respond to futures price changes mostly in the long run and less so in the short run, with the 75% quantile plot showing rejection of the null hypothesis at the 5% significance level for any period length above 3 months. This result, combined with that obtained from Figure 3.4, is intuitively mutually supportive. There is very little evidence from Figure 3.4 that prices are affected by speculative trading, but rather that speculators ultimately determine their positions in accordance with long-run price projections.

As in the case of the time-domain causality tests, the relationship between volatility and speculator positions is also somewhat ambiguous here. From Figure 3.6, there is an interesting pattern that emerges as volatility is most strongly affected by speculator positions within a period length of 2-3 months (to the right of the second vertical reference line). From Figure 3.7, it can be seen that there is very little evidence, collectively, that volatility is a significant factor in explaining speculator positions. Both of these results are generally consistent with the results obtained from the time-domain causality tests.

Finally, given the overall significance, publicity, and controversy within the oil and corn markets, graphs for these two commodities are presented individually in Figure 3.8 and Figure 3.9, respectively. Interestingly, these two figures tell a rather similar story. For both commodities, the null hypothesis that changes in futures prices do not affect speculator positions (Case B) is rejected in the long run (more than 3 months). For oil, the null hypothesis cannot be rejected for some period lengths shorter than 1 month. Results for Case D are quite similar with the null hypothesis that volatility does not cause speculator positions being rejected for period lengths greater than 2 months. This suggests evidence that speculators also respond to volatility in the long run in these two markets.[8]

Figure 3.8 and Figure 3.9 convey slightly differing results regarding Cases A and C. Although there is almost no evidence that speculator positions explain changes in either oil and corn futures prices in the long run, there is some evidence of explanatory power in the short run (1-3 weeks) for corn. There is, on the other hand, little evidence that oil futures prices are affected by positions in the short run. The figures also provide little evidence to reject Case C's null hypothesis at any frequency, i.e., volatility does not appear to be affected by speculator positions—in either market.

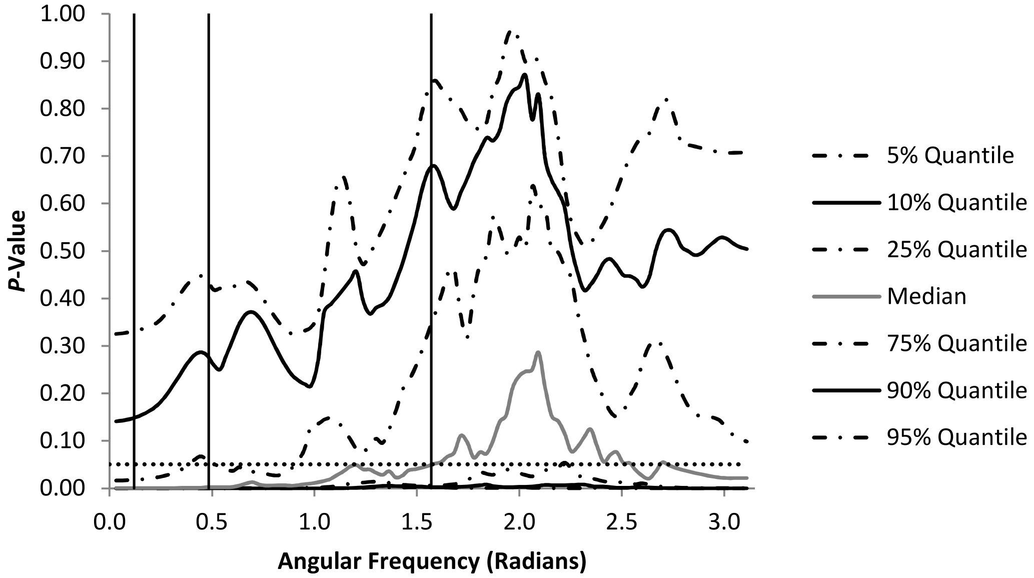
Figure 3.4. H_0: Speculator Positions Do Not Explain Futures Price Changes (Case A).



Note: From left to right, the vertical lines in the above figure serve as reference lines corresponding to period cycles of 1 year, 3 months, and 1 month.

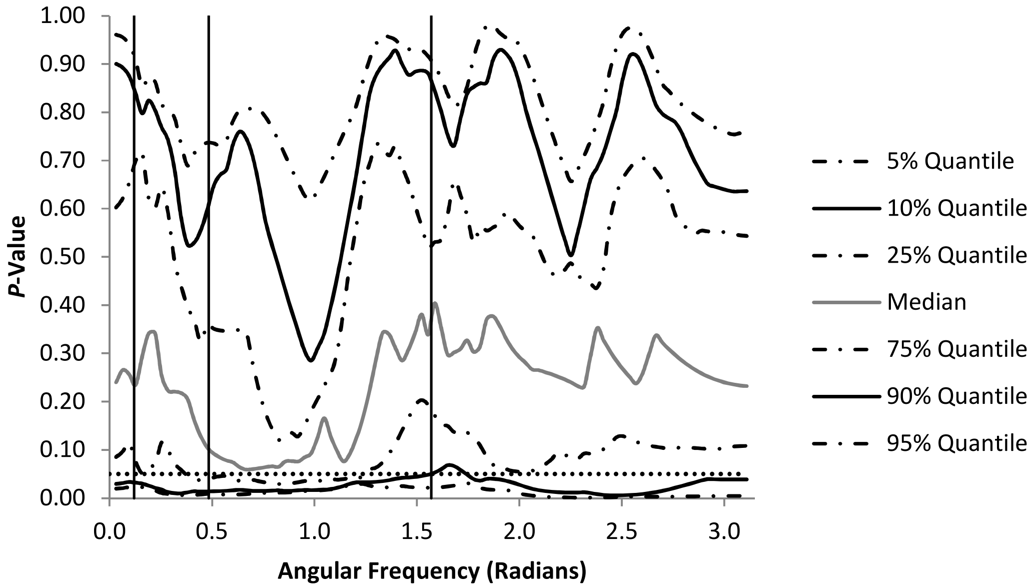
[8] Interestingly, the time-domain results reported in Table 3.1 show no evidence to reject the null hypothesis for Case D in either the oil or the corn market.

Figure 3.5. H_0: Changes in Futures Prices Do Not Explain Speculator Positions (Case B).



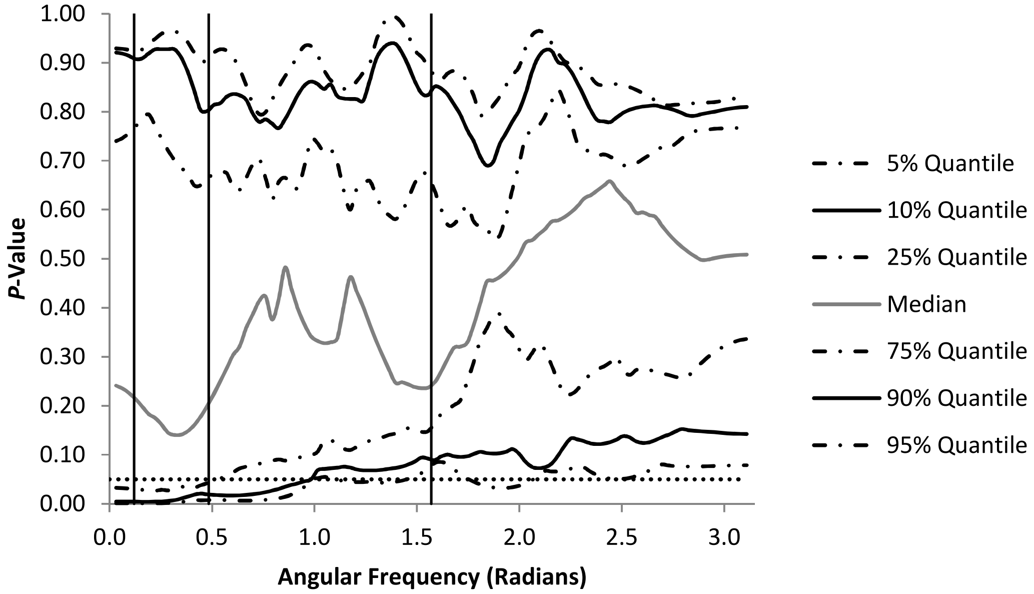
Note: From left to right, the vertical lines in the above figure serve as reference lines corresponding to period cycles of 1 year, 3 months, and 1 month.

Figure 3.6. H_0: Speculator Positions Do Not Explain Futures Price Volatility (Case C).



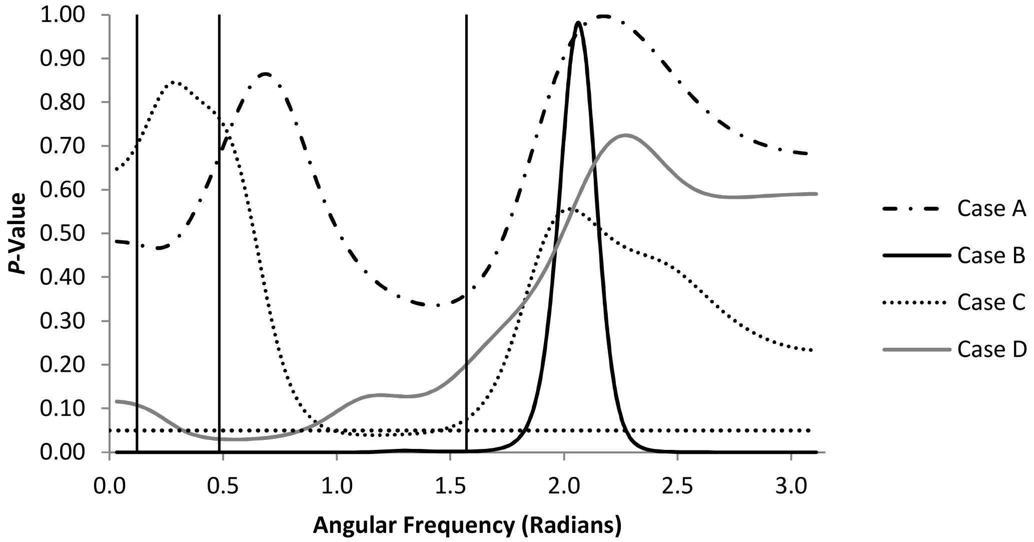
Note: From left to right, the vertical lines in the above figure serve as reference lines corresponding to period cycles of 1 year, 3 months, and 1 month.

Figure 3.7. H_0: Futures Price Volatility Does Not Explain Speculator Positions (Case D).



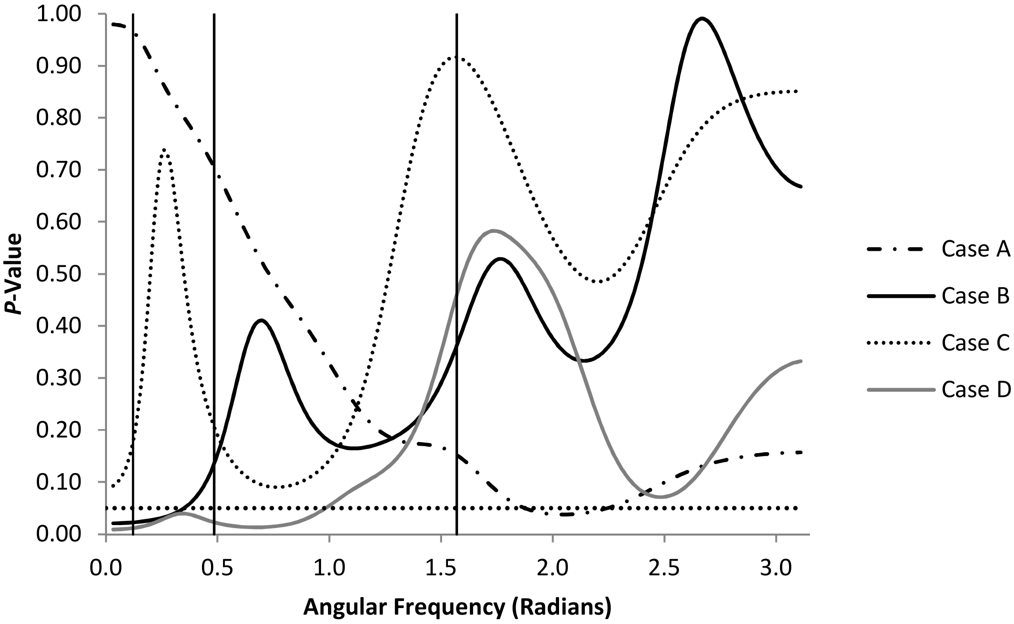
Note: From left to right, the vertical lines in the above figure serve as reference lines corresponding to period cycles of 1 year, 3 months, and 1 month.

Figure 3.8. Frequency-Domain Causality Tests (Oil).



Note: From left to right, the vertical lines in the above figure serve as reference lines corresponding to period cycles of 1 year, 3 months, and 1 month.

Figure 3.9. Frequency-Domain Causality Tests (Corn).



Note: From left to right, the vertical lines in the above figure serve as reference lines corresponding to period cycles of 1 year, 3 months, and 1 month.

3.7. Conclusion

There has been substantial debate recently as to the extent that speculators have been driving commodity futures prices higher with their increasingly long positions in futures markets during periods of price increases. This study attempts to provide insight into this debate by testing for causal linkages for 19 commodities with actively traded futures markets. Pairwise, the set of relationships tested in this study are between i) speculator futures positions and changes in futures prices and ii) speculator futures positions and futures price volatility. Two methods of testing for causality are implemented: time-domain causality and frequency-domain causality (spectral analysis). Whereas tests conducted in the time domain seek to determine the extent to which past values of one time series significantly explain current values of another time series, tests conducted in the frequency domain seek to determine the fraction of the total power at a given frequency (or period length) of one series that is contributed by another series. This allows us to distinguish causality in the short run separately from causality in the long run according to period (cycle) length.

Collectively, the results from the time-domain causality tests find little evidence that speculator positions significantly explain changes in futures prices. Conversely, there is very strong evidence that changes in futures prices significantly explain speculator positions. This is true on a commodity-by-commodity basis as well as in the aggregate SUR model framework. The time-domain causality tests show some evidence that speculator positions explain futures price volatility. There is no evidence that the converse is true in this case, that speculator positions are explained by volatility.

The collective results of the frequency-domain causality tests provide significant additional insight into the more conventional time-domain causality tests. Intuitively so, our results show that there is much less evidence that speculator positions significantly explain futures price changes in the long run as opposed to the short run. Conversely, there is strong evidence that speculator positions are explained by futures price changes in the long run, but less so in the short run. As with the time-domain causality tests, directional tests for causality between speculator positions and futures price volatility are slightly more ambiguous. However, there is very little collective evidence that speculator positions are explained by futures price volatility. There is weak evidence of the converse, that futures price volatility is explained by speculator positions, particularly in a time-frame of 2-3 months.

Results of the frequency-domain causality tests were presented individually for oil and corn due to their economic significance. For neither commodity is there evidence that speculator positions explain changes in futures prices in the long run (i.e., beyond 1-3 weeks). There is, however, evidence of significant explanatory power in the short run (1-3 weeks) for corn. Also in both instances, there is strong evidence that changes in futures prices explain speculator positions in the long run (more than 3 months). There is statistically significant evidence that oil and corn speculator positions are explained by futures price volatility in the long run (more than 3 months) but not in the short run, and there is no evidence that speculator positions explain volatility at any time horizon.

The results of this study should be relevant for policymakers debating the extent to which speculator activity should be regulated in commodity derivatives markets. There is much rhetoric that speculators have been causing futures prices to increase by taking long positions in futures markets and have been causing undue volatility as well. Our study shows that it is possible that speculators have had some influence over price and volatility changes in the very short run (1-4 weeks) but shows no evidence of this influence at all in the long run (more than 3 months). If policymakers are concerned with the ability of speculators to drive futures prices higher and are proposing speculative trading limits to mitigate this risk, it may be more efficient to consider short-term trading restrictions to more appropriately target the unregulated market distortions.

3.8. Appendix

The purpose of this appendix is to provide an overview of spectral analysis for readers who are unfamiliar with this approach to testing for causality in the frequency domain. To first provide an intuitive understanding of what spectral analysis seeks to accomplish, a very simple illustrative example will be presented followed by a more formal theory.

3.8.1. Spectral Analysis Overview

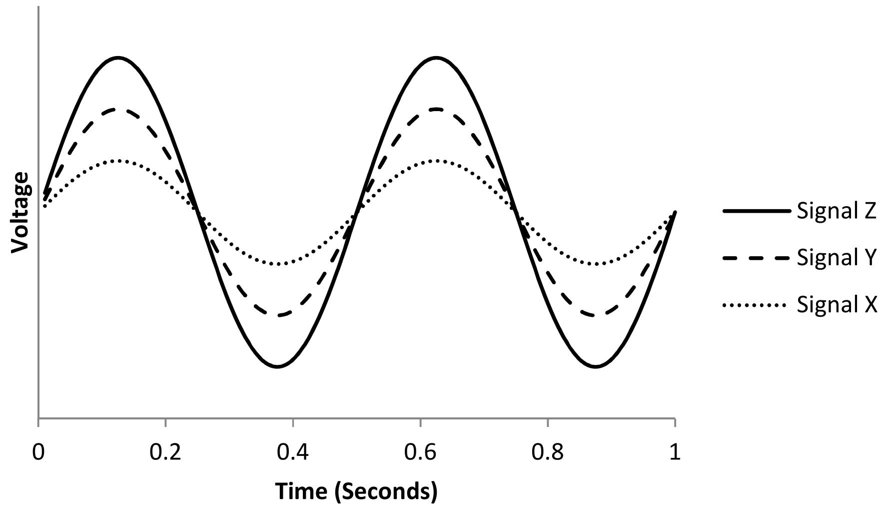
Consider the three signals displayed in Figure 3.10. The signals may be interpreted as sound waves in a wire measured over time, with the vertical axis representing voltage. As can be seen from the figure, the frequency of each of the three signals is exactly the same (2 Hz).[9] Suppose also that one maintains the hypothesis that signal Z is composed deterministically by the combination of signals X and Y. A test of causality would then seek to determine the extent to which signal X, for example, is a significant contributor to the overall power of signal Z (since they are all of the same frequency).

Utilizing a Fourier transform, these simple time series plots can be depicted as spectral density plots as shown in Figure 3.11. Since each signal is composed of only one frequency,

[9] 1 Hz equals 1 cycle per second. All signals in Figure 3.9 complete a cycle in 0.5 seconds, so they all have a frequency of 2 Hz.

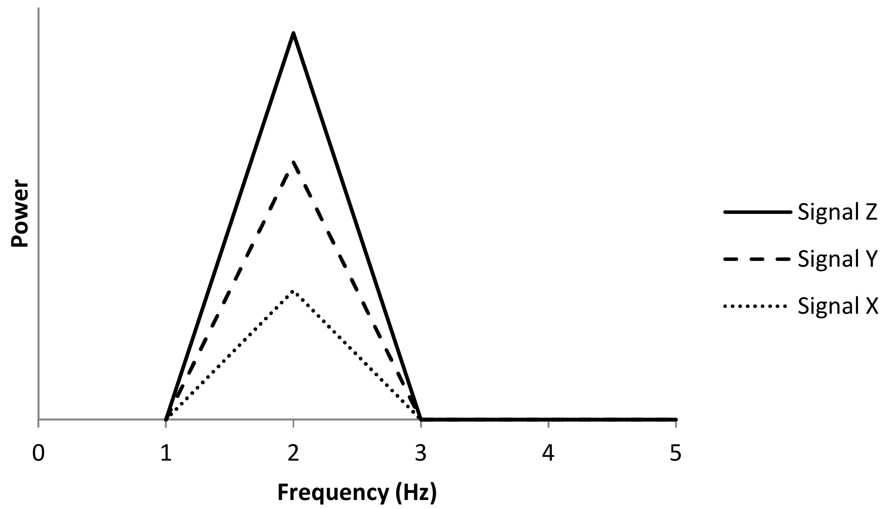
the spectral density plot consists of a peak at this frequency (2 Hz).[10] From a purely visual (non-statistical) perspective, it can be seen that signal X contributes much less to the fraction of total power at the 2 Hz frequency of signal Z than does signal Y. In an extremely simplified form, this is the essence of what causality in the frequency-domain seeks to explain. In a more realistic setting, signal Z would consist of many different frequencies. Signals X and Y would not perfectly explain signal Z and there would also be unobservable noise (error terms) apparent in time-series Z. As such, the spectral density plot of signal Z would be substantially more complex and it would be nearly impossible to draw conclusions of frequency-domain causality visually. As in our study, one would employ spectral analysis to draw statistical conclusions.

Figure 3.10. 2 Hz Sin Waves of Varying Amplitude.



[10] Note that power, indicated on the vertical axis of Figure 3.10, is a measure that can be interpreted as the square of voltage and does not refer to power in the statistical sense of hypothesis testing.

Figure 3.11. Power Spectral Density of 2 Hz Sin Waves.



3.8.2. Spectral Analysis Theory

Consider time series data produced by some univariate data generating process X_t. Supposing the first moment of this process is $m_t \equiv E[X_t] = 0$, the second moments are written as $\sigma^2 \equiv E[(X_t)^2]$ and $\mu_\tau \equiv E[X_t X_{t-\tau}]$. In conventional time series applications, the series x_t consists only of real numbers. However, a generalization can be made such that x_t is a series of complex numbers. The above moments can then be written as $\bar{\sigma}^2 \equiv E[X_t \bar{X}_t]$ where $\bar{X}$ is the complex conjugate of X. (It can be noted that excluding complex numbers results in a specification of moments as in σ^2 and μ_τ.) This generalization allows one to conduct spectral analysis in the frequency domain as opposed to the originally-specified time domain.

Given the series x_t, a Fourier transformation allows the series to be transformed from the time domain to the frequency domain as follows:

$$f(\omega) = \frac{1}{\sqrt{2\pi}} \int f(t) e^{-i\omega t} dt \qquad (3.20)$$

where ω is measured in angular frequency, $f(t)=X_t$, and $f(\omega)$ is the spectral density of the series. If the data generating process X_t, Y_t is bivariate and wide-sense stationary, the autocorrelation and cross-correlation functions specified in the time domain are:

$$V_{xx}(\tau)=\lim_{T\to\infty}\frac{1}{T}\int_0^T x(t)\,x(t+\tau)\,dt \tag{3.21}$$

$$V_{xy}(\tau)=\lim_{T\to\infty}\frac{1}{T}\int_0^T x(t)\,y(t+\tau)\,dt \tag{3.22}$$

Applying the transformation given in (3.20) to the functions in (3.21) and (3.22) results in autospectral and cross-spectral densities as follows:

$$S_{xx}(\omega)=\int_{-\infty}^{\infty} V_{xx}(t)\,e^{-i\omega t}\,dt \tag{3.23}$$

$$S_{xy}(\omega)=\int_{-\infty}^{\infty} V_{xy}(t)\,e^{-i\omega t}\,dt \tag{3.24}$$

It can be noted here that equations (3.23) and (3.24) represent a general form for the elements of matrix S presented in equation (3.13), which are correspondingly used for hypothesis testing as outlined in the text.

3.9. References

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CHAPTER 4. A BOUNDS-TESTING EMPIRICAL ANALYSIS OF GRANGER CAUSALITY IN COMMODITY FUTURES SPECULATION

4.1. Abstract

Speculation in commodity derivative markets has frequently been blamed for exacerbating futures price or volatility increases. However, speculation may be defined in various ways. We propose two distinct measures to address the empirical question of whether speculation has indeed been a causal factor. One measure represents the net long position of speculators, a flow, and the other the absolute magnitude, a stock. We use a bounds-testing approach to account for potential level relationships among variables of interest. This allows us to distinguish long-run causality from the short-run using an error correction model when appropriate. We find little evidence suggesting that speculation influences futures prices in either the long-run or short-run. There is, however, some evidence that speculation influences volatility. We find convincing evidence that speculative trading is affected by futures prices, particularly in the short-run.

4.2. Introduction

Derivative instruments are generally claimed to provide two essential benefits to commodity markets: price discovery and risk management. Commodity producers, consumers, and handlers frequently use derivatives to hedge various forms of risk connected to the production of an underlying asset. As these instruments are available for anyone to trade, entities with no commercial attachment to the underlying asset, speculators, may also choose to invest. Over the years, however, speculators have been frequently blamed for driving commodity prices and volatility to fundamentally unwarranted levels to the detriment of both producers and consumers. As such, the extent to which speculators should be allowed to participate in these markets has been a subject of intense political debate. Perhaps the most notable historical example of policy actively addressing this concern was the ban on onion futures trading, enforced in 1958 and still in effect today.

The debate surrounding speculation has continued in recent years as commodity prices surged to unprecedented levels in mid-2008 and again in 2010-2011. The passing of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010 has given further authority to the Commodity Futures Trading Commission (CFTC) to regulate derivative markets. Furthermore, in October 2011, the CFTC voted to mandate position limits in an effort to curb what has been termed excessive speculation.

This regulation and disapprobation directed at speculators has advanced despite a considerable literature finding very little evidence that speculators have in fact played a role in exacerbating price or volatility increases (Sanders, Boris, and Manfredo, 2004; Irwin, Sanders, and Merrin, 2009; Sanders and Irwin, 2010; Stoll and Whaley, 2010; Sanders and Irwin, 2011; Buyuksahin and Harris, 2011; CFTC, 2008a; Aulerich, Irwin, and Garcia, 2010). Much of this literature has focused on passive investment in commodity indexes through managed funds, exchange traded funds (ETFs), or exchange traded notes (ETNs) benchmarked to popular indexes such as the S&P GSCI or DJ-UBSCI. The reason for this focus has been due to the passive net long positions of these holdings, as contracts are rolled just prior to expiration. Presumably, this is in an effort to realize gains from commodity price appreciation over time.

There are, however, those who have claimed a causal link exists between speculative trading and increases in commodity prices or volatility. In an International Food Policy Research Institute (IFPRI) report, Robles, Torero, and von Braun (2009), find evidence that speculation has influenced food prices. Tang and Xiong (2010) claim that the "financialization" of commodity markets has resulted in prices no longer being solely determined by fundamentals of supply and demand. As recently as October 2011, in commemoration of World Food Day, a letter was submitted by Oxfam America jointly addressed to G20 finance ministers, U.S. Treasury Secretary Timothy Geithner, and the CFTC imploring further regulation to curb excessive speculation (Geewax, 2011). The letter was endorsed by over 450 economists around the world. Michael Masters, a hedge fund manager, has been unequivocal in his insistence that commodity futures markets are becoming dominated by speculative interests resulting in excessive price increases and volatility swings, thereby undermining the conventional benefits of derivative markets (Masters, 2008). In regards to these claims, academics have responded that they are weakened by a heavy reliance on the argument that correlation implies causation (Irwin, Sanders, and Merrin, 2009; Stoll and Whaley, 2010). It is certainly clear that speculative investments in commodity futures markets have increased dramatically in the past decade, at a time when commodity prices also surged to unprecedented levels. It is less clear, however, that these investments have been the driving factor of price and volatility spikes.

One of the most common statistical approaches used to test for a causal link between commodity speculation and prices or volatility, adopted by many of the references cited earlier, is that of Granger causality (Granger, 1969) in a bivariate framework. The rationale behind such tests is that one event should precede another in time if it is a causal factor. An assumption in these studies, however, has been that there is only one measure taken to be representative of commodity market speculation. This measure is most often based on some variant of open interest for a certain class of traders in data made available by the CFTC as part of its large trading reporting system.[1] A limitation of this approach is that one is effectively choosing whether it is the "stock" (magnitude of speculation) or "flow" (change in net long positions) of speculative trading that should be used to test for causality. Aulerich, Irwin, and Garcia (2010) recognize this issue and use two models individually to test for causation, with the stock being used in one model and the flow separately in another, with results presented separately as well.

There is a conceptual problem, however, that arises when modeling the stock effect of speculation on futures prices. So as to obtain a stationary series, prices are typically differenced (or taken as returns) and causality is tested in the following model.[2]

[1] These data are publicly available and published weekly by the CFTC. The data will be described in more detail in section 4.3 of this paper.
[2] For the purposes of illustration, only one lag of each variable is included as a regressor. The scope of what follows would not change if there were additional lags.

$$\Delta P_t = \alpha + \beta X_{t-1} + \gamma \Delta P_{t-1} + \varepsilon_t \tag{4.1}$$

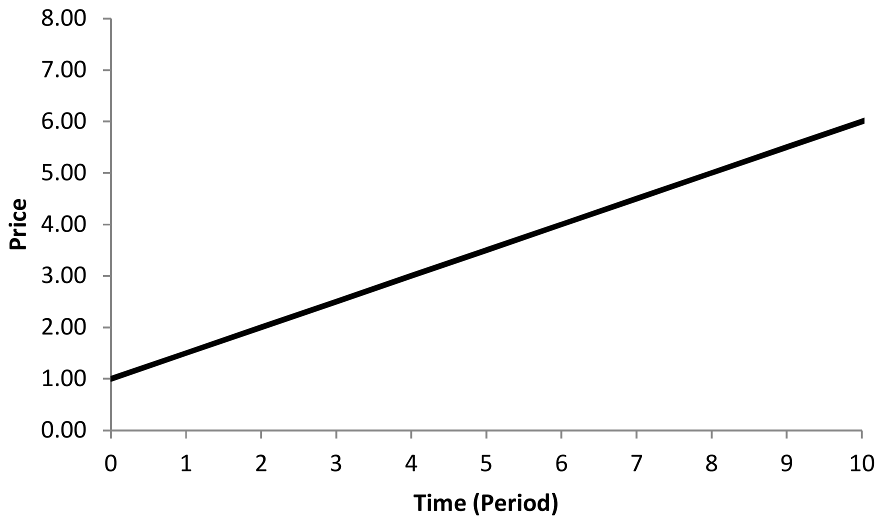
In this model, $\Delta P_t \equiv P_t - P_{t-1}$, where P_t is the price at time t, $X_{t-1} \equiv \frac{SL_{t-1}}{(SL_{t-1} + HL_{t-1})}$, is the percentage of long open interest held by speculative traders, and SL_{t-1} (HL_{t-1}) is the number of speculator (hedger) long positions in contracts.[3] In this case, speculation is said to "Granger cause" futures prices if one rejects the null hypothesis that $\beta = 0$.

Suppose that β is estimated in a regression based on equation (4.1), and for simplicity assume that $\hat{\beta} = 1$ and $\alpha = \gamma = 0$. Normalizing P_0 to unity, ΔP would be a simple 45 degree line as a function of X with an intercept of 0. Suppose that $SL_0 = HL_0 = 1$, so that $X_0 = 0.5$. This would imply that $P_1 = 1.5$. Now suppose that SL and HL stay unchanged at $SL_t = HL_t = 1$ for many periods, resulting in an unchanged speculative measure, $X_t = 0.5$. In this situation, $P_2 = 2$, $P_3 = 2.5$, and so on. That is, price continues to increase indefinitely over time even though the extent of speculation remains the same. This is illustrated in Figure 4.1 with price a function of time.

A potential solution to this problem would be to regress price levels on X rather than in differenced form, ΔP. However, P is typically found to be integrated of order 1, $I(1)$, whereas X may or may not be stationary. The matter may be further complicated by the addition of other exogenous variables that also may or may not be stationary. Another possible solution might be to use X in first-differences if all variables are believed to be non-stationary, but this does not account for the possibility that the variables may be cointegrated.

[3] Alternatively, one could use $R_t = ln(\frac{P_t}{P_{t-1}})$ in place of ΔP_t. ΔP_t is used for ease of exposition.

Figure 4.1. Price as a Function of Time, Given Level of Speculation, $(P_t \mid X_t)$**.**



Our paper contributes to the existing empirical literature seeking to determine the effect, or lack thereof, of speculation on prices and volatility (or the reverse) in two ways. First, we simultaneously include both a "stock" and "flow" measure of speculation into one model to capture two different effects of speculation. Second, we test for causality in the long-run as distinct from the short-run. Causality in the long-run is implied by the existence of level relationships among variables of interest. Our methodology applies the bounds-testing approach developed by Pesaran, Shin, and Smith (2001), henceforth denoted as PSS. Using this approach, we first account for possible cointegrating relationships before testing for short-run Granger causality. Data on trader positions for 19 different commodity markets are obtained from the aforementioned commitment of traders (COT) reports and disaggregated commitment of traders (DCOT) reports published weekly by the CFTC.

In the event that there is evidence of cointegration, an error correction model is applied when subsequently testing for Granger causality. Evidence of causality due to exogenous regressors beyond the significance of an error correction term would stem from a short-run relationship. This approach has been used in economic applications when there is some ambiguity in determining whether exogenous explanatory variables of interest are $I(0)$ or $I(1)$ (Narayan and Smyth, 2003; Tang and Lean, 2009; Groenewold and Tang, 2007; Keho, 2009; Wolde-Rufael, 2006). The approach does not require pretesting whether these variables are $I(0)$ or $I(1)$ when testing for cointegration.[4]

There are two key empirical results highlighted in this paper. First, we find no evidence to support claims that futures prices have been affected by speculative trading. This is a result that is consistent with previous literature that has largely focused on commodity index traders. Second, and more novel to this paper, we find some evidence that speculative trading has influenced futures price volatility, particularly in the long-run. We also find that speculative trading is strongly affected by futures prices in the short-run.

The remainder of this paper is organized as follows. Section 4.3 describes the CFTC data used for our analysis in detail, including potential limitations and weaknesses. Section 4.4 provides the methodology we use to test for cointegration and short-run Granger causality. Section 4.5 presents a discussion of the main results and potential policy implications. Section 4.6 provides concluding remarks.

4.3. Data

In this paper we seek to determine whether speculator positions affect futures prices or volatility in the sense of "Granger causality." We also test the reverse, whether futures prices or volatility affect speculator positions. We make a distinction between short-run and long-run causality by first testing for the existence of cointegrating relationships. The following discussion will describe the data used for speculator positions, followed by a brief discussion of how matching futures prices and volatility data were obtained.

In an effort to maintain transparency in commodity derivative markets, the CFTC publishes weekly, and makes publicly available, data on trader positions in its commitment of traders (COT) reports as part of its large trader reporting system (LRTS). Through the LRTS, traders are required to report their positions if they meet or exceed the daily commodity-specific limit set by the CFTC at market close. Traders are classified as either

[4] Technically speaking, the PSS approach allows us to detect the existence of a long-run level relationship. This is a cointegrating relationship when the dependent variable series contains a unit root and the estimated residuals of the model are stationary. When the variables are stationary, this should be interpreted as a long-run level relationship (not cointegration).

commercial or non-commercial entities, with an additional non-reporting classification used so that total open interest is accurately reflected in the reports. Data are collected on positions in each outstanding contract for a given commodity and subsequently aggregated so that the final reports show open interest (on both the long and short side) for a given trader classification in all outstanding contracts. Reports are provided for “futures only” contracts as well as a “futures and options combined” format, where options are converted into futures contracts based on delta-weighting.

In an attempt to provide further transparency, the CFTC began publishing disaggregated commitment of traders (DCOT) reports in 2009 with data retroactively compiled dating back to June 2006. The DCOT reports also show open interest for all outstanding futures contracts (or also futures-and-options combined) as provided in the COT reports. These reports disaggregate the classification of traders into four distinct categories. The first is producers, merchants, processors, or users (traders with a direct connection to the underlying asset, typically interpreted as hedgers). The second is swap dealers, which are difficult to categorize precisely as speculators or hedgers because clients may include counterparties of either group. Money managers and other reportables constitute the third and fourth groups of traders in the DCOT reports. As in the COT reports, the DCOT reports also use non-reportable positions to reconcile total open interest.

For our analysis, we use data from both COT and DCOT futures-only reports. The advantage of the COT reports is that weekly data are available beginning in 1992, thereby providing more observations. The advantage of the DCOT reports, at the expense of a longer data set, is that trader classifications are somewhat more precise, specifically for commercial traders. Using the COT reports, speculators are defined in our analysis as both non-commercial (large speculators) and non-reporting traders (small speculators). Using the DCOT reports, speculators are defined as managed money funds, other reportables, and non-reportables. The range of data available from the COT reports is October 1992 to October 2011. For DCOT reports, the data are available from June 2006 to October 2011.

Beginning in 2006, the CFTC also began publishing another data set showing open interest held by traders classified as “index traders” in a supplemental commitment of traders (SCOT) report. This classification of traders was discussed in the previous section and has been the focus of significant political debate and in-depth econometric analysis. Index traders are extracted from both commercial and non-commercial categories in the COT reports and are reported as a separate classification of traders in the SCOT reports.

Our analysis does not focus on index traders for three main reasons. First, previous studies referenced earlier have explored the effect of index traders on prices in some detail. Second, and more fundamentally, we seek to determine the extent to which speculators are affecting (or are affected by) futures prices or volatility. Commodity index traders are considered passive investors and, as noted by Stoll and Whaley (2010), they are not speculators. They do not typically take a directional view on commodity markets and thus do not fit within our definition of speculation. Third, as shown by Sanders, Irwin, and Merrin (2010), approximately 85% of index trader positions (for agricultural futures markets) are held by swap dealers. In the DCOT reports, swap dealers have been removed from the category of commercial traders used in the original COT reports. As noted earlier, swap dealer counterparties may include both speculators and hedgers. Our analysis focuses on speculators. Including swap dealers would dilute this analysis substantially.

We use two measures to represent speculative trading. The first of these is $S_t^1 \equiv SL_t / SS_t$, measuring the extent to which speculators maintain a relative long-to-short position, with SL_t corresponding to speculative long positions and SS_t corresponding to speculative short positions. This measure is somewhat analogous to the "percent net long" measure used by other studies e.g., (Sanders, Boris, and Manfredo, 2004; CFTC, 2008a). The second measure we use is $S_t^2 \equiv SOI_t / HOI_t$ where SOI_t is total speculator open interest and HOI_t is total hedger open interest at time t.[5] This is somewhat analogous to one of the two measures used by Aulerich, Irwin, and Garcia (2010) and is motivated by Working's (1960) measure of excessive speculation. Working's measure is commonly referred to as the

[5] Using COT data, "commercial" investors are treated as hedgers. Using DCOT data, "producers, merchants, users, and processors" are treated as hedgers.

"T-index" and seeks to quantify speculation as excessive only relative to the needs of hedgers.

COT and DCOT reports provide weekly position data as of Tuesday's market close. A matching series of nearby futures prices reflecting settlement prices is then used for the price series P_t. Rolling is assumed to occur 14 days prior to expiration of the nearby contract, at which point the first deferred contract becomes the nearby used in the price series. Futures price volatility is calculated as the (mean of the) log-range estimate proposed by Alizadeh, Brandt, and Diebold (2002).

$$V_\tau = \frac{1}{T}\sum_{\tau=1}^{T} \ln\left(\ln\left(h_\tau\right) - \ln\left(l_\tau\right)\right) \tag{4.2}$$

In (4.2), h_τ (l_τ) denote the daily high (low) observed futures prices. Values of $\tau = 1, 2, \ldots, T$ correspond to days of the week between successive position observations, with $\tau = T$ corresponding to each Tuesday, the day that position data are made available. For weeks in which a "limit-movement" day has occurred (i.e., $h_\tau = l_\tau$), we use the median for the volatility estimate instead of the mean to avoid a measure of $-\infty$.

Before proceeding to the methodology, some of the weaknesses of the data must be addressed. One of the limitations inherent in the data collected by the CFTC through the LRTS is that it does not identify investors specifically based on their trading strategy, whether they are hedging or speculating. The CFTC data are trader-specific. This means that a trader classified as a commercial investor will have all trades classified as commercial, regardless of whether the intent is to hedge risk or to speculate. It is well known that commercial traders, due to their deep knowledge of the markets in which they operate, may have a unique opportunity to also place speculative trades. A possible justification for why this factor might be minimal, however, is that traders classified as commercial may often be internally prohibited from making speculative trades when considering tolerable risk exposure in business operations. It is also unlikely that a truly commercial investor would classify himself as non-commercial and thereby subject himself to speculative trading limits.

Another limitation of these data is that they are made available weekly and include all outstanding contracts when reporting open interest. The data do not show contract-specific open interest. Clearly, some information is lost by relying on weekly data as opposed to daily data. The use of nearby futures prices is also somewhat problematic, particularly if there is substantial open interest in deferred contracts. This problem is mitigated somewhat by recognizing that, for most commodities, the nearby contract is the most actively traded.

4.4. Methods

The purpose of this section is to outline the methodology used to assess causality. Formally, the null hypotheses are stated as follows in six separate cases.

$$\begin{aligned}
&H_0: \text{ Speculator positions do not Granger cause futures prices. (Case A)}\\
&H_0: \text{ Futures prices do not Granger cause speculator positions. (Case B1)}\\
&H_0: \text{ Futures prices do not Granger cause speculator positions. (Case B2)}\\
&H_0: \text{ Speculator positions do not Granger cause futures price volatility. (Case C)}\\
&H_0: \text{ Futures price volatility does not Granger cause speculator positions. (Case D1)}\\
&H_0: \text{ Futures price volatility does not Granger cause speculator positions. (Case D2)}
\end{aligned} \tag{4.3}$$

As discussed in the previous section, two measures of speculation will be used for this analysis, requiring us to test the effect of futures prices and volatility on speculation for each measure independently as in cases B1, B2 and D1, D2. As seen in (4.3), four data series are required for the hypothesis tests: two measures of speculation, futures price levels, and futures price volatility. Our methodology consists of two stages. In the first stage, we test for a cointegrating relationship between the dependent variable of interest and exogenous independent variables. This stage consists of a series of nested tests with the procedure outlined diagrammatically for Case A in Figure 4.2. This stage makes use of the bounds-testing approach within an autoregressive distributed lag (ARDL) framework proposed in PSS.

In the second stage, we test for short-run Granger causality. If in the first stage there is evidence of a cointegrating relationship, the second stage proceeds using an error correction term as warranted. If there is no evidence of cointegration, the second stage proceeds without the inclusion of an error correction term that would account for a long-run equilibrium relationship. A summary of the second-stage procedure is illustrated in Figure 4.3. The remainder of this section will describe these two stages in detail.

4.4.1. Stage One: Cointegration Tests

There is a conceptual problem with estimating the effect of speculation, as defined using our two measures, on the difference in prices (or returns), as is typically done to ensure stationarity. As discussed in the introduction, a resolution to this difficulty is to model the effect of speculation on price levels. Doing so, however, presents an additional problem in that prices typically contain a unit root.

The advantage of the PSS approach is that we do not need to know the order of integration of the exogenous explanatory variables to determine whether there is a cointegrating relationship. Whether the model exhibits cointegration may be definitively concluded depending on the magnitude of the F-statistic generated in this test. This is particularly useful in our application as the measures of speculation may be either $I(0)$ or $I(1)$.

As shown in PSS, the critical values that constitute the bounds are determined by assuming first that all regressors are purely $I(1)$, and then assuming they are all $I(0)$. If the resulting F-statistic is above the upper bound, we reject the null hypothesis of no cointegration, or more generally that there is no long-run level relationship between variables. If, on the other hand, the F-statistic is below the lower bound, we fail to reject the null hypothesis of no cointegration. If the F-statistic lies between the lower and upper bound, we cannot conclusively determine whether cointegration exists.

Figure 4.2. Stage One: Procedure for Long-Run Level Relationship Tests.

Determine optimal dependent variable lag length by minimizing AIC of an AR model.

$$\Delta P_t = \alpha^{AR} + \sum_{i=1}^{k} \beta_i^{AR} \Delta P_{t-i} + \varepsilon_t^{AR}$$

Specify the full model and determine optimal independent variable lag lengths.

$$\Delta P_t = \alpha + \sum_{h=1}^{k^*} \beta_h \Delta P_{t-h} + \sum_{i=0}^{m^*} \gamma_i \Delta S_{t-i}^1 + \sum_{j=0}^{n^*} \delta_j \Delta S_{t-j}^2 + bP_{t-1} + gS_{t-1}^1 + dS_{t-1}^2 + \varepsilon_t$$

Conduct an F-test of $H_0^1 : b = g = d = 0$, $H_A^1 : b \neq 0, g \neq 0, \text{or } d \neq 0$

Reject H_0^1? — No → Conclude that there is no evidence of a level relationship between variables. → $ECT_t = \varnothing$

Yes ↓

Conduct a t-test of $H_0^2 : b = 0$, $H_A^2 : b \neq 0$

Reject H_0^2? — No → (Type 1 Degeneracy). Conclude that there is no evidence of a long-run level relationship between variables. $P \sim I(1)$ → $ECT_t = \varnothing$

Yes ↓

Conduct an F-test of $H_0^3 : g = d = 0$, $H_A^3 : g \neq 0 \text{ or } d \neq 0$

Reject H_0^3? — No → (Type 2 Degeneracy). Conclude that there is no evidence of a long-run level relationship between dependent and independent variables. $P \sim I(0)$ → $ECT_t = \varnothing$

Yes ↓

Specify a long-run relationship in levels.

$$P_t^{LR} = a^{LR} + g^{LR} S_t^1 + d^{LR} S_t^2 + \varepsilon_t^{LR}$$

Is S_t^1 significant? — No → Conclude a long-run level relationship between P_t and S_t^2. Cointegration if $P_t \sim I(1)$ and ε_t^{LR} stationary. → $ECT_t = \widehat{\varepsilon_t^{LR}}$, $g^{LR} = 0$

Yes ↓

Is S_t^2 significant? — No → Conclude a long-run level relationship between P_t and S_t^1. Cointegration if $P_t \sim I(1)$ and ε_t^{LR} stationary. → $ECT_t = \widehat{\varepsilon_t^{LR}}$, $d^{LR} = 0$

Yes ↓

Conclude there is a long-run level relationship between P_t and both S_t^1 and S_t^2. A cointegrating relationship if $P_t \sim I(1)$ and ε_t^{LR} stationary. → $ECT_t = \widehat{\varepsilon_t^{LR}}$ → Proceed to short-run causality tests (stage two).

Figure 4.3. Stage Two: Procedure for Short-Run Granger Causality Tests.

Specify the full model with error correction term (ECT_t) included when warranted.

$$\Delta P_t = \alpha^{SR} + \sum_{h=1}^{k^*} \beta_h^{SR} \Delta P_{t-h} + \sum_{i=1}^{m^*} \gamma_i^{SR} \Delta S_{t-i}^1 + \sum_{j=1}^{n^*} \delta_j^{SR} \Delta S_{t-j}^2 + \phi ECT_{t-1} + \varepsilon_t^{SR}$$

↓

Conduct an F-test of $H_0^4 : \gamma_i^{SR} = \delta_j^{SR} = 0, \forall i, j$, $H_A^4 : \gamma_i^{SR} \neq 0, \delta_j^{SR} \neq 0,$ for any i, j.

Reject H_0^4?

No → STOP: Conclude there is no evidence that speculation Granger causes futures prices.

Yes → STOP: Conclude there is evidence that at least one measure of speculation Granger causes futures prices.

The first stage, testing for a long-run level relationship among a set of variables, begins by initially specifying an AR model for the dependent variable as follows,[6]

$$\Delta P_t = \alpha^{AR} + \sum_{i=1}^{k} \beta_i^{AR} \Delta P_{t-i} + \varepsilon_t^{AR} \tag{4.4}$$

$$\Delta S_t^1 = \alpha^{AR} + \sum_{i=1}^{k} \beta_i^{AR} \Delta S_{t-i}^1 + \varepsilon_t^{AR} \tag{4.5}$$

Optimal AR lag length k^* is chosen by minimizing the Akaike Information Criteria (AIC) for each case. We allow for a maximum number of dependent or independent variable lags of seven. Once the optimal number of dependent variable lags has been chosen, the full model is specified as follows,

[6] Only the methodology for Cases A and B1 described in (4.3) will be presented in our exposition henceforth so as to save space. The remaining cases (B2, C, D1, and D2) are entirely analogous. It should also be noted that the coefficients in these two equations are not the same although they appear as such. For example, α^{AR} in equation (4.4) is not the same as α^{AR} in equation (4.5). We present the equations in this manner to economize on notation.

$$\Delta P_t = \alpha + \sum_{h=1}^{k^*} \beta_h \Delta P_{t-h} + \sum_{i=0}^{m} \gamma_i \Delta S^1_{t-i} + \sum_{j=0}^{n} \delta_j \Delta S^2_{t-j} + bP_{t-1} + gS^1_{t-1} + dS^2_{t-1} + \varepsilon_t \quad (4.6)$$

$$\Delta S^1_t = \alpha + \sum_{h=1}^{k^*} \beta_h \Delta S^1_{t-h} + \sum_{i=0}^{m} \gamma_i \Delta P_{t-i} + \sum_{j=0}^{n} \delta_j \Delta S^2_{t-j} + bS^1_{t-1} + gP_{t-1} + dS^2_{t-1} + \varepsilon_t \quad (4.7)$$

Optimal independent variable lags are again chosen by minimizing the AIC in each case. Equations (4.6) and (4.7) provide a characterization of the unrestricted model used to test for the presence of cointegration. It should be noted that it is not necessary that the number of dependent and independent variable lags (k, m, n) be equal. The null hypothesis of no cointegration for the variables in equation (4.6) is: $H^1_0 : b = g = d = 0$ against the alternative that at least one of b, g, d is not equal to 0. The restricted models for Cases A and B1 are then,

$$\Delta P_t = \alpha^r + \sum_{h=1}^{k^*} \beta^r_h \Delta P_{t-h} + \sum_{i=0}^{m^*} \gamma^r_i \Delta S^1_{t-i} + \sum_{j=0}^{n^*} \delta^r_j \Delta S^2_{t-j} + \varepsilon^r_t \quad (4.8)$$

$$\Delta S^1_t = \alpha^r + \sum_{h=1}^{k^*} \beta^r_h \Delta S^1_{t-h} + \sum_{i=0}^{m^*} \gamma^r_i \Delta P_{t-i} + \sum_{j=0}^{n^*} \delta^r_j \Delta S^2_{t-j} + \varepsilon^r_t \quad (4.9)$$

The PSS bounds-testing approach allows us to potentially conclude that there is evidence of cointegration if the resulting F-statistic is above the value of the upper bound. We can conclude that there is no evidence of cointegration if the resulting F-statistic is below the value of the lower bound. As shown in PSS, the F-statistic obtained from this test has a non-standard distribution. Critical values for the bounds at various significance levels may be found in Table CI(iii) Case III of PSS. As seen in the table, the critical values depend on the number of exogenous regressors. Thus, critical values defining the bound in our model are (4.94, 5.73) for all cases.

As illustrated in Figure 4.2, a failure to reject H^1_0 leads us to immediately conclude that there is no evidence of a long-run level relationship between variables. The first stage ends and we would then test for short-run causality without the inclusion of an error correction term (ECT_t). On the other hand, if H_0^1 is rejected in favor of the alternative, we then test for the possibility of two types of degenerate level relationships as presented in PSS before continuing to the second stage with the inclusion of the error correction term.

The first type of degeneracy arises when the dependent variable (ΔP_t) does not depend on its own lagged level term (P_{t-1}), but only on the lagged level of the exogenous regressor(s), i.e., $b=0$ but $g \neq 0$ or $d \neq 0$. We use a t-test as specified by H_0^2 to test for this degeneracy. A failure to reject H_0^2 would imply that the dependent variable series is $I(1)$ and there is no meaningful interpretation to a long-run level relationship between dependent and independent variables.

If H_0^2 is rejected, we then test for the possibility of a second type of degeneracy. In this case, the dependent variable depends only on its own lagged level, and not on the lagged levels of any exogenous regressors. To formally test for this case, we conduct an F-test that these exogenous variables are jointly insignificant as specified by H_0^3 in Figure 4.2. A failure to reject H_0^3 again implies that there is no long-run level relationship between the dependent variable and exogenous independent variable(s). The second stage would proceed without the inclusion of an error correction term.

Once we have ruled out the possibility of these two types of degeneracy, we know there is a long-run level relationship with at least one, possibly both, exogenous regressors. The final step of this stage is to determine which exogenous regressors should be included in the specification of a long-run level relationship. As illustrated in Figure 4.2, we test for the significance of the two regressors in turn, S_t^1 and S_t^2 in the figure, with the error correction term equal to the fitted residuals with non-significant regressors excluded. This error correction term is then carried forward to the second stage and we may conclude that a long-run level relationship exists between the dependent variable and one, or both, exogenous regressors. This level relationship is a cointegrating relationship if it is true that the dependent variable series is $I(1)$ and ε_t^{LR} is stationary.

4.4.2. Stage Two: Short-Run Granger Causality

Testing for short-run causality is straightforward as illustrated in Figure 4.3. If the variables are determined to be cointegrated, an error correction term is included in the model prior to testing for short-run Granger causality. This error correction model is specified for cases A and B1 respectively as[7]

$$\Delta P_t = \alpha^{SR} + \sum_{h=1}^{k^*} \beta_h^{SR} \Delta P_{t-h} + \sum_{i=1}^{m^*} \gamma_i^{SR} \Delta S_{t-i}^1 + \sum_{j=1}^{n^*} \delta_j^{SR} \Delta S_{t-j}^2 + \phi ECT_{t-1} + \varepsilon_t^{SR} \tag{4.10}$$

$$\Delta S_t^1 = \alpha^{SR} + \sum_{h=1}^{k^*} \beta_h^{SR} \Delta S_{t-h}^1 + \sum_{i=1}^{m^*} \gamma_i^{SR} \Delta P_{t-i} + \sum_{j=1}^{n^*} \delta_j^{SR} \Delta S_{t-j}^2 + \phi ECT_{t-1} + \varepsilon_t^{SR} \tag{4.11}$$

In (4.10) and (4.11), it should be noted that we only include past values of regressors when determining short-run Granger causality. The rationale behind this is the essence of Granger causality, that if one event is claimed to "cause" another, it should precede it in time. The error correction term, ECT_t for (4.10) in Case A is obtained as the residuals saved from the following linear regression as specified in the first stage.

$$P_t = a^{LR} + g^{LR} S_t^1 + d^{LR} S_t^2 + \varepsilon_t^{LR} \tag{4.12}$$

Likewise, for Case B1, ECT_t is obtained as the residuals saved from the regression

$$S_t^1 = a^{LR} + b^{LR} P_t + d^{LR} S_t^2 + \varepsilon_t^{LR} \tag{4.13}$$

Once an appropriate model has been specified, the short-run effect of speculation on futures prices or volatility can be tested using Granger causality. If it is determined that cointegration is present among the variables, the model is specified as in (4.10) or (4.11). If there is no evidence of cointegration, causality is tested without the inclusion of the error correction term, ECT_{t-1}.[8] Testing for Granger causality as specified in (4.3) involves testing the null hypothesis (for Case A) $H_0^4 : \gamma_i^{SR} = \delta_j^{SR}, \forall i, j$ against the alternative

[7] Once again, it should be noted that the coefficients (and optimal lags) in these two equations are not the same although they are presented as such to save on notation.
[8] In the event that the F-statistic does not fall outside of the bounds, a definitive conclusion regarding cointegration cannot be determined. In these cases, we test for Granger causality under the assumption that there is no cointegration.

$H_A^4: \gamma_i^{SR} \neq 0,\ \delta_j^{SR} \neq 0,$ for any i, j. In other words, we test whether the two measures of speculation are jointly insignificant in explaining price levels. For the cases in (4.3) where one measure of speculation is the dependent variable (B1, B2, D1, and D2), we test only whether futures prices (or volatility) significantly explain this measure of speculation. The second measure of speculation is left as an explanatory variable. For Case B1, as presented in (4.11), this amounts to the test $H_0^4: \gamma_i^{SR} = 0, \forall i$ against the alternative $H_A^4: \gamma_i^{SR} \neq 0,$ for any i.

4.5. Results and Discussion

Consistent with the methodology outlined in the previous section, results are presented sequentially for the two stages involved in the analysis. In the first stage, we test for the presence of level relationships among the variables, which would imply long-run causality. In the second stage, we test for short-run Granger causality. The method described to test for level relationships does not require knowledge of the exogenous explanatory variables' order of integration.

We test for the presence of level relationships at the 5% significance level using the model defined (for Case A as an example) in equation (4.6). The results of this test are presented in Table 4.1 and Table 4.2 as F-statistics. A large F-statistic results in a rejection of the null hypothesis of no level relationship whereas a small value results in a failure to reject. For F-statistics falling between the bounds obtained from PSS, a definitive conclusion cannot be made.

From the COT data (Table 4.1), it is clear that there is very little evidence of level relationships in testing the effect of speculation on futures prices (Case A). In this case, we fail to reject the null hypothesis of no cointegration for all 19 commodity markets. This immediately suggests a lack of evidence that futures prices are driven, in the long run, by speculative trading.

Table 4.1. Long-Run Level Relationship Test F-Statistics (H_0^1) - COT Data.

Commodity	Case A	Case B1		Case B2		Case C		Case D1		Case D2	
Cocoa	1.94	15.72	*	12.67	*	37.64	*	14.94	*	8.95	*
Coffee	1.47	16.07	*	7.93	*	42.95	*	15.07	*	9.53	*
Copper	0.31	22.50	*	7.78	*	38.90	*	19.19	*	7.77	*
Corn	1.18	7.83	*	6.70	*	24.02	*	7.29	*	9.94	*
Cotton	0.05	19.17	*	12.87	*	22.32	*	18.52	*	14.15	*
Crude Oil	1.28	16.35	*	7.05	*	26.48	*	15.28	*	1.98	
Feeder Cattle	2.08	15.97	*	18.25	*	29.05	*	13.46	*	21.54	*
Gold	2.58	17.20	*	13.00	*	59.35	*	11.61	*	9.24	*
Heating Oil	0.88	25.18	*	8.09	*	28.19	*	23.25	*	14.76	*
Lean Hogs	0.86	15.08	*	4.91		30.24	*	12.61	*	3.79	
Live Cattle	2.45	11.01	*	10.63	*	33.42	*	8.39	*	8.64	*
Natural Gas	4.75	18.52	*	4.02		32.47	*	17.68	*	2.49	
Silver	0.26	17.05	*	16.05	*	54.18	*	16.80	*	16.17	*
Soybean Meal	1.06	10.34	*	12.80	*	27.57	*	8.97	*	23.54	*
Soybean Oil	0.88	14.02	*	10.27	*	36.28	*	11.98	*	11.03	*
Soybeans	1.19	7.31	*	8.40	*	25.92	*	7.59	*	8.20	*
Sugar	0.17	11.76	*	8.79	*	26.87	*	10.88	*	12.26	*
Wheat (CBOT)	2.26	18.70	*	9.03	*	36.54	*	17.02	*	12.75	*
Wheat (KCBOT)	2.32	10.14	*	12.70	*	38.78	*	10.44	*	11.47	*

Table 4.2. Long-Run Level Relationship Test F-Statistics $(\mathbf{H}_0^1)$ - DCOT Data.

Commodity	Case A	Case B1	Case B2	Case C	Case D1	Case D2
Cocoa	2.15	4.78	5.86 *	12.71 *	5.66	5.27
Coffee	0.80	4.55	5.42	11.36 *	4.24	6.77 *
Copper	3.77	7.34 *	7.09 *	16.09 *	7.48 *	6.53 *
Corn	2.06	1.61	5.53	15.09 *	1.81	5.05
Cotton	0.23	4.65	4.27	5.00	4.84	3.77
Crude Oil	0.61	2.48	3.73	7.64 *	2.70	2.05
Feeder Cattle	1.39	6.18 *	4.75	10.38 *	6.41 *	4.16
Gold	0.07	5.75	5.38	10.75 *	5.46	4.64
Heating Oil	1.68	9.38 *	4.38	9.11 *	8.42 *	2.64
Lean Hogs	0.27	5.02	2.32	19.61 *	4.73	2.23
Live Cattle	1.84	3.16	5.53	15.05 *	2.55	4.78
Natural Gas	2.82	1.80	5.23	13.25 *	2.24	0.90
Silver	0.94	5.06	3.56	13.53 *	4.46	9.30 *
Soybean Meal	1.58	5.48	3.49	10.18 *	4.53	3.33
Soybean Oil	1.28	6.47 *	2.96	9.24 *	3.28	3.91
Soybeans	2.67	5.16	6.20 *	10.15 *	5.13	6.63 *
Sugar	0.58	1.98	4.57	12.88 *	1.84	3.57
Wheat (CBOT)	1.69	3.97	5.30	14.90 *	3.49	5.27
Wheat (KCBOT)	2.12	2.81	4.32	14.69 *	2.76	3.63

Using both COT and DCOT data, there are no instances of the first type of degeneracy. (Results are not shown.) In all instances, there exists a long-run relationship between the dependent variable and its own level. This test corresponds to H_0^2 depicted in Figure 4.2.

Following the sequence of the procedure in Figure 4.2, we find a number of instances of the second type of degeneracy. Results are provided in Table 4.3 from COT data as *p*-values corresponding to the hypothesis test H_0^3 in Figure 4.2. Asterisks denote a rejection of the null hypothesis at a 5% significance level. Blank values indicate that the first stage did not proceed to this step due to a failure to reject the earlier null hypothesis, H_0^1. (Case A is not displayed since they would all be blank values.) Instances in which H_0^3 is rejected (those with asterisks) indicate that there is a long-run level relationship between the dependent variable in question and at least one of the independent exogenous regressors.

Dickey-Fuller tests of the variables of interest reveal that the vast majority of series under consideration contain unit root processes as seen in Table 4.9 and Table 4.10 in the appendix. Instances of insignificance in Table 4.3, however, imply that the independent variable is stationary. A possible explanation for these seemingly contradictory results may be a lack of power in our hypothesis tests. Dickey-Fuller tests specify a null hypothesis of a unit root. A failure to reject (possibly due to a lack of power) would therefore imply that the dependent series contains a unit root. A failure to reject the null hypothesis (H_0^3) in our procedure, however, implies that there is no evidence of a long-run level relationship and the series is then stationary. Thus, a lack of power may lead us to seemingly contradictory beliefs about the order of integration of the independent series in question.

Table 4.3. *P*-values for Long-Run Level Relationship F-Test $(\mathbf{H}_0^3)$ - COT Data.

Commodity	Case B1	Case B2	Case C	Case D1	Case D2
Cocoa	0.16	0.00 *	0.00 *	0.40	0.07
Coffee	0.95	0.43	0.00 *	0.90	0.10
Copper	0.00 *	0.93	0.00 *	0.01 *	0.92
Corn	0.44	0.33	0.07	0.86	0.00 *
Cotton	0.22	0.16	0.09	0.31	0.02 *
Crude Oil	0.08	0.00 *	0.12	0.10	
Feeder Cattle	0.01 *	0.00 *	0.34	0.58	0.00 *
Gold	0.00 *	0.00 *	0.00 *	0.00 *	0.05 *
Heating Oil	0.35	0.85	0.14	0.37	0.00 *
Lean Hogs	0.66		0.03 *	0.81	
Live Cattle	0.06	0.01 *	0.98	0.09	0.10
Natural Gas	0.00 *		0.09	0.00 *	
Silver	0.86	0.39	0.20	0.97	0.35
Soybean Meal	0.83	0.08	0.00 *	0.87	0.00 *
Soybean Oil	0.64	0.12	0.31	0.81	0.03 *
Soybeans	0.53	0.02 *	0.32	0.15	0.01 *
Sugar	0.45	0.69	0.00 *	0.40	0.00 *
Wheat (CBOT)	0.00 *	0.03 *	0.00 *	0.00 *	0.00 *
Wheat (KCBOT)	0.66	0.01 *	0.00 *	0.08	0.03 *

For instances in which H_0^3 is rejected, we then test for the extent to which exogenous regressors are individually significant in the specification of a long-run level relationship. Table 4.4 provides the *p*-values for these individual tests of significance, as labeled in each case. (Only COT results are shown.) Case A is again excluded from this table since there are no instances of a long-run level relationship. Blank values indicate instances in which any of the previous hypothesis tests H_0^1, H_0^2 or H_0^3 were not rejected and the first stage has already terminated. This table presents one of the key findings of this paper, whether there is a long-run level relationship between a dependent variable series and exogenous factors.

Table 4.4. Exogenous Regressor *p*-values (COT Data).

	Case B1		Case B2		Case C		Case D1		Case D2	
Commodity	**P**	**S^2**	**P**	**S^1**	**S^1**	**S^2**	**V**	**S^2**	**V**	**S^1**
Cocoa			0.00*	0.01*	0.21	0.00*				
Coffee					0.00*	0.00*				
Copper	0.00*	0.00*			0.00*	0.17	0.00*	0.00*		
Corn									0.00*	0.00*
Cotton									0.00*	0.00*
Crude Oil			0.00*	0.00*						
Feeder Cattle	0.00*	0.00*	0.00*	0.00*					0.15	0.00*
Gold	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
Heating Oil									0.00*	0.00*
Lean Hogs					0.00*	0.00*				
Live Cattle			0.00*	0.00*						
Natural Gas	0.11	0.00*					0.01*	0.00*		
Silver										
Soybean Meal					0.00*	0.00*			0.00*	0.00*
Soybean Oil									0.00*	0.00*
Soybeans			0.00*	0.00*					0.00*	0.10
Sugar					0.00*	0.00*			0.00*	0.57
Wheat (CBOT)	0.00*	0.00*	0.00*	0.00*	0.68	0.00*	0.68	0.00*	0.00*	0.00*
Wheat (KCBOT)			0.00*	0.58	0.00*	0.00*			0.00*	0.03*

Table 4.4 shows that the level of speculation is individually affected by futures price levels in the long-run in 4 instances for Case B1 and 8 instances for Case B2 using COT data.

The union of these two cases shows that futures price levels affect at least one measure of speculation in 10 instances. This provides some evidence that, in the long-run, speculation is affected by futures prices. Moreover, this long-run level relationship can be interpreted as a cointegrating relationship if the Dickey-Fuller tests (Table 4.9 and Table 4.10) are accurate in characterizing the order of integration since the fitted residuals here are found to be always stationary.

Cases A, B1, and B2 are collectively consistent with previous literature that has failed to find causality running from speculation to futures prices, but rather the opposite (Sanders, Boris, and Manfredo, 2004; Stoll and Whaley, 2010; Aulerich, Irwin, and Garcia, 2010). These results are qualitatively similar when using DCOT, particularly for Case A where we find no evidence of level relationships (Table 4.2). However, for Cases B1 and B2, we are unable to reject the null hypothesis of no level relationships as often using DCOT data. This can be seen by the relatively low F-statistics in Table 4.2. (For this reason, we present results in Table 4.4 from COT data only.) There are 5 and 7 instances respectively where a definitive conclusion regarding level relationships cannot be made. Differences between data sets may be a result of the DCOT data providing only a third as many observations as the COT data.

There are many similarities when testing the effect of futures price volatility on speculation. There is significant evidence of a long-run level relationship between speculation and volatility when S^2 is the dependent variable (Case D2 in Table 4.3). A key finding of this paper, however, can be seen by comparing Case A with Case C, which tests the effect of speculation on volatility. In Case C, we reject the null hypothesis of no level relationships in 9 instances, versus 0 in Case A. Whereas there is very little evidence of long-run causality running from speculation to futures price levels, this highlights some evidence of long-run causality from speculation to volatility. This is also apparent for exogenous regressors individually as seen Table 4.4 for COT data. Here, we see that the individual measures of speculation, S^1 and S^2, significantly explain volatility in the long-run in 7 and 8 instances respectively (Case C). The sign of the coefficient estimates obtained in generating

Table 4.4 (for COT data) are presented in Table 4.5. These signs represent the long-run marginal effect of the column variable on the dependent variable under consideration in each case. Case A is again excluded since there are no long-run effects on futures prices observed. Blanks also represent a failure to realize a long-run level relationship.

Table 4.5. Long-run Marginal Effects (COT Data).

	Case B1		Case B2		Case C		Case D1		Case D2	
Commodity	P	S^2	P	S^1	S^1	S^2	V	S^2	V	S^1
Cocoa			+	+		-				
Coffee					+	+				
Copper	-	-			-		-	-		
Corn									-	-
Cotton									-	-
Crude Oil			+	+						
Feeder Cattle	-	+	-	+						-
Gold	+	+	-	+	+	+	+	+	+	+
Heating Oil									-	-
Lean Hogs					-	-				
Live Cattle			-	+						
Natural Gas		+					-	-		
Silver										
Soybean Meal					+	-			-	-
Soybean Oil									-	-
Soybeans			-	+					-	
Sugar					+	-			-	
Wheat (CBOT)	-	+	-	+		+		+	-	+
Wheat (KCBOT)			+		+	+			+	+

Results of the second stage are reported in Table 4.6 and Table 4.7 using COT and DCOT data respectively. These tables present the results for short-run Granger causality tests as described in the previous section. *P*-values are reported for the null hypothesis that a particular explanatory variable (or variables jointly in Case A and Case C) is not statistically significant in explaining the dependent variable under consideration. In each case, asterisks next to the *p*-value denote a rejection of the null hypothesis at varying significance levels as defined in the footnotes to the tables. Our results show no evidence that speculation is a significant factor in explaining futures prices in the short run using either COT or DCOT data (Case A). On the contrary, futures prices are found to be a significant factor in the determination of our first measure of speculation SL/SS (Case B1). Using COT data, there are 15 instances of significance (at 5%) and 7 instances using DCOT data. We find little evidence that the second measure of speculation SOI/HOI is significantly explained by futures prices in the short-run.

Table 4.6. *P*-values from Granger Causality Tests (COT Data).

	Case A		Case B1		Case B2		Case C		Case D1		Case D2	
Commodity	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]
Cocoa	0.08	*	0.00	***	0.84		0.07	*	0.11		0.09	*
Coffee	0.06	*	0.00	***	0.28		0.00	***	0.84		0.43	
Copper	1.00		0.13		0.90		0.04	**	0.25		0.33	
Corn	0.41		0.26		0.64		0.74		0.91		0.39	
Cotton	0.70		0.44		0.07	*	0.01	**	0.19		0.21	
Crude Oil	0.92		0.00	***	0.21		0.08	*	0.32		0.09	*
Feeder Cattle	0.42		0.00	***	0.41		0.81		0.24		0.21	
Gold	0.72		0.05	**	0.95		0.68		0.19		0.41	
Heating Oil	0.80		0.00	***	0.33		0.11		0.64		0.49	
Lean Hogs	0.43		0.00	***	0.48		0.53		0.83		0.63	
Live Cattle	0.07	*	0.00	***	0.88		0.05	*	0.25		0.49	
Natural Gas	0.84		0.02	**	0.45		0.37		0.66		0.58	
Silver	0.61		0.03	**	0.87		0.51		0.20		0.03	**
Soybean Meal	0.06	*	0.02	**	0.06	*	0.01	**	0.75		0.63	
Soybean Oil	0.37		0.00	***	0.08	*	0.00	***	0.57		0.46	
Soybeans	0.15		0.25		0.63		0.23		0.54		0.30	
Sugar	0.93		0.04	**	0.56		0.16		0.28		0.56	
Wheat (CBT)	0.92		0.00	***	0.96		0.22		0.09	*	0.08	*
Wheat (KCBT)	0.93		0.00	***	0.03	**	0.03	**	0.07	*	0.00	***

[a] Low *p*-values suggest rejection of the null hypothesis. For example, in Case A this would imply that speculator positions are significant in explaining prices.
[b] *, **, and *** denote rejection of the null hypothesis at a significance level of 10%, 5%, and 1% respectively.

Table 4.7. *P*-values from Granger Causality Tests (DCOT Data).

	Case A		Case B1		Case B2		Case C		Case D1		Case D2	
Commodity	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]	***p*-val.**[a]	**Sig.**[b]
Cocoa	0.10	*	0.00	***	0.99		0.67		0.96		0.83	
Coffee	0.78		0.05	*	0.17		0.00	***	0.48		0.85	
Copper	0.92		0.08	*	0.72		0.01	***	0.06	*	0.79	
Corn	0.12		0.60		0.85		0.65		0.86		0.83	
Cotton	0.41		0.65		0.30		0.50		0.22		0.58	
Crude Oil	0.71		0.14		0.77		0.04	**	0.95		0.31	
Feeder Cattle	0.30		0.00	***	0.01	***	0.90		0.13		0.03	**
Gold	0.81		0.18		0.35		0.04	**	0.58		0.59	
Heating Oil	0.20		0.01	***	0.02	**	0.27		0.93		0.71	
Lean Hogs	0.47		0.00	***	0.60		0.92		0.47		0.23	
Live Cattle	0.02	**	0.08	*	0.75		0.76		0.28		0.74	
Natural Gas	0.71		0.00	***	0.63		0.39		0.55		0.47	
Silver	0.83		0.15		0.86		0.01	**	0.73		0.87	
Soybean Meal	0.25		0.45		0.80		0.32		0.20		0.93	
Soybean Oil	0.90		0.03	**	0.53		0.21		0.51		0.75	
Soybeans	0.38		0.56		0.59		0.38		0.71		0.17	
Sugar	0.17		0.20		0.51		0.81		0.76		0.56	
Wheat (CBT)	0.47		0.03	**	0.89		0.09	*	0.55		0.97	
Wheat (KCBT)	0.62		0.29		0.37		0.03	**	0.25		0.10	

[a] Low *p*-values suggest rejection of the null hypothesis. For example, in Case A this would imply that speculator positions are significant in explaining prices.
[b] *, **, and *** denote rejection of the null hypothesis at a significance level of 10%, 5%, and 1% respectively.

Comparing short-run results for Cases A and C, we again see that speculation is a more significant factor in explaining volatility in the short-run than futures prices. We find 6 instances in which volatility is affected by speculation using both COT and DCOT data (not necessarily the same commodities). There is also very little evidence that our measures of speculation are significantly explained by volatility in the short run for both the COT and DCOT data (Cases D1 and D2).

Table 4.8 presents a summary of long-run and short-run causality results for each case at a significance level of 5%. Blank values indicate a failure to observe causality running from the variable on the left of the double arrow to the variable on the right in each column. A value of "Y" indicates evidence of causality in the short-run (SR) or long-run (LR).[9]

Table 4.8. Summary of Causality Results (COT Data).

	$S \Rightarrow P$ (Case A)		$P \Rightarrow S^1$ (Case B1)		$P \Rightarrow S^2$ (Case B2)		$S \Rightarrow V$ (Case C)		$V \Rightarrow S^1$ (Case D1)		$V \Rightarrow S^2$ (Case D2)	
Commodity	**SR**	**LR**	**SR**	**LR**	**SR**	**LR**	**SR**	**LR**	**SR**	**LR**	**SR**	**LR**
Cocoa			Y			Y		Y				
Coffee			Y				Y	Y				
Copper				Y			Y	Y		Y		Y
Corn												
Cotton							Y					
Crude Oil			Y			Y						
Feeder Cattle			Y	Y		Y						
Gold			Y	Y		Y		Y		Y		Y
Heating Oil			Y									
Lean Hogs			Y					Y				
Live Cattle			Y			Y						
Natural Gas			Y	Y						Y		Y
Silver			Y								Y	
Soybean Meal			Y				Y	Y				
Soybean Oil			Y				Y					
Soybeans						Y						
Sugar			Y					Y				
Wheat (CBOT)			Y	Y		Y		Y		Y		Y
Wheat (KCBOT)			Y		Y	Y	Y	Y			Y	
Total Instances	**0**	**0**	**15**	**5**	**1**	**8**	**6**	**9**	**0**	**4**	**2**	**4**

Case A: Speculative trading SL / SS and SOI / HOI does not Granger cause futures prices.
Case B1: Futures prices do not Granger cause speculative trading SL / SS.
Case B2: Futures prices do not Granger cause speculative trading SOI / HOI.
Case C: Speculative trading SL / SS and SOI / HOI does not Granger cause futures price volatility.
Case D1: Futures price volatility does not Granger cause speculative trading SL / SS.
Case D2: Futures price volatility does not Granger cause speculative trading SOI / HOI.

[9] Only results from COT are presented due to relatively inconclusive long-run results using DCOT data. As discussed previously, this may be due to a lack of power which may also be accentuated using the DCOT data which contain about a third of the observations of COT data.

As can be seen, there is no evidence that commodity futures prices are driven, in the long-run or short-run, by speculative trading (Case A). This is true using both COT and DCOT data (not shown here). Although we classify a different group of traders as speculators in our analysis, this is a result that has also been generated by the studies cited earlier which focus on index traders as a group allegedly responsible for influencing commodity futures prices. Conversely, there is strong evidence that futures prices affect speculative trading. This is particularly true in the short-run for Case B1. In other words, the relative long-to-short positions of speculative traders are strongly influenced by futures prices in the short-run. This may be due to trend-following behavior that tends to disappear in the long-run.

Interestingly, whereas there seems to be no evidence of a long-run cointegrating equilibrium with futures prices the dependent variable series, the same is not true for volatility. Futures price volatility seems to be frequently driven by a long-run level relationship with speculative trading (Case C). This is a result that, to our knowledge, has not emerged in previous literature and is obtained when using both COT and DCOT data (9 and 7 instances respectively). This result suggests that, although prices do not seem to respond to speculative trading in the long-run, price volatility frequently does. The results of Cases D1 and D2 collectively suggest that there is some evidence of the converse as well. Based on these tests alone, there is some justification to the argument that futures price volatility and speculative trading are closely linked in the long-run.

As previously noted, results obtained using DCOT data are notably less conclusive than results obtained using COT data. This may be due to several factors. First, there are more than three times as many observations using COT data (992 versus 279). This may give us more power to reject the null hypothesis of no causality. Second, trader classifications are slightly different in the two data sets. Whereas swap dealers are included in the classification of “hedgers” in the COT data, they have been removed from the category of conventional “hedgers” in the DCOT reports. As such, the open interest held by swap dealers is not considered in the analysis using the DCOT data. Finally, there may be structural changes that have occurred over the past 10 years that would disproportionately affect the DCOT data as opposed to the COT data. Despite the possibility of structural breaks, it would be difficult to determine precisely when they may have occurred and is beyond the scope of this analysis.

4.6. Conclusion

In this paper, we seek to determine the extent to which speculative trading has affected, or is affected by, commodity futures prices and futures price volatility. We define speculation using two separate measures as obtained from data made available by the Commodity Futures Trading Commission Large Trader Reporting System. The first measure represents the "flow" of speculative trading whereas the second measure is representative of the "stock" of speculative positions relative to hedgers.

Given our measures of speculation, there is a conceptual difficulty in regressing the difference in prices on the level of speculation. Methodologically, this may seem appropriate if the regressor is found to be stationary. However, this implies that prices may increase indefinitely even as speculation remains fixed. Alternatively, if speculation is found to contain a unit root, one may consider a model that is entirely in first differences to test for causality. This may be problematic because the variables may be cointegrated.

As a solution, we use a bounds-testing approach developed by Pesaran, Shin, and Smith (2001) which provides several advantages. First, as an error correction model, this approach accounts for the possibility of a long-run level relationship among the variables in question. Second, knowledge of exogenous explanatory variables' order of integration is not required to make a determination regarding the existence of cointegration depending on the magnitude of the test statistic. By specifying an error correction model in this manner, we can conclude whether a particular explanatory variable significantly affects a dependent variable in the long-run. Finally, by accounting for cointegration, this approach allows us to subsequently test for Granger causality in the short-run as distinct from the long-run. In our context, it is desirable to conclude whether speculation affects futures price levels (or futures price volatility) in the long-run as well as the short-run.

Our results suggest that futures price levels are not affected by speculative trading in either the long-run or short-run. There is, however, some evidence that speculation is a causal factor for futures price volatility in the long-run. We also find slight evidence that volatility is affected by speculative trading in the short-run. In the other direction, we find that futures prices significantly influence speculative trading, particularly speculators maintaining net long positions in the short-run. This may be due to trend-following behavior. There is slight evidence which suggests volatility may also be affected by speculative trading in the long-run. There is very little evidence, however, that volatility significantly explains speculation in the short-run.

4.7. Appendix

Table 4.9. Dickey-Fuller Unit Root Tests: *p*-values (COT Data).

Commodity	P		S^1		S^2		V	
Cocoa	0.63	*	0.00		0.29	*	0.16	*
Coffee	0.60	*	0.01		0.18	*	0.13	*
Copper	0.76	*	0.00		0.17	*	0.09	*
Corn	0.81	*	0.34	*	0.37	*	0.27	*
Cotton	0.56	*	0.00		0.22	*	0.18	*
Crude Oil	0.69	*	0.09	*	0.49	*	0.15	*
Feeder Cattle	0.90	*	0.43	*	0.17	*	0.36	*
Gold	1.00	*	0.03		0.24	*	0.04	
Heating Oil	0.85	*	0.03		0.20	*	0.15	*
Lean Hogs	0.60	*	0.23	*	0.03		0.34	*
Live Cattle	0.83	*	0.36	*	0.27	*	0.37	*
Natural Gas	0.24	*	0.01		0.77	*	0.11	*
Silver	0.94	*	0.01		0.17	*	0.02	
Soybean Meal	0.61	*	0.03		0.29	*	0.29	*
Soybean Oil	0.82	*	0.01		0.23	*	0.33	*
Soybeans	0.74	*	0.22	*	0.27	*	0.32	*
Sugar	0.70	*	0.02		0.22	*	0.15	*
Wheat (CBOT)	0.53	*	0.07	*	0.22	*	0.28	*
Wheat (KCBOT)	0.60	*	0.07	*	0.29	*	0.26	*

Note: Asterisks denote the presence of a unit root for the given series.

Table 4.10. Dickey-Fuller Unit Root Tests: *p*-values (DCOT Data).

Commodity	P		S^1		S^2		V	
Cocoa	0.69	*	0.26	*	0.59	*	0.44	*
Coffee	0.86	*	0.28	*	0.45	*	0.42	*
Copper	0.57	*	0.39	*	0.44	*	0.44	*
Corn	0.81	*	0.52	*	0.53	*	0.46	*
Cotton	0.65	*	0.32	*	0.55	*	0.48	*
Crude Oil	0.58	*	0.53	*	0.63	*	0.46	*
Feeder Cattle	0.89	*	0.57	*	0.46	*	0.55	*
Gold	0.99	*	0.27	*	0.24	*	0.38	*
Heating Oil	0.71	*	0.30	*	0.56	*	0.49	*
Lean Hogs	0.62	*	0.60	*	0.60	*	0.53	*
Live Cattle	0.91	*	0.70	*	0.42	*	0.58	*
Natural Gas	0.34	*	0.10	*	0.39	*	0.52	*
Silver	0.86	*	0.28	*	0.12	*	0.27	*
Soybean Meal	0.71	*	0.28	*	0.49	*	0.48	*
Soybean Oil	0.80	*	0.13	*	0.58	*	0.49	*
Soybeans	0.78	*	0.50	*	0.13	*	0.48	*
Sugar	0.66	*	0.32	*	0.61	*	0.40	*
Wheat (CBOT)	0.60	*	0.38	*	0.52	*	0.43	*
Wheat (KCBOT)	0.61	*	0.31	*	0.58	*	0.46	*

Note: Asterisks denote the presence of a unit root for the given series.

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CHAPTER 5. THE TRADE-OFF BETWEEN BIOENERGY AND EMISSIONS WITH LAND CONSTRAINTS

A modified version of the paper to be submitted to a peer-reviewed journal

5.1. Abstract

Agricultural biofuels require the use of scarce land, and this land has opportunity cost. We explore the objective function of a social planner who includes a land constraint in the optimization decision to minimize environmental cost. The results show that emissions should be measured on a per acre basis. Conventional agricultural life cycle assessments for biofuels report carbon emissions on a per gallon basis, thereby ignoring the implications of land scarcity and implicitly assuming an infinite supply of the inputs needed for production. Switchgrass and corn are then modeled as competing alternatives to show how the inclusion of a land constraint can influence life cycle rankings and alter policy conclusions.

5.2. Introduction

The merits of biofuels relative to their fossil fuel counterparts often include independence from foreign oil supplies and lower greenhouse gas (GHG) emissions. That biofuels accomplish the first of these is not often disputed. The degree to which biofuels achieve the latter, however, has been vigorously debated. The controversies notwithstanding, the U.S. Congress first passed renewable fuel volume mandates in the Energy Policy Act of 2005. These mandates became known as the Renewable Fuel Standard (RFS). In 2007, the mandates were expanded through the enactment of the Energy Independence and Security Act (EISA), and the corresponding renewable fuel standards are now referred to as RFS2. In phases, EISA requires that 36 billion gallons of renewable fuel be blended into transportation fuel by 2022. In addition to the increased volume mandates, there are two key modifications to the original 2005 energy policy. The first is the disaggregation into four types of biofuels: renewable fuels, advanced biofuels, biomass-based diesel, and cellulosic biofuels. The second is the specification of GHG emission reduction thresholds for each category that must be met in order to qualify under RFS2.

In accordance with EISA, the Environmental Protection Agency (EPA) was delegated the responsibility of overseeing the implementation of RFS2. In this regard, the EPA conducted life cycle assessments (LCAs) for various biofuel pathways that would potentially be used in fulfillment of the RFS2 mandates. In their final rule, which became effective July 1, 2010, the EPA determined that corn grain ethanol produced at facilities coming online after 2007 would satisfy the 20% reduction in GHG emissions required to qualify as a renewable fuel (EPA 2010a). Likewise, cellulosic ethanol produced from both corn stover and switchgrass via enzymatic fermentation was determined to qualify as cellulosic biofuel as defined in EISA.

The purpose of the LCA is to measure all of the GHG emissions associated with the production and use of a particular biofuel in what is known as a "well-to-wheels" approach. The LCA conducted by the EPA, as well as other conventional agricultural LCAs, measures GHG emissions as the amount of carbon dioxide equivalent emitted per unit of energy provided by the pathway (i.e., gCO_2e/mmBTU). This measurement is compared to a gasoline baseline so as to determine the percentage reduction in GHG emissions generated. This then determines whether the biofuel pathway qualifies within a specified category of biofuels. Well-known LCA models such as the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model and Biofuel Energy Systems Simulator (BESS) similarly measure emissions per gallon.[1] In their paper on indirect land use change, Searchinger *et al*. (2008) make use of GREET life cycle assessments whereby emissions are also measured per gallon. Farrell *et al*. (2006) determine emissions per gallon in an earlier work. However, there is a significant shortcoming of these per gallon LCAs in that they do

[1] Throughout this paper, the measure of emissions per gallon is treated as being a scaled equivalent to emissions per mmBTU once a BTU/gal assumption is made. It is also equivalent to emissions per mile driven once a mile/gallon assumption is made.

not account for the critical role that land scarcity plays in ranking biofuel pathways according to their emissions reduction potential.

The environmental ranking of biofuel pathways that one obtains based on a measurement of emissions per gallon is not necessarily the same as one would obtain after accounting for differences in energy yields per acre. For example, according to the EPA analysis in the 2022 scenario (EPA 2010b), switchgrass used for production of cellulosic ethanol leads to a 110% reduction in GHG emissions. Corn grain ethanol leads to a 21% reduction. It would seem that switchgrass is the more environmentally friendly of the two choices. However, if the quantity of gasoline displaced by production of ethanol from an acre of corn grain plus corn stover is sufficiently greater than that displaced from an acre of switchgrass, it is conceivable that corn could be the environmentally superior feedstock choice on a per acre basis. Although demonstrated here with corn and switchgrass, this same concept of potentially incorrect per acre emissions rankings is valid when comparing any single energy crop with a crop that generates multiple sources of energy from the same unit of land.

The case for a per acre measurement of emissions becomes even more compelling if there is an additional value to biofuel production beyond that associated with carbon. Assuming for the moment that corn yields more energy per acre than switchgrass, then more value derived from biofuel production results in a higher opportunity cost of choosing to grow switchgrass. Thus, even though switchgrass has a substantially better carbon profile per gallon than corn, there is a point at which it is not optimal from a social planner’s perspective to choose switchgrass for production of biofuels if corn (both grain and stover) is available as an alternative feedstock. This could be due to either low carbon prices or high external values to biofuel production.

Deriving value from two sources on the same unit of land is not a new concept in agriculture, but it has not been adequately represented in a life cycle emissions setting. Farmers that choose to harvest corn for silage attribute value to both the grain and the stover on the same unit of land. The same is true in ascribing value to the production of soybean oil and soybean meal from one acre of soybeans. The value of both of these commodities is embedded in a farmer's decision to grow soybeans. Moreover, in deciding whether to grow soybeans or corn, a farmer also takes into account per acre yield differences across crops and would not choose to grow soybeans simply because the price per bushel is higher than that of corn. A per acre measure of social cost, emissions, is also consistent with this logic where commonality resides in the fact that there is a fixed amount of land available to grow crops. The requirement that emissions be measured per acre then is a result that falls out of any model that acknowledges a fixed amount of land.

The purpose of this paper is to explore the implications of conventional agricultural LCAs that do not consider the effects of land scarcity and the corresponding opportunity cost of feedstock choice. A two-stage optimization model is presented in which the social planner includes all internal and external costs. In the first stage, the social planner chooses the optimal amount of land to allocate to biofuel production given alternative potential uses of land. In the second stage, the social planner determines how to use the land that has been allocated to biofuel production. Our focus will be on the second stage. The second-stage optimization consists of a two-part objective function that the social planner maximizes by choosing among available biofuel pathways subject to a land constraint. The first part of the objective function is the cost associated with net GHG emissions given a price on carbon. This portion represents the environmental benefit associated with biofuel production. The second part of the objective function represents an external value associated with biofuel production that might be due to a desire to reduce dependence on imported oil. For the purposes of this study, we consider two competing feedstock choices: corn and switchgrass. In the case of corn, both grain and stover are used for production of ethanol.

The optimal solution to the social planner's problem will depend on three key factors: the relative energy yield per acre of corn and switchgrass, the price of carbon, and the external value to biofuel production. Even when there is no external value to production, the results will show that it is highly unlikely that switchgrass would be optimally chosen as a feedstock for biofuel production in the midwestern United States. It is more conceivable, however, that switchgrass would dominate corn for this purpose in southern and southeastern states. In a more realistic setting where there is an additional external value to biofuel production, switchgrass becomes even more unlikely to be optimally chosen outside of these regions.

The remainder of the paper is organized as follows. In section 5.3, a model is introduced that is taken as the optimization problem that a social planner (i.e., U.S. society) would solve. In section 5.4, data and parameter assumptions required to solve the model are presented and described. The optimization problem is then solved numerically based on the defined parameter assumptions. Results are obtained numerically in section 5.5 by using the model to generate an "optimality frontier," which will be interpreted as an implied carbon price curve. The magnitudes of implied carbon prices will be used to illustrate the likelihood of switchgrass being optimal when compared to projected carbon prices. In addition to solving a general model over a range of assumptions, the model will also be solved for specific crop reporting districts for a particular set of biofuel and carbon policies. A discussion of the policy implications of the results is subsequently presented, and section 5.6 provides concluding remarks.

5.3. The Model

The goal of society is separated into two maximization stages considered to be additively separable. In the first stage, the social planner has a fixed amount of land available and chooses to allocate land to either the production of biofuels or some other alternative. This alternative can be thought of as land allocated to food production. In this stage, the social planner faces a trade-off between bioenergy and food production.

Some may argue that land availability is not fixed, that additional land could be brought into production if necessary. There are two justifications for this assumption in our model. First, it should be recognized that there is fixed amount of land available worldwide in a physical sense. In the optimization problem that follows, letting this be the amount of land the social planner has at his disposal would not change the results as we are interested in how the land is allocated between crops used for biofuels. We do not attempt to explain how land is allocated between cropland and forestland, for example. A second point is that converting land (possibly forests) into cropland has a significant emissions cost through indirect land use change. The magnitude of additional land converted into cropland would certainly be diminished due to this cost. At some point, the (emissions) cost of conversion would become prohibitively high.

5.3.1. First-Stage Optimization

The first-stage maximization problem is then represented as follows:

$$\max_{\eta_b,\eta_f} b(\eta_b)\eta_b + f(\eta_f)\eta_f \tag{5.1}$$

subject to

$$\eta_b + \eta_f \leq T \tag{5.2}$$

$$\eta_b \geq 0, \eta_f \geq 0 \tag{5.3}$$

where η_b, (η_f) is the fraction of land devoted to biofuel (food and feed) production, $b(\eta_b)$ is the value associated with biofuel production, and $f(\eta_f)$ is the value associated with food and feed production. T is the (fixed) amount of land that the social planner has at his disposal. We do not attempt to solve this maximization problem. Arriving at functional forms for $b(\eta_b)$ and $f(\eta_f)$ are beyond the scope of this paper, although it is reasonable to assume that $\frac{\partial b(\eta_b)}{\partial \eta_b} < 0$ and $\frac{\partial f(\eta_f)}{\partial \eta_b} > 0$. For our purposes, we simply recognize that one of the solutions to the problem is the optimal share of land devoted to biofuel production, η_b^*.

5.3.2. Second-Stage Optimization

In the second stage, the social planner has already determined the amount of land available for biofuel production, η_b^*. From this available land, the social planner seeks to minimize the cost associated with emissions while maximizing the value attributable to biofuel production by choosing among potential biofuel pathways subject to a land constraint. For simplicity, we normalize η_b^* to be equal to 1, which amounts to a normalization of T given in the first stage. The model is expressed as

$$\max_{\{\eta_i\}}\left[-P\sum_i \gamma_i\eta_i + S\sum_i \delta_i\eta_i\right] \tag{5.4}$$

subject to

$$\sum_i \eta_i \le 1 = \eta_b^* \tag{5.5}$$

$$\eta_i \ge 0, \forall i \tag{5.6}$$

Here, η_i is the share of land devoted to biofuel pathway i, γ_i is the amount of GHG emissions corresponding to pathway i measured in tons of CO_2e per acre, δ_i is the energy yield corresponding to pathway i measured in gal/acre, P is the price of carbon in $/t, and S is the positive externality associated with biofuel production measured in $/gal. The term on the left-hand side of the maximand is the total cost associated with GHG emissions. (The negative sign makes it a benefit to be maximized.) The term on the right-hand side corresponds to the total "non-carbon" value attributable to biofuel production as previously motivated. The social planner thus maximizes the total value of biofuel production as shown in (5.4) subject to constraints (5.5) and (5.6).

Equations (5.2) and (5.5) represent a land constraint. While these are seemingly obvious constraints to include in the social planner's problem, their significance has been largely ignored in conventional agricultural LCAs and corresponding policy decisions. The land constraints simply state that the sum of land shares cannot be greater than one. The presence of this land constraint is what induces opportunity cost. Without this constraint, one would effectively be arguing that there is no opportunity cost associated with pathway choice and that land is costlessly available. Trivially, the optimal pathway in this case would be the one that reduces emissions the most in absolute terms, since land would be unconstrained, an indefensible supposition.

The first-order Kuhn-Tucker conditions corresponding to (5.4) are

$$-P\gamma_i + S\delta_i - \lambda \le 0 \text{ with C.S.C.: } \eta_i\left(-P\gamma_i + S\delta_i - \lambda\right) = 0 \ \forall i \tag{5.7}$$

where there is one FOC given by (5.7) for each biofuel pathway i in the choice set, and λ is the Lagrangian multiplier on the land constraint, representing the shadow value of an additional unit of land made available for biofuel production. From these FOCs, it can be seen that an interior solution only exists when $-P(\gamma_i - \gamma_j) = S(\delta_i - \delta_j)$ for $i \neq j$. In other words, the share of land devoted to two biofuel pathways will only be simultaneously positive if the difference between per acre emissions and per acre biofuel yield for pathways i and j, weighted by the respective prices for carbon, P, and per gallon biofuel value, S, coincidentally happen to be equal. For all practical purposes, this is a zero probability event. Thus, the solution to our problem will virtually always be a corner solution, where only one biofuel pathway is optimal.

For this study, we consider only two potential biofuel pathways, i.e., $i \in \{c, s\}$. Here, the subscript c denotes a pathway where land is allocated to corn; corn grain is used for production of ethanol and corn stover is used for production of cellulosic ethanol. The subscript s denotes a pathway where land is allocated to switchgrass, which is used for production of cellulosic ethanol. The problem explicitly considered in this paper is thus represented as

$$\max_{\eta_c, \eta_s} \left[-P\left(\gamma_c \eta_c + \gamma_s \eta_s\right) + S\left(\delta_c \eta_c + \delta_s \eta_s\right) \right] \tag{5.8}$$

subject to

$$\eta_c + \eta_s \leq 1 \tag{5.9}$$

$$\eta_c \geq 0, \eta_s \geq 0 \tag{5.10}$$

5.3.3. Alternative Social Planner Problem

Given that conventional agricultural LCAs measure emissions as gCO_2e/gal, it is worthwhile to consider an alternative social planner problem making use of these measurements and to determine whether or not it would provide the same theoretical solution as that obtained with emissions measured per acre. Rather than choosing the share of acres devoted to each pathway, suppose a social planner chooses the share of gallons produced from each biofuel pathway, having an LCA measure of emissions in gCO_2e/gal. This analogous social planner problem would be specified as follows:

$$\max_{g_c,g_s}\left[-P\left(\phi_c g_c+\phi_s g_s\right)+S\left(g_c+g_s\right)\right] \tag{5.11}$$

subject to

$$g_c+g_s\le 1 \tag{5.12}$$

$$g_c\in\{0,1\},\, g_s\in\{0,1\} \tag{5.13}$$

where ϕ_i is emissions measured as gCO$_2$e/gal, g_i is the share of gallons produced from pathway i, and all other notation is as before. Here, the constraint given by (5.13) is explicitly making use of the reality that an interior solution where $0<g_c^*<1$ and $0<g_s^*<1$ is essentially a zero probability event. Then, the question can be asked under what conditions the solutions given by (5.8) will be the same as those of (5.11). In other words, if $\eta_c^*=1$, under what conditions will we be guaranteed that $g_c^*=\eta_c^*=1$?

Multiplying (5.8) by a scalar factor, $\frac{1}{\delta_c}$, does not change the optimal solution to the problem (although the value of the objective function is indeed altered). This results in

$$\max_{\eta_c,\eta_s}\left[-P\left(\phi_c\eta_c+\frac{\gamma_s}{\delta_s}\eta_s\right)+S\left(\eta_c+\frac{\delta_s}{\delta_c}\eta_s\right)\right] \tag{5.14}$$

Equation (5.14) shows that in order for the solutions in (5.8) and (5.11) to be the same, (5.11) must be formulated as

$$\max_{g_c,g_s}\left[-P\left(\phi_c g_c+\beta\phi_s g_s\right)+S\left(g_c+\beta g_s\right)\right] \tag{5.15}$$

where β is the relative energy yield ratio between pathways c and s and where $g_i=\eta_i$. The implications of this result are best seen by rewriting (5.15) as

$$\max_{g_c,g_s}\left[-P_c\phi_c g_c-P_s\phi_s g_s+S_c g_c+S_s g_s\right] \tag{5.16}$$

where $P_c=P$ and $S_c=S$ as before, but now it is apparent that we need a pathway-specific carbon price P_s as well as a pathway-specific biofuel production value S_s such that $P_s=\beta P$ and $S_s=\beta S$ to account for the fact that different biofuel pathways have differing energy yields per acre of land. For example, if corn has a higher energy yield per acre than switchgrass, the per gallon external production value as well as the carbon price on emissions for ethanol produced from switchgrass must be discounted by β. This is a very strong requirement and not likely to be implemented in practice. Nevertheless, it is a requirement that must be met in order to ensure that the opportunity costs arising from a land constraint be embedded in a social planner's problem in which life cycle emissions are measured on a per gallon basis.

5.4. Data and Parameters

The purpose of this section is to first present and describe the methodology and results of the LCAs conducted by the EPA in which emissions are measured on a per mmBTU basis. These measurements are then converted to a per acre basis to be used in the model described in the previous section. When parameters are used that deviate from those used in the EPA analysis, a justification is provided based on relevant literature.

The EPA has conducted LCAs for the production of ethanol from corn grain and cellulosic ethanol from corn stover and switchgrass. The LCAs utilizing corn grain and corn stover are combined into one pathway in order to obtain per acre emissions associated with corn. Likewise, the LCA for switchgrass is used to obtain per acre emissions associated with switchgrass as a feedstock for production of cellulosic ethanol. The EPA methodology is relevant to our work because we use all of the EPA assumptions including those related to indirect land use. The Appendix provides an overview of this methodology.

Table 5.1 displays the average annual emissions for the categories specified in the EPA analysis along with emissions from the 2005 gasoline baseline used for comparison and the corresponding percentage reduction in emissions that each pathway generates. As can be seen from the table, the production of cellulosic ethanol from corn stover (129% reduction in GHG emissions) meets the EISA requirements as a cellulosic (and advanced) biofuel whereas production of ethanol from corn grain (21% reduction) meets only the requirement for a renewable fuel.

Table 5.1. EPA Annualized GHG Emissions by Biofuel Pathway (gCO_2e/mmBTU).

Emissions Category	Corn Grain Ethanol	Cellulosic Ethanol Corn Stover	Cellulosic Ethanol Switchgrass
Int'l Land Use Change	31,797	0	15,073
Fuel and Feedstock Transport	4,265	2,418	2,808
Domestic Farm Inputs and Fertilizer N_2O	8,281	1,660	4,217
Domestic Soil Carbon	-4,033	-10,820	-2,487
Domestic Livestock	-3,746	9,086	3,462
Domestic Rice Methane	-209	434	-1,555
Int'l Farm Inputs and Fertilizer N_2O	6,601	0	1,310
International Livestock	3,458	0	-245
International Rice Methane	2,089	0	-920
Tailpipe	880	880	880
Fuel Production Emissions	27,851	-32,628	-32,628
Total	77,233	-28,969	-10,087
2005 Gasoline Baseline	98,204	98,204	98,204
Percent Change from Gasoline Baseline	-21.4%	-129.5%	-110.3%

Given the measure of emissions as shown in Table 5.1, it is a simple exercise to convert to a measure of emissions per acre if we know the amount of energy provided by an acre of feedstock (i.e., mmBTU/acre). However, 2022 yield projections, particularly for switchgrass, are highly uncertain. Moreover, there is also uncertainty as to the external value of biofuel production. Making parameter assumptions for each of these, while resulting in an easily determinable solution to the model, provides little information given the extensive range of possible outcomes of these parameter values. For this reason, we have chosen to model various potential scenarios so as to generate an "optimality frontier," interpreted as an implied carbon price curve. On one side of the frontier, corn is optimal for biofuel production while switchgrass is optimal on the other side over a range of possible yields and external biofuel production values.

5.4.1. Corn Grain Ethanol

In converting GHG emissions from a per mmBTU basis to a per acre basis, some care is required in order to properly account for how emissions change with varying yields. This is particularly relevant for emissions associated with land use change, which is the largest contributor to emissions in the production of corn grain ethanol. With the exception of land use change, it is assumed that emissions as measured in g/mmBTU do not change as yields change. For example, the plant emissions associated with production of one gallon of ethanol are the same regardless of whether corn yields are 180 bu/acre or are 10% lower at 162 bu/acre. Emissions due to land use change must be treated differently. In this case, if corn yields are 162 bu/acre, 10% more land devoted to corn is necessary to produce a certain volume of ethanol. Thus, emissions associated with land use change must be 10% higher on a per gallon basis. On a per acre basis, however, emissions associated with land use change are constant.

In order to calculate emissions from land use change for varying yields, the values from the EPA analysis are used as a baseline. For simplicity, it is assumed that the marginal contribution to emissions from an additional gallon of ethanol (or acre of land) due to land use change is equal to the average contribution as determined by the EPA.

5.4.2. Cellulosic Ethanol from Corn Stover

With emissions measured per acre, corn grain ethanol constitutes only one part of the biofuel pathway utilizing corn as a feedstock. The corn stover can also be used for production of cellulosic ethanol. Combining this pathway together with the production of corn grain ethanol to obtain a net measure of emissions associated with corn is a bit more complicated and requires a few more assumptions.

There are two critical, often controversial, assumptions that must be made in any LCA that uses corn stover as a feedstock for production of cellulosic ethanol. These are the rate of corn stover removal and the conversion rate of corn stover to ethanol. It is recognized in the EPA impact analysis that, while needed, specific guidelines for determining sustainable removal rates do not yet exist (EPA 2010b). It is generally accepted that some amount of residue must remain on the field for protection against erosion and to provide nutrients for the next crop. However, there is not widespread agreement as to what constitutes a sustainable removal rate, recognizing that a field's susceptibility to erosion is dependent on a number of factors, including tillage, timing of field operations, soil type, field specific characteristics (e.g., slope), and of course the amount of residue left on the field.

Sheehan *et al*. (2003) estimate corn stover removal rates of 40% for corn under mulch till and 70% under no-till. Perlack *et al*. (2005) use removal rates of 33%, 54%, and 68% depending on whether the type of tillage is the current (2004) tillage mix, increased no-till, or all no-till in the commonly referenced "Billion Ton Study." There has been some criticism directed at the Billion Ton Study for not being conservative enough on removal rates, suggesting that these are too high because of their focus on soil erosion as the limiting factor whereas soil organic carbon (SOC) is an additional constraint (Wilhelm *et al*. 2007). The default removal rate assumed in GREET (version 1.8c) is 50%.

The EPA provides an in-depth discussion of the issues surrounding sustainable removal rates, ultimately using assumptions of 0%, 35%, and 50% based on whether the type of tillage is conventional tillage, conservational tillage, or no-till, respectively. In addition to the wide range of removal rates cited in the literature, it is reasonable to assume that in the near-term corn stover would be most advantageously removed from cropland managed under no-till first, given that there is very little stover currently being removed for production of cellulosic ethanol. For these reasons, a removal rate of 50% is assumed for this study.

There is also some disagreement surrounding the conversion rate of agricultural residue into ethanol as cited throughout the literature. According to Kadam and McMillan (2003), who cite unpublished National Renewable Energy Laboratory (NREL) data, the theoretical ethanol yield from corn stover is 115 gallons per dry ton. However, this technology is still in its infancy and significant commercial scale production has yet to be realized. For this reason, there is a great deal of speculation about what a reasonable conversion rate on a commercial scale might be. Sometimes a distinction is made between near-term and long-term technology, with a higher conversion rate assumed in a long-term scenario.

In the EPA impact analysis, different conversion rates are used depending on the year in which GHG emissions are modeled. For the 2012, 2017, and 2022 scenarios, the EPA uses conversion rates of 71.9, 89.8, and 92.3 gallons per dry ton, respectively. GREET assumes a conversion rate of 90 gallons per dry ton as a default value in both near-term (2010) and long-term (2020) scenarios. In their technical report for NREL, Aden *et al*. (2002) cite a conversion rate of 87.9 gallons per dry ton. However, in a subsequent analysis, this number is revised sharply downward to 71.9 gallons per dry ton (Aden 2008). In their study, Tokgoz *et al*. (2007) use a conversion rate of 70 gallons per dry ton. For our analysis, we seek to avoid controversial speculation regarding technology progression and assume a conversion rate of 70 gal/ton.

Based on the assumptions discussed thus far, a per acre measure of emissions associated with cellulosic ethanol production from corn stover can be calculated. It should be noted that there are no emissions associated with land use change in the case of ethanol production from corn stover. This is consistent with the EPA assumption that emissions from land use change are already accounted for in the use of corn grain (whether from food and feed or from biofuel production). Having obtained a measure of emissions per acre for ethanol produced from corn grain and corn stover, we need to simply combine these two measures to arrive at a per acre measure of emissions associated with corn, using both grain and stover as feedstocks for biofuel production.

5.4.3. Cellulosic Ethanol from Switchgrass

As with the LCA for production of cellulosic ethanol from corn stover, there are two particular components of the LCA utilizing switchgrass that have a great deal of uncertainty. The first, as with corn stover, is the conversion rate. The EPA assumes that the conversion rate of switchgrass to ethanol is the same as that of corn stover to ethanol. In reality, these rates should be slightly different because of differing cellulose, hemicellulose, and lignin contents of the respective biomass as shown by Spatari, Zhang, and MacLean (2005) who used a conversion rate of 87.2 gal/ton for switchgrass versus 89.8 for corn stover. Thus, using a conversion rate that is constant across feedstocks results in a minor penalty against corn.

The second source of uncertainty is in regard to switchgrass yields, which vary widely throughout the literature. As stated in the EPA impact analysis, commonly reported yields based on field trials range from 1 to 12 tons per acre depending on, among other things, geographical location, switchgrass variety, and soil attributes (EPA 2010b). Khanna, Dhungana, and Clifton-Brown (2008) reported an average yield in Illinois of 3.9 tons/acre. Lemus *et al*. (2002) came to a similar conclusion for Iowa switchgrass yields of the "Cave-In-Rock" variety at 3.8 tons/acre. Higher switchgrass yields are typically observed in the south where growing conditions are considered to be more favorable. Cassida *et al*. (2005) reported a range of switchgrass yields in the south central U.S. of 4.8 to 8.8 tons per acre.

In the proposed ruling issued by the EPA in 2009, switchgrass yields for 2022 were projected at 6.3 (wet) tons per acre. This projection was revised substantially upward in the final rule to 7.8 tons/acre. This highly variable data and widespread disagreement on switchgrass yields underscores the need for our model to be applied over a range of yields for the purposes of sensitivity.

Khanna, Chen, Huang, and Onal (2011) estimate switchgrass yields for the entire continental U.S. at the crop reporting district (CRD) level. These estimates are based on a biogeochemical model described by Jain, Khanna, Erickson, and Huang (2010) in detail. The estimates make use of experimental field trials for switchgrass based in Illinois and the model extrapolates to the continental U.S. based on specific regional attributes, including climate and soil conditions. We also use these data on switchgrass yields for the portion of our study seeking to determine optimality at a regional level under a given set of policies. However, in using these field trial data, we make an adjustment by reducing yields in all districts by 25% to account for yield loss when grown at a commercial scale.[2]

[2] Iowa State University extension corn yield trials for 5 counties averaged approximately 225 bu/acre in 2010 (Iowa State University Extension and Outreach, accessed January 12, 2012). The actual observed commercial yields in these counties in 2010 were approximately 170 bu/acre, a 25% reduction. Switchgrass yields used by Khanna, Chen, Huang, and Onal (2011) are correspondingly reduced by 25% in our analysis.

Table 5.2 summarizes the per acre emission calculations for each pathway discussed here maintaining the yield assumptions made by the EPA. Corn grain ethanol and cellulosic ethanol are presented separately. The row labeled "Total" represents total emissions not including a gasoline displacement credit based on the amount of energy provided by the pathway on a per acre basis. In order to arrive at a measure of emissions for corn, the totals from corn grain ethanol and cellulosic ethanol from corn stover are combined. For the numerical analysis, the measure of emissions including the gasoline displacement credit is used so as to keep separate the carbon and non-carbon portion of each pathway.

Table 5.2. EPA Annualized GHG Emissions by Biofuel Pathway (tCO_2e/acre).

Emissions Category	Corn Grain	Corn Stover	Switchgrass
International Land Use Change	3.14	0	1.73
Fuel and Feedstock Transport	0.42	0.07	0.25
Domestic Farm Inputs and Fertilizer N_2O	0.82	0.05	0.37
Domestic Soil Carbon	-0.40	-0.42	-0.30
Domestic Livestock	-0.37	0.27	0.30
Domestic Rice Methane	-0.02	0.02	-0.12
International Farm Inputs and Fertilizer N_2O	0.64	0	0.12
International Livestock	0.35	0	-0.02
International Rice Methane	0.20	0	-0.07
Tailpipe	0.10	0.02	0.07
Fuel Production Emissions	2.77	-0.94	-2.84
Total	7.64	-0.38	-0.21
Total Including Gasoline Displacement	-2.08	-3.78	-9.09

5.5. Results

In our model, we want to keep separate the value attributable to carbon (through P and γ_i) and all other value associated with ethanol production ethanol (through S and δ_i). Thus, accounting for the energy content of ethanol and emissions associated with gasoline production, each gallon of ethanol produced by a given pathway generates an additional carbon credit. This adjusted measure of GHG emissions associated with each feedstock is shown in Table 5.2 in the last row labeled “Total Including Gasoline Displacement.”

Having established a methodology for determining a per acre measure of emissions, we now have everything that is required for our optimization model to proceed. For the empirical portion of this study, the optimization model and methodology for converting emissions from a per gallon basis to a per acre basis were programmed in Matlab and the “fmincon” routine was used to obtain solutions to equations (5.8) through (5.10).

5.5.1. General Results: No External Biofuel Value

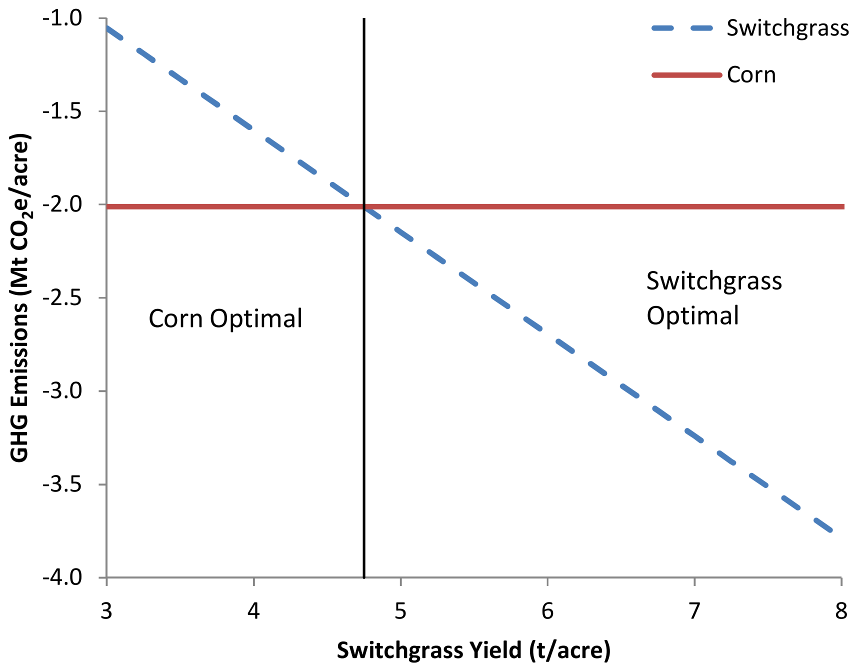
We use the optimization model first in a general sense, i.e., not region specific. The model is solved over a range of switchgrass yields and external production values. This results in an optimality frontier representing a switching point between corn and switchgrass as optimally chosen feedstocks. For this general case, corn yields are normalized to 165 bu/acre. The ranges considered for this portion of the analysis are 3-12 tons/acre for switchgrass yields and \$0 to \$1.00 per gallon for the external value.

This subsection describes the general results when there is no external value to biofuel production. Only the cost associated with GHG emissions is considered. In the next subsection, a more realistic scenario is presented in which there is an additional external value to biofuel production beyond that associated with carbon.

The results of this subsection show that when emissions are measured per acre, there is a range of yield assumptions whereby the social planner optimally allocates cropland to corn even if there is no external biofuel production value. Figure 5.1 illustrates these results. Switchgrass yields are presented on the horizontal axis and GHG emissions are shown on the vertical axis.

From Figure 5.1, it can be seen that emissions associated with switchgrass increase as switchgrass yields decrease, moving leftward along the horizontal axis. Emissions associated with corn are constant as yields are held fixed at 165 bu/acre. As a result of measuring emissions per acre, there is a threshold level of switchgrass yields representing an optimality frontier. This threshold, 4.8 tons/acre, is determined as the intersection of the two lines depicted in Figure 5.1. For any switchgrass yields less than 4.8 tons/acre, corn is optimal since emissions associated with corn are lower than those of switchgrass.

Figure 5.1. GHG Emissions With No External Value To Biofuel Production.

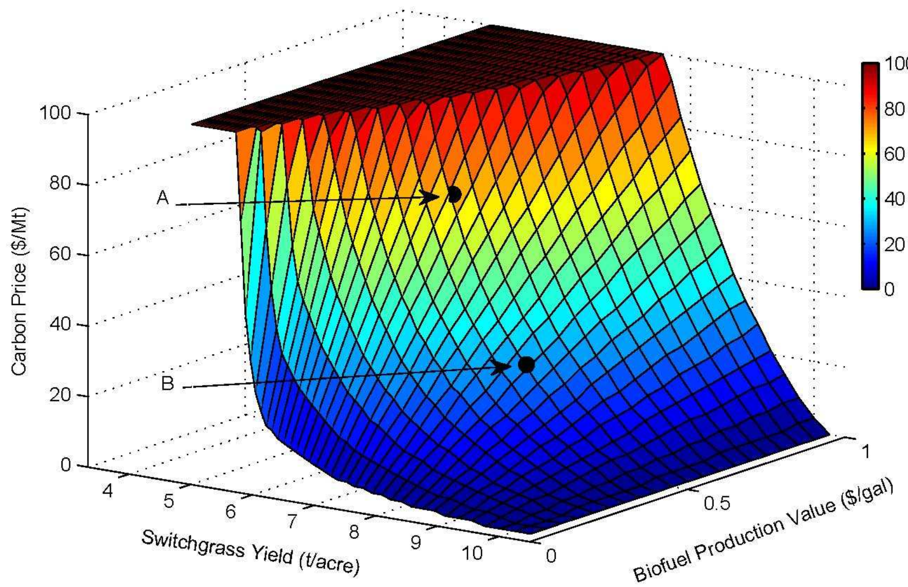


The results shown here are particularly significant given the current debate in the U.S. Midwest as to whether corn or switchgrass would be better for emissions reduction. These results show that the answer to this question depends on whether emissions are considered per acre or per gallon. As we argue, a realistic social planner problem requires that emissions be measured per acre. If this is the case, it is unlikely that switchgrass would be an optimal feedstock choice for production of biofuels in the Midwest based on reasonable yields for that region.

5.5.2. General Results: With External Biofuel Value

Whereas the previous subsection illustrated results when there is no external value to biofuel production, this subsection provides a more realistic setting in which there is an additional per gallon value to biofuel production, possibly resulting from a desire to reduce dependence on imported oil. For this case, we model equations (5.8) through (5.10) as in the previous subsection, but we add an additional dimension to allow for variability in the external value to biofuel production. The numerical results are illustrated in Figure 5.2.

Figure 5.2. Optimality Frontier: Implied Carbon Price by Switchgrass Optimality.



Consistent with Figure 5.1, corn is always optimal whenever switchgrass yields are below 4.8 t/acre, as seen in Figure 5.2 by the cutoff of the surface plot at this point. For yields lower than this, there is no carbon price that would cause switchgrass to become optimal since emissions reduction favors corn. Conversely, whenever switchgrass yields are greater than 10.2 t/acre, switchgrass is always optimal, since switchgrass reduces emissions more than corn and has a higher energy yield per acre.

Between these two bounds, switchgrass is better from an emissions reduction perspective, but corn is better from an energy perspective. Thus, assigning a higher weight to the carbon portion of equation (5.8), through increasing carbon prices, causes switchgrass to be favored more relative to corn. The surface of Figure 5.2 can then be interpreted as an implied carbon price curve. Between switchgrass yields of 4.8 t/acre and

10.2 t/acre, there is a carbon price that is implied if switchgrass is indeed considered the optimal feedstock for any given external biofuel production value.

Using a $0.45 per gallon biofuel tax credit as a frame of reference for the external value to biofuel production, Figure 5.2 shows that the implied carbon price based on EPA relative yield assumptions is $72/t. This is illustrated as point A in Figure 5.2. The implied carbon price at these yield assumptions steadily increases from $8/t with a $0.05 external production value to over $100/t once the external value rises above $0.65 per gallon. Most near- to long-term projections of carbon prices lie within a range around $30/t. As shown in Figure 5.2, with a $0.45 per gallon external value to biofuel production, switchgrass yields would need to be at least 8.1 t/acre for switchgrass to be optimal relative to corn. This is represented by point B in Figure 5.2.

5.5.3. Region-Specific Results

In this subsection, we apply the same optimization model to region-specific data on corn and switchgrass yields. For this case, we use 2006-2010 average non-irrigated corn yields at the district level. These data are obtained from the National Agricultural Statistics Service (NASS). Our switchgrass yields are those used by Khanna, Chen, Huang, and Onal (2011), discounted by 25% as explained earlier. These yields for corn and switchgrass are displayed in Figure 5.3 and Figure 5.4 respectively.[3]

We consider three alternative policy scenarios. The first, analogous to section 5.5.1, considers a scenario in which there is no external value associated with biofuel production. In this scenario, it is only emissions that are significant. The second scenario is analogous to section 5.5.2. For this scenario, we consider an external value to biofuel production of $0.45 per gallon. Carbon prices are exogenously fixed at $5/t in this scenario to represent a near-term scenario in which carbon emissions are not highly valued. The third and final scenario also considers a $0.45 per gallon external value but ascribes a higher carbon price of $30/t to represent a more long-term scenario reflecting carbon price projections. These latter two

[3] This analysis excludes western states since corn is not a significant crop in this area.

scenarios provide a sense for how the optimal solution might change as the relative weights between bioenergy and emissions are altered.

Figure 5.3. 2006-2010 Average Non-Irrigated Corn Yields.

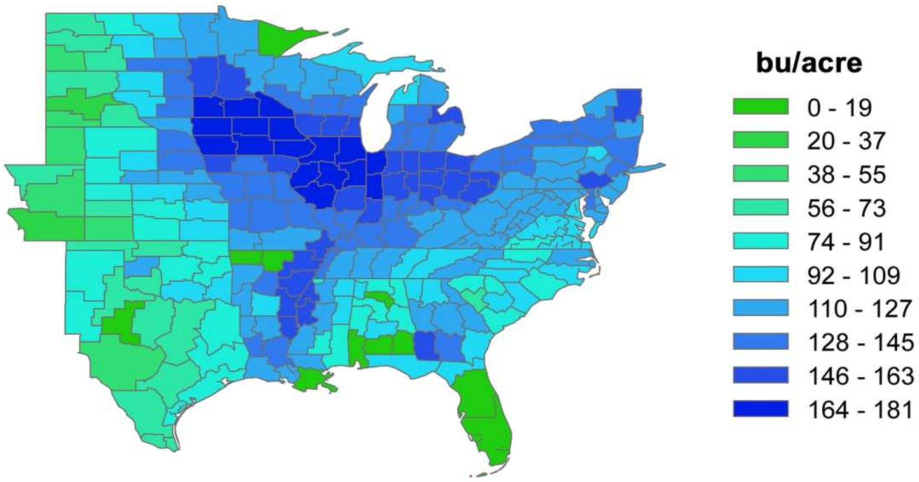
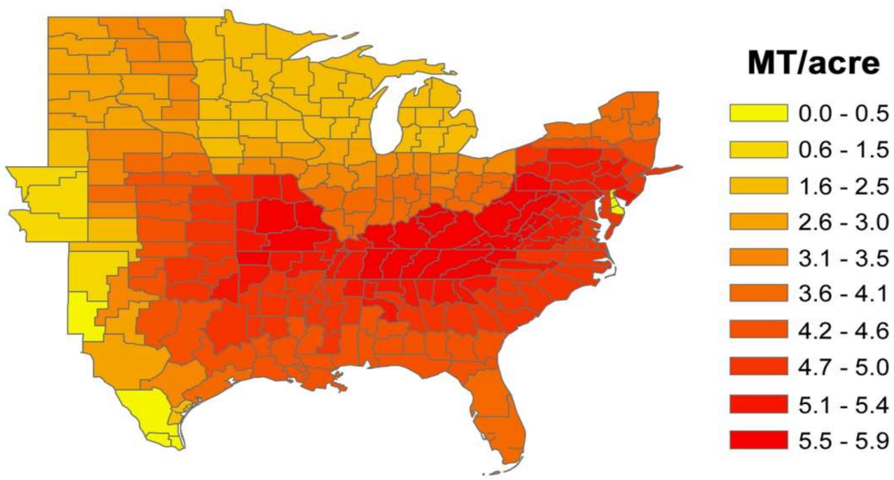
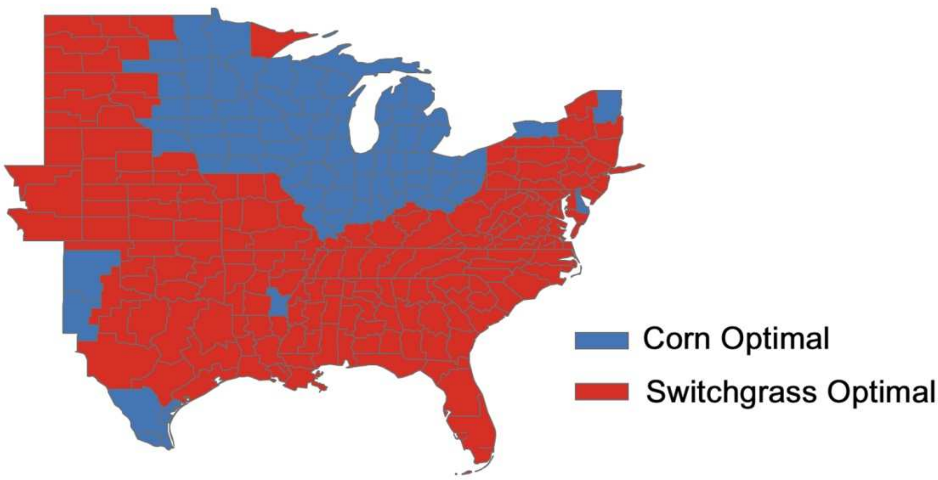


Figure 5.4. Switchgrass Yield Estimates.



The results of the first scenario are presented in Figure 5.5. With no external value ascribed to biofuel production, this scenario reflects a comparison between biofuel pathways purely from an emissions perspective. As one might expect, corn is found to be optimal in regions where non-irrigated land is particularly well-suited to corn production, i.e., the Corn Belt. In these regions, there is no price for carbon that would cause switchgrass to be optimally chosen in our model since corn is the favored crop when considering emissions alone. Moving westward from Iowa and Minnesota, corn yields on non-irrigated cropland fall dramatically in the western Dakotas and Nebraska. Thus, switchgrass is found to be optimal even though yields are not particularly high in these regions (2.5 – 3.5 tons/acre). Moving southward from the Corn Belt, non-irrigated corn yields do not fall as dramatically. However, switchgrass is known to grow particularly well in temperate climates with large amounts of solar radiation. For this reason, switchgrass is also found to be optimal moving southward.

Figure 5.5. Region-Specific Solutions: $S = \$0$.



Results for the second scenario are provided in Figure 5.6. Here, we allow for an external value to biofuel production of \$0.45 and a somewhat low carbon price of \$5/t. Here, it can be seen that the situation is dramatically reversed from that of the previous scenario. In this scenario, there are only scattered regions in the south and two districts in the western Dakotas where switchgrass is still optimal. Corn acreage generally yields larger quantities of biofuel relative to switchgrass, even at low to moderate corn yields. Therefore, coupled with a low value on carbon emissions, ascribing an external value to bioenergy production causes corn to become optimal in most regions considered in our analysis.

Figure 5.6. Region-Specific Solutions: $\mathbf{S} = \$0.45, \mathbf{P} = \$5$.

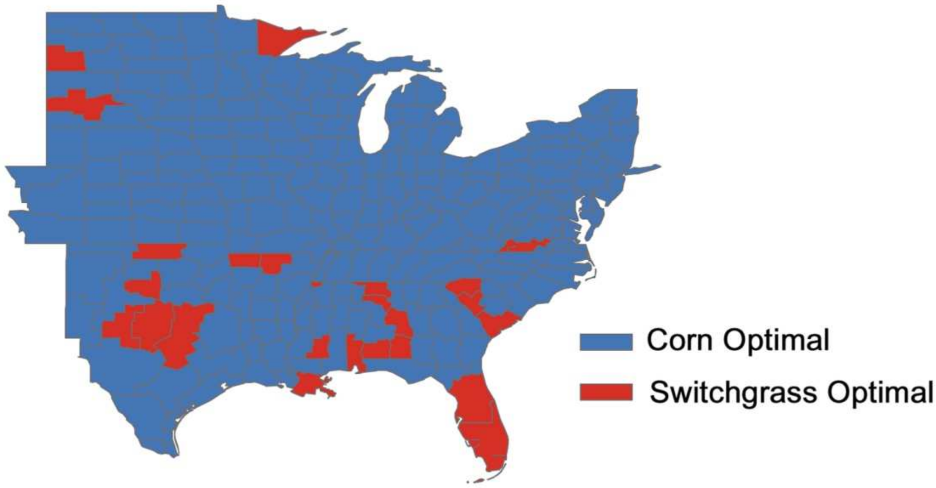
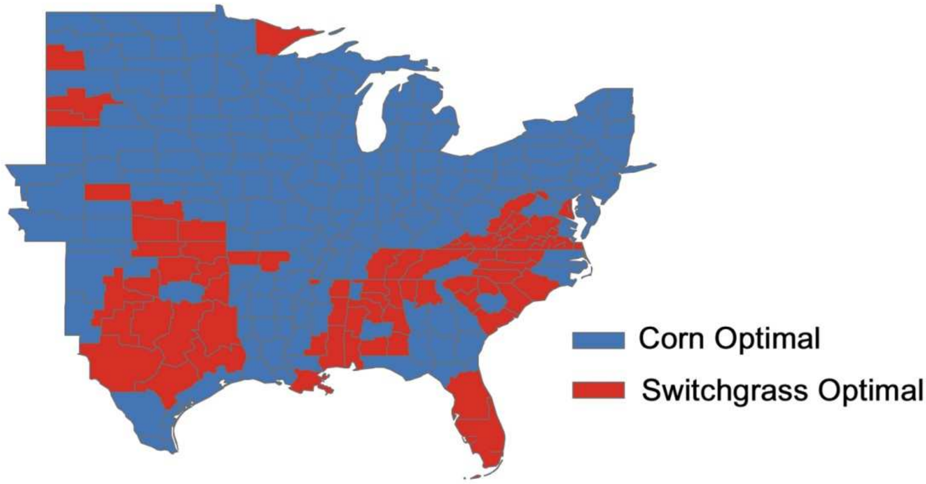


Figure 5.7 illustrates the results of the third and final scenario, reflective of a long-term scenario with a higher price on carbon. Here, it can be seen that switchgrass is optimally chosen more often in southern states where switchgrass yields are relatively high. It is worth noting, however, that despite relatively low corn yields on non-irrigated cropland in the western plains states (North Dakota, South Dakota, Kansas, and Eastern Colorado), corn is found to be optimal in the vast majority of districts within these regions. Again, this is due to the relative weights ascribed to the emissions and bioenergy portions of the optimization problem (i.e., the left-hand and right-hand terms of equation (5.8), respectively). A comparison of Figure 5.6 and Figure 5.7 thus provide a regional qualitative snapshot of the trade-off between bioenergy and emissions discussed in this paper as the weights on these terms are altered.

Figure 5.7. Region-Specific Solutions: $\mathbf{S} = \$\mathbf{0.45}, \mathbf{P} = \$\mathbf{30}$ **.**



In recent years, switchgrass has received significant attention as a potential feedstock that could be most suitable for meeting both environmental goals and satisfying the RFS2 mandate for cellulosic biofuel production. This has been especially true in the past three years following a study prepared by Schmer *et al*. (2008) for the Proceedings of the National Academy of Sciences. In their study, Schmer *et al*. estimated that switchgrass, used for production of cellulosic ethanol, produces 540% more energy than it requires in inputs. Their study is based on field-trials of switchgrass grown in the mid-continental United States (Nebraska, South Dakota, and North Dakota) with average yields ranging from 2.3 to 5.0 tons/acre. Schmer *et al*. strongly imply that, consistent with their results, switchgrass should play a prominent role in the production of U.S. biofuels.

Our study would support these results only outside the Corn Belt and only if we consider carbon emissions alone, ignoring any potential external value to biofuel production. As described in the previous discussion, allowing for this external value of $0.45 causes corn to become optimal in the majority of CRDs considered in our analysis, including Nebraska and the Dakotas. It is important to recognize that conventional agricultural LCAs would support the implication made by Schmer *et al*. that it would be environmentally preferable to grow switchgrass in these regions by failing to account for the trade-off between bioenergy and emissions on a per acre basis.

As shown by the EPA, switchgrass generates a 110% reduction in GHG emissions whereas corn grain ethanol generates only a 21% reduction. However, when emissions are measured per acre, the gap between these reductions narrows because of differing per acre energy yields. With an added external value to biofuel production, the rankings are often reversed at low to moderate carbon prices such that corn becomes optimal in most districts, particularly in the Corn Belt and surrounding regions. Thus, expanding on the previous sections, our results suggest that under a realistic scenario of low carbon prices and some external value to biofuel production, it is unlikely switchgrass would be an optimal feedstock when compared to non-irrigated cropland used to grow corn.

5.6. Conclusion

In this paper, we describe a model constructed to be representative of the interests of U.S. society in producing biofuels. These interests focus on minimizing environmental damage associated with the use and production of advanced biofuels while maximizing the value associated with production subject to a land constraint. The structure of this model was designed to encompass opportunity costs associated with selection among competing alternative biofuel pathways stemming from land scarcity. The structure of the model then requires that GHG emissions be measured on a per acre basis, rather than on a per gallon basis as is done in most agricultural LCAs.

Drawing upon the data and parameter assumptions used by the EPA in conducting LCAs for corn grain ethanol and cellulosic ethanol produced from corn stover and switchgrass, a per acre measurement of GHG emissions was calculated for corn, using both grain and stover, as well as for switchgrass. The optimal pathway was then determined numerically over a range of corn yields, switchgrass yields, and an external biofuel production value in accordance with the optimization model that was presented. The general solutions to this model resulted in an implied carbon price curve, which represents the minimum carbon price required for switchgrass to be an optimal feedstock choice relative to corn in the production of biofuels. Following these results, we solve the model regionally by considering corn and switchgrass yields at the district level. This allows us to determine which regions of the U.S. would most likely be used to grow corn (or switchgrass) to produce biofuels from a social planner perspective.

The general results of our empirical analysis show that at corn yields of 165 bu/acre and switchgrass yields (4 t/acre), there is no carbon price at which switchgrass is optimal. This is because, at these yields, corn provides more energy per acre as well as having a better carbon profile per acre. Conventional agricultural LCAs would predict that switchgrass would have a better carbon profile than would corn, as they do not take into account differing energy yields per acre once a land constraint is imposed. Under the relative yield assumptions made by the EPA and an external value to biofuel production of \$0.45 per gallon, the implied carbon price at which switchgrass is optimally chosen is \$72/t.

Our regional analysis suggests that it is highly unlikely switchgrass would be an optimal feedstock for biofuel production within the Corn Belt. In our model, switchgrass becomes more viable moving southward or westward from the Corn Belt, but only if there is no positive external benefit to biofuel production or if carbon prices are relatively high.

Given that most reasonable near- to mid-term projections of carbon prices lie in a range of \$5/t to \$30/t, the results of this study indicate that one should be cautious when suggesting that switchgrass is an environmentally superior choice relative to corn, even on what is sometimes considered marginal cropland. There is a trade-off between GHG emissions (or emissions reduction) and energy production that must be considered. The presence of a land constraint makes this trade-off less obvious than what is often implied by conventional LCAs. Policymakers would be wise to consider the implications of a land constraint when drawing upon the conclusions of agricultural LCAs so as to design policies that are environmentally focused while acknowledging the need for production of alternative transportation fuels.

5.7. Appendix

5.7.1. EPA Life Cycle Methodology

To obtain GHG emissions on a life cycle basis, the EPA analyzed two separate scenarios for each biofuel pathway considered in a consequential LCA approach. The first scenario was constructed as a baseline or business-as-usual case in which the volume of biofuels produced in 2022, the final year by which the RFS2 mandates must be phased in, is simply the forecast taken from the 2007 Annual Energy Outlook. Then, in order to determine the average GHG impact of a marginal gallon of biofuel from a specific pathway, a control case is modeled in which the volume of biofuel corresponding to that pathway is set equal to the volume observed in the RFS2 mandates. All of the other biofuel volumes are held constant at the baseline value. For example, in the reference case for renewable biofuel (i.e., ethanol produced from corn grain), the volume modeled is 12.3 billion gallons. The allowable volume under RFS2 for non-advanced renewable biofuel is 15 billion gallons. Each of these scenarios is modeled, and GHG emissions for each are calculated. The difference in emissions between the two scenarios represents the additional emissions associated with 2.7 billion gallons of renewable biofuel.

5.7.2. EPA Biofuel Modeling Approach

The EPA draws on various models and data sources in order to obtain GHG emission measurements. Measures of GHG emissions in domestic categories are obtained using the Forest and Agricultural Sector Optimization Model (FASOM) together with emission factors taken from GREET, DAYCENT (a daily version of the CENTURY ecosystem model) and the Intergovernmental Panel on Climate Change (IPCC) as appropriate. For GHG emissions originating from international sources, Food and Agricultural Policy Research Institute (FAPRI) models are combined with Winrock satellite data. Tailpipe emissions are obtained from Motor Vehicle Emissions Simulator (MOVES) results.

In its impact analysis, the EPA reports a measurement of GHG emissions on a gCO_2e/mmBTU basis for each emission category. The EPA considered various time frames for the amortization of emissions in the proposed rule but decided on 30 years for the final rule with no discounting. Average annual emissions for each category are then easily obtained by dividing the cumulative emissions observed throughout the time frame considered by 30.

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CHAPTER 6. GENERAL CONCLUSIONS

The unifying theme of this dissertation is its focus on the effects of individual decisions and external factors on commodity markets and land used for grain production. The dissertation begins by recognizing that agricultural commodity markets have witnessed unprecedented price and volatility fluctuations in recent years. This has generated significant debate regarding the market-based or policy-oriented forces that may have played a role. The chapters of this dissertation, each written as a stand-alone essay, seek to address a specific component within this debate.

The first essay, chapter 2, proposes a behavioral mechanism that could be used to explain why producers' hedging decisions appear to be strongly correlated with the level of futures prices. This essay draws on prospect theory as the underlying decision-making framework which would induce producers to hedge more of their expected output in futures markets as futures prices rise. An implication of this result is that a bullish demand shock within a given crop year could exacerbate price or volatility swings as harvest approaches. This could occur when producers commit more of their future production in advance of harvest by taking a larger short futures position. With some claiming that speculative trading is causing extreme price and volatility fluctuations in commodity markets, this essay shows it is conceivable that hedgers may also play a role if prospect theory is used as the behavioral framework.

The second essay, chapter 3, uses an empirical approach to test for the extent to which speculative trading has contributed to commodity price and volatility fluctuations. This essay tests for bidirectional Granger causality in 19 actively-traded commodity markets both individually and in aggregate. Tests of causality are conducted first in the time domain and then in the frequency domain using spectral analysis. Using spectral analysis allows a determination to be made regarding short-run causality as distinct from long-run causality. The results of this essay show that there is little evidence suggesting that speculative trading has been a driving factor of prices, particularly in the long run. There is some evidence suggesting that speculation has impacted volatility.

The third essay, chapter 4, extends the empirical analysis of chapter 3 by considering two distinct measures of speculation in an attempt to determine whether speculators have influenced commodity prices or volatility. Using a bounds-testing approach to detect cointegration among variables in their level form, long-run causality exists when there is evidence of a level relationship. Short-run Granger causality is determined by applying an error correction model to account for this cointegrating relationship. The results of the empirical analysis support the findings of the previous essay by failing to find significant evidence that speculative trading has influenced commodity futures prices. The key finding of this essay, however, is evidence suggesting that speculation has affected volatility, particularly in the long-run.

The fourth and final essay, chapter 5, addresses a shortcoming of conventional agricultural life cycle assessments (LCAs) which measure greenhouse gas emissions per unit of energy. By failing to account for the opportunity cost associated with constrained land use, these LCAs may improperly rank biofuel pathways with respect to their emissions reduction potential. Corn and switchgrass are modeled as competing alternatives for biofuel production. The results of this essay suggest that it is unlikely switchgrass would be considered optimal when LCAs are conducted per acre. This is especially true in midwestern states. Under relatively high carbon prices and/or relatively low external benefits to biofuel production, switchgrass may be optimally grown in some southern regions or scattered districts in the western prairie states.