ESSAYS ON THE BEHAVIOR OF COMMODITY PRICES
AND ECONOMIC EXPERIMENTAL DESIGN

BY

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To the Faculty of Washington State University:

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This dissertation consists of three studies on the behavior of commodity prices and on economic experimental design. The first study investigates the extent to which speculative trading in futures markets contributes to volatility in cash markets. By analyzing coffee, crude oil and wheat we find that futures and cash prices are cointegrated in levels and exhibit bi-directional causality in variance. Thus, factors causing higher futures price volatility will also cause higher cash price volatility. Results suggest increases in speculative activity are associated with decreases in futures price volatility, thus cash price volatility. On balance it appears that policies which limit speculative trade contribute to de-stabilizing cash prices, rather than reducing volatility as intended.

The second study investigates the existence of futures market risk premiums. We argue that since the risk premiums are paid to futures market speculators by cash market inventory holders, then if it exists we should find evidence from the behavior of
the cash market storers. By analyzing two types of soybean cash market inventory holders, producers and commercial elevators, we do not find evidence that the cash market storers have paid risk premiums. Moreover, we separate our analysis for the period before and after the fourth quarter of 2007, with the commodity markets being characterized by high price levels and volatility in the latter sub-period. We find that both types of cash market storers changed their risk preferences between the two sub-periods. However, the evidence suggest they have not paid risk premiums in either period.

The third study investigates the effect of the revelation of posted bids in second-price experimental auctions for apple quality attributes under an experimental design where information is added progressively across rounds. We find that the revelation of posted bids does not bias the following bids and that having increased information on the apple increases the accuracy of participants’ following bids. Therefore, the final round bids are used to elicit consumers’ willingness to pay for the apple attributes of interest in this study. Consumers are found to prefer large, firm, sweet, crisp apples with fewer defects.
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Dedication

To my parents Cheng Li and Xiufen Zhang,

and to my husband Xin Zhao.
CHAPTER 1 INTRODUCTION

This dissertation consists of three studies. The first two studies are stand-alone but related, and concern the behavior of commodity prices. The third study is on economic experimental design.

First Study

Starting from late 2007, most commodity markets have experienced an increase in average price levels, accompanied by higher volatility. Several studies have attempted to explain this price behavior and some of them blame speculators for the recent price action based on the observation that speculative positions increased significantly before price increases were observed (Masters, 2008; Masters, 2010; Singleton, 2012). Influenced by these accusations, the U.S. Commodity Futures Trading Commission (CFTC) approved limits on the size of speculative positions for 28 core physical commodities in October 2011, intending to mitigate speculative influence in futures markets. These limits immediately stirred debate regarding their necessity or effectiveness in managing speculators and the potential adverse effect on commercial entities that use derivatives to hedge price risk.

Several other studies fail to find causality between speculation and price movements and concluded that speculators do not destabilize futures markets (Brunetti and Büyükşahin, 2009; Büyükşahin and Harris, 2011; Sanders and Irwin, 2011; Hamilton and Wu, 2012; Irwin and Sanders, 2012; Bohl and Stephan, 2013). However, these appear to have had less influence in driving recent policy initiatives.
Despite the number of previous studies, the body of the research is not complete. Most of the earlier studies focus on speculative influences on price levels rather than price volatility. Further, they are directed at speculative influences on commodity futures prices and do not explicitly examine the influence on cash prices. In this paper we examine whether speculation in futures markets contributes to increased volatility in cash prices. This is an important consideration because cash price volatility reflects the price risk faced by both producers and consumers of the physical commodity and much of the debate about speculative influence is really a debate about the way other market participants are impacted by futures market activity. The focus of this work is on crude oil, wheat, and coffee. These products differ in terms of commodity category (they cover energy, both imported and exported food stuffs, as well as both thin and deep futures markets), and the characteristics of their futures markets. Crude oil is the largest natural resource commodity in futures trading, wheat futures contracts are one of the oldest and most actively traded agricultural futures in the U.S., and the coffee futures market represents both a thin market and one with no domestic production. Further, the potential of the coffee futures market to impact the price risk faced by cash market participants has already been alluded to by Fortenbery and Zapata (2004).

The conclusions are similar across the three different commodities. First, the futures and cash prices of each of the three commodities are cointegrated. Second, there exists bi-directional volatility spillover between the futures and cash prices for all the three commodities. Therefore, factors causing higher futures price volatility will also cause higher cash price volatility. No evidence is found to support the hypothesis that
increases in speculative positions increase futures price volatility, thus they do not impact cash price volatility. In fact, there is strong evidence suggesting that increases in speculative positions actually contribute to decreased futures price volatility. As a result, the CFTC limits on the size of speculative positions for the 28 core physical commodities approved in October 2011 is not expected to contribute to the stabilization of commodity prices, either in futures or cash markets. In order for public policy initiatives to impact market volatility in a positive way a more complete understanding of the drivers of recent price volatility is necessary.

Second Study

Keynes (1930) first introduced the concept of a risk premium in commodity futures markets in the theory of “normal backwardation”, where risk premiums were defined as the difference between the expected spot price at expiration and the current futures price. He argued that the opportunity for hedging was valuable for cash market inventory holders such that they were expected to pay to transfer the downward cash price risk to the futures market speculators. This payment measured the downward futures price bias compared to the expected cash price at expiration, which was also called the futures market risk premium. However, the empirical search for risk premiums has not resulted in a general consensus. One common point of the studies is that they all have been focused on the futures market. We argue that if the futures risk premium exists, it is given to the speculators by the hedgers to get rid of the risk of their physical positions on the cash market. Therefore, analyzing cash market players’ willingness to pay to reduce their price risk will provide more insight into the existence
of futures risk premiums. Lin and Fortenbery (2006) constructed a structural model to depict the optimal storage decision of two types of agents who held stocks: producers and commercial elevators. They found that the marginal risk premiums had positive and negative values, but the average marginal risk premium was significantly positive for both the producers and the commercial elevators over 1986 to 2002, so that on average the marginal risk premium was an incentive for the storers to hold one more unit of inventory. Moreover, the mean Arrow-Pratt risk premiums over the same time period were also significantly positive for both the producers and the commercial elevators, indicating that the cash market might pay a risk premium to the futures market during their study period.

Similar to Lin and Fortenbery (2006), this study looks for commodity market risk premiums from the cash market, i.e., whether the cash market storers are willing to pay futures market speculators to lock in the price of their inventories. We use soybeans as an example because there had been less government price influence on soybeans relative to other storable commodities (Lin and Fortenbery 2006). There are two types of storers on the soybean cash market: producers who hold on-farm inventories and commercial elevators who hold off-farm inventories. We analyze the two types of storers separately since they face different storage problems. The time period studied in this paper is from the first quarter of 1986 to the fourth quarter of 2012. Therefore this paper extends the study period in Lin and Fortenbery (2006) from 2002 to 2012. However, the contribution is not only an extension of time. Starting from late 2007, most commodity markets, including the soybean market, experienced an increase in
average price levels, accompanied by higher volatility. This paper does not only search for futures risk premiums that storers are willing to pay to speculators, but also looks for any changes in the risk premium characteristics after the fourth quarter of 2007 when the commodity markets began experiencing high price levels and high price volatility.

The utility maximization problems of the representative producer and representative commercial elevator are studied. Three components are specified in the marginal cost of the optimal inventory decision rules: the marginal transaction cost, marginal risk premium and marginal storage cost. The mean marginal transaction cost is negative in both sub-periods for the producer and the commercial elevator indicating that it serves as an incentive for holding one more unit of inventories. The producer’s marginal transaction cost is bigger in magnitude after the fourth quarter of 2007. This may be because the transportation cost dominates the producer’s transaction cost which is expected to increase due to the increase in crude oil price after the fourth quarter of 2007. The mean marginal risk premium of the producer is negative before the fourth quarter of 2007 and positive after that, and is positive for the commercial elevator in both time periods but is bigger in magnitude in the second period. This indicates that on average the cash market inventory holders are compensated more for holding one more unit of inventory after the fourth quarter of 2007 due to the higher market risk.

The producers and the commercial elevators present variable risk preferences within each sub-period as well as between the two periods. On average, the producer is risk-seeking before the fourth quarter of 2007 and risk-averse after that; while the
commercial elevator is risk-seeking in both periods. Therefore, no risk premium should be found on the futures market in the first time period because the overall cash market is risk-seeking. The producer might be willing to pay the risk premium to remove the risk in the second period, but they transfer the risk to the commercial elevator and the commercial elevator serves as the final representative of the cash market to the futures market. Since the commercial elevator is risk-seeking in the second period, no risk premium should be observed after the fourth quarter of 2007 either. In conclusion, the overall soybean cash market does not pay risk premiums over 1986 to 2012. This conclusion is consistent with most studies on the existence of risk premiums of a single commodity futures market.

Third Study

Experimental auctions, such as second price auctions (Vickrey 1961), are a popular method for eliciting individuals’ revealed preferences for goods and services. Recent studies include eliciting consumers’ willingness to pay (WTP) for fruits (e.g., Carrillo-Rodriguez, et al. 2013), ornamental plants (e.g., Yue, et al. 2012), and meat (e.g., Feuz, et al. 2004), etc. To help the participants understand the market mechanism and improve the accuracy of their bids, the experimental auctions often have multiple rounds and the winning bids are posted for the participants to observe before the next round begins (Shogren 2001).

However, the role of the posted bids in multi-round auctions is still an on-going debate (Milgrom and Weber, 1982; List and Shogren, 1999; Corrigan and Rousu, 2006). Different studies have reached different conclusions. But the common component of
the experimental auctions in these studies is they provide the same non-price information in every round of the auction. In this paper, we design a multi-round second-price experimental auction on apples where participants are given different information in each round. We are interested in the effect of posted bids on the bids in the following round. Specifically, we want to address whether the posted bids provide information that would increase participants’ bidding accuracy. Or do the posted bids cause “irrational” participant behavior so that the subsequent bids are biased? Moreover, this study provides valuable information to apple breeding scientists by informing them about consumers’ valuations on apples’ key external appearance and eating quality attributes which are objectively or instrumentally measured.

We find that the revelation of posted bids does not bias the bidding process in the following round. This might be due to consumers’ general familiarity with apples and apple market prices. Also, we find that having increased information about the apple increases the accuracy of the participants’ bids. Therefore, the final round bids are used to analyze consumers’ WTP for the apple attributes.

Size, defects coverage, crispness, firmness, sweetness and tartness are the attributes of interest. Three regression models for BID3 are fitted which differ in the measures used for the taste attributes (firmness, sweetness and tartness), while dummy variables are used for size, defects coverage, and crispness. Consumers’ degree of liking of the taste attributes, their feeling of the intensity of the taste attributes, and the scientific measure of the taste attributes are used for the three regressions. All three models give significantly positive estimates for size, crispness, firmness and sweetness, and
significantly negative estimates for defects. This suggests that BID3 gives accurate consumers’ valuations on the attributes. The estimates from the regression using scientific measures for the taste attributes show that consumers are willing to pay $0.13 more for big apples relative to small ones; $0.23 more for crisp apples relative to not crisp ones; $0.03 more for apples with firm flesh compared to the ones with creamy flesh; $0.07 for apples of more sweetness and $0.15 less for apples with more defects. Tartness is only significant in the model where consumers’ degree of liking is used for the taste attributes. The coefficient is positive, meaning the more the consumers like the tartness of an apple, the more they will pay for the apple. The insignificance of tartness in the other two models indicates that consumers have heterogeneous preferences on tartness: consumers who prefer tart (less tart) apples will pay more (less) for an apple when they feel strong intensity of tartness of the apple, or the scientific instrumental measure shows a higher level of tartness of the apple.

These results are useful to breeders and the industry in developing apple varieties with the quality characteristics most appealing to consumers.
References


CHAPTER 2 DO SPECULATORS IN FUTURES MARKETS MAKE CASH MARKETS MORE VOLATILE?

Abstract

This paper investigates the extent to which speculative trade in futures markets contributes to volatility in cash markets. By analyzing coffee, crude oil and wheat we find that futures and cash prices are cointegrated in levels and exhibit bi-directional causality in variance. Thus, factors causing higher futures price volatility will also cause higher cash price volatility. Results suggest increases in speculative activity are associated with decreases in futures price volatility, thus cash price volatility. On balance it appears that policies which limit speculative trade contribute to de-stabilizing cash prices, rather than reducing volatility as intended.

Key words: speculation, cash price volatility, cointegration, causality in variance, crude oil, wheat, coffee
Introduction

Beginning in late 2007, most commodity markets experienced an increase in average price levels, accompanied by higher volatility (Figure 2.1). Several studies have attempted to explain this price behavior. Many have focused on the futures markets of the underlying commodities. Some of them blame speculators for the recent price action based on the observation that speculative positions increased significantly before price increases were observed (Masters, 2008; Masters, 2010; Singleton, 2012). Influenced by these accusations, the U.S. Commodity Futures Trading Commission (CFTC) approved limits on the size of speculative positions for 28 core physical commodities in October 2011, intending to mitigate speculative influence in futures markets. These limits immediately stirred debate regarding their necessity or effectiveness in managing speculators and the potential adverse effect on commercial entities that use derivatives to hedge price risk.

Several other studies failed to find causality between speculation and price movements and concluded that speculators do not destabilize futures markets (Brunetti and Büyükşahin, 2009; Büyükşahin and Harris, 2011; Sanders and Irwin, 2011; Hamilton and Wu, 2012; Irwin and Sanders, 2012). These appear to have had less influence in driving recent policy initiatives.

Despite the number of previous studies, the body of the research is not complete. Most of the earlier studies focused on speculative influences on price levels rather than price volatility. Further, they were directed at speculative influences on commodity futures prices and did not explicitly examine the influence on cash prices. In this paper
we examine whether speculation in futures markets contributes to increased volatility in cash prices. This is an important consideration because cash price volatility reflects the price risk faced by both producers and consumers of the physical commodity and much of the debate about speculative influence is really a debate about the way other market participants are impacted by futures price activity. The focus of this work is on crude oil\(^1\), wheat, and coffee. These products differ in terms of commodity category (they cover energy, both imported and exported food stuffs, as well as both thin and deep futures markets), and the characteristics of their futures markets. Crude oil is the largest natural resource commodity in futures trading, wheat futures are one of the oldest and most actively traded agricultural futures in the U.S., and the coffee futures market represents both a thin market and one with no domestic production. Further, the potential of the coffee futures market to impact the price risk faced by cash market participants has already been alluded to Fortenbery and Zapata (2004).

**Literature review**

Masters(2008; 2010) and Singleton (2012) argued speculators were a major driver in the 2008 run-up in commodity futures, particularly energy futures prices. Their conclusions were based on observing increases in speculative futures positions prior to observing futures price increases. They essentially observed correlation with position changes leading price changes, but did not rigorously test for causality.

Several other studies introduced more rigor to test for the existence of excessive

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\(^1\) For crude oil, spot market and spot price are often used instead of cash market and cash price. But in this paper we do not interchange the words and use cash market and cash price for all the three commodities.
speculation. Alquist and Gervais (2011) used Working’s T-index (Working, 1960) to test for excessive speculation and found that the index did increase in 2008 when the price of oil increased dramatically. However, this index also reached similar levels in 2003 and 2005 when oil prices were low. Moreover, the index was low at the end of 2010 when the net long non-commercial positions in futures markets were high, suggesting that speculative pressures were subdued by hedging demand from commercial firms. Their findings suggested that it may be misleading to claim excessive speculation merely by noticing a high level of speculative positions. Similar results were presented by Ripple (2008) and Büyükşahin and Harris (2011).

Irwin and Sanders (2012) pointed out that Singleton’s measure of index fund positions in oil futures was in fact inferred from CFTC data on agricultural futures which had little relation to index funds’ actual positions in oil. Hamilton and Wu (2012) demonstrated that the agricultural index fund positions used by Singleton predicted the futures price of oil more accurately than the futures prices of agricultural commodities. Moreover, their model also predicted the U.S. stock market. They argued, therefore, that the positive predictive correlation found by Singleton (2012) on the basis of a very short sample period was probably driven by the 2008 recession. Hamilton and Wu (2012) extended the sample period by two years and found the predictive correlation breaks down.

Some studies have analyzed speculative price influences using more detailed non-public data. Brunetti and Büyükşahin (2009) employed the CFTC Large Trader Reporting System (LTRS) which offers unique, highly disaggregated position-level
data to analyze five futures markets: crude oil, natural gas, corn, three-month Eurodollars and the mini-Dow. They considered both returns and volatility and concluded that speculative trading activity reduced futures price volatility. Brunetti, Büyükşahin and Jeffrey (2011) studied specific categories of traders and tested whether positions taken by speculators, such as hedge funds and swap dealers, caused changes in oil futures prices or price volatility. Their results were consistent with speculators providing liquidity to the market and reacting to market conditions rather than vice versa.

Büyükşahin and Harris (2011) also employed CFTC LTRS to test the relation between crude oil prices and trading positions of various types of traders in the crude oil futures market. Using Granger causality tests between price and position data at daily and multiple day intervals, they found little evidence that the non-commercial (speculative) position changes Granger-cause price changes; instead, they suggested that price changes preceded changes in speculative positions. Similarly, Sanders and Irwin (2011) found no statistically significant relationship between growth in the volume of oil futures contracts and oil futures returns, realized volatility or implied volatility.

Some earlier studies have directly tested the speculative influence on commodity cash price volatility. Figlewski (1981), Chen, Cuny and Haugen (1995) and Bessembinder and Seguin (1992) found a positive contemporaneous association between different cash prices and their corresponding futures market trading activities. Nevertheless, the findings could not be used as evidence of futures speculation causing
higher cash price volatility because correlation is not causation (Figlewski, 1981). Kamara (1982) found that the introduction of commodity futures trading generally reduced or at least did not increase cash price volatility. Antoniou and Foster (1992) and Gulen and Mayhew (2000) considered time-varying patterns of price volatility and came to a similar conclusion. These studies all considered the impact of a new futures market on cash price stability. Darrat and Rahman (1995) reported no evidence of causality running from S&P 500 futures trading (both volume and open interest) to cash price volatility. By contrast, Chatrath, Ramchander and Song (1996) argued that currency futures trading (trading volume) had a significant positive (and hence destabilizing) causal impact on the cash price volatility. Adrangi and Chatrath (1998) reported that surges in the participation of large speculators and small traders destabilize exchange rate volatility.

Bohl and Stephan (2013) is the only published paper we find which has directly tested the speculative influence on commodity cash price volatility in the current market environment. The authors tested whether the current growing size of speculative positions increased cash price volatility in six heavily traded agricultural and energy commodity markets. They approximated the conditional volatility of the cash market weekly return using a GARCH model and analyzed how it is affected by speculative open interest. They did not find robust evidence over the six commodity markets that the cash price volatility was increased due to the increase of speculative positions.

The existing literature concerning speculative influences on commodity cash market volatility is not complete. On the one hand, studies have focused on the
relationship between speculation and futures prices. However, it is not reasonable to informally extend recent futures market work to cash markets directly since short term fluctuations in commodity futures prices may not lead to cash price instability. For example, Alquist, Kilian and Vigfusson (2011) examined the out-of-sample accuracy of daily and monthly oil futures prices and found no compelling evidence that oil futures prices help forecast the oil spot price. On the other hand, all the studies focusing on the impact of futures trading activity on cash price volatility directly used a variable (trading volume or open interest) in one market and a variable (cash price volatility) in another market without first determining the actual pricing relationship between the two markets. We argue that this kind of testing suffers from information loss. Instead of testing the relationship of speculation in futures markets on cash price volatility directly, we first test whether there is a causal relationship in both mean and variance between the futures and cash prices for one commodity. In cases where volatility spillover exists, we then test whether speculators’ activities in the futures market affect futures price volatility. If the increase of speculative positions in the futures market increases (decreases) the futures price volatility, then it will also increase (decrease) the corresponding cash price volatility when volatility spillover effects are found.

**Data and methodology**

**Data**

The analysis presented here focuses on three markets: coffee, crude oil, and wheat. Futures and cash prices for all three markets are daily prices provided by the Commodity Research Bureau (CRB). The coffee futures price is for the nearby Coffee
C contract traded on the Intercontinental Exchange (ICE). It is the world benchmark for Arabica coffee. The coffee futures price series is continuous and the rollover from contract to contract takes place on the first business day of each delivery month.

The crude oil futures price is for the second nearby Brent Crude contract also traded on ICE. It is generally accepted as the world’s crude oil benchmark. The second nearby is chosen because there is a futures contract for oil delivery every month. Thus, the nearby is always for delivery in the current month.

The wheat futures price is for the #2 Soft Red Winter Wheat contract traded at the Chicago Mercantile Exchange (CME). Similar to coffee, we use the nearby contract to develop a continuous futures price series that rolls over on the first business day of each delivery month.

To detect long-run relationships, the initial sample period runs from January 1, 1990 through January 23, 2012. Since the different markets vary slightly in trading days, the numbers of observations for the three commodities are not equal. There are 5,514, 5,590 and 5,553 observations coffee, oil, and wheat, respectively.

The futures market position data are from the CFTC Commitments of Traders reports (COT). These reports provide each Tuesday’s open interest for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC.

Causality in variance

Following Granger, Robins and Engle (1986) who discuss causality in variance, we test whether futures price Granger-causes cash price in variance in the following
way. First, two information sets are considered: $I_n: CP_{n-j}, j \geq 0$, and $J_n: CP_{n-j}, FP_{n-j}, j \geq 0$, where $CP$ stands for cash price and $FP$ for futures price.

Second, the futures price Granger-causes cash price in variance if:

$$E[(CP_{n+1} - E(CP_{n+1}|J_n))^2|I_n] \neq E[(CP_{n+1} - E(CP_{n+1}|J_n))^2|J_n]$$

The reverse relationship from the cash price to the futures price is defined similarly.

We use the multivariate generalized autoregressive conditional heteroscedasticity model (M-GARCH model) to test for the causality in variance between futures and cash prices:

$$X_t = E(X_t | J_{t-1}) + \varepsilon_t$$

where $X_t$ is a $2 \times 1$ vector of the futures and cash prices and $E(X_t | J_{t-1})$ is a $2 \times 1$ vector of conditional means of the two prices given the information set. $\varepsilon_t$ is the error term, which will be modeled as a GARCH (1,1) – BEKK representation (Engle and Kroner, 1995). This leads to:

$$\varepsilon_t \sim N(0, H_t)$$

$$H_t = C_t C_t + A \varepsilon_{t-1}' \varepsilon_{t-1} A + G H_{t-1} G$$

where $h_{FP}$ and $h_{CP}$ are conditional variances of the futures and cash prices, respectively.

Expanding this expression gives the conditional variance for the futures price:

$$h_{FP,t} = \sigma_1 + a_{11} \varepsilon_{FP,t-1}^2 + 2a_{12} \varepsilon_{FP,t-1} \varepsilon_{CP,t-1} + a_{21} \varepsilon_{CP,t-1}^2 + g_{11} h_{FP,t-1} + 2g_{12} \varepsilon_{FP,t-1} + 2g_{21} h_{FP,CP,t-1} + g_{22} h_{CP,t-1}$$

Therefore, the cash price does not cause the futures price in variance if and only if $a_{21} = 0$ and $g_{21} = 0$. 

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Similarly, the conditional variance for the cash price is:

\[ h_{CP,t} = c_2 + a_{12}^2 e_{FP,t-1}^2 + 2a_{12}a_{22} e_{FP,t-1} e_{CP,t-1} + a_{22}^2 e_{CP,t-1}^2 + g_{12}^2 h_{FP,t-1} + 2g_{12}g_{22} h_{FP-CP,t-1} + g_{22}^2 h_{CP,t-1} \]

The futures price does not cause the cash price in variance if and only if \( a_{12} = 0 \) and \( g_{12} = 0 \).

In order to estimate the parameters in the GARCH (1,1) model and test for the causality in variance, we need to first model the price means, \( E(X_t|I_{t-1}) \). If the two price series (cash and futures) are stationary, we could use a vector autoregression model (VAR) for the means. If they are non-stationary, we could take differences and then estimate a VAR on the differences. However, if the commodity price pairs are not stationary but are integrated of the same order, then we could estimate a cointegration model (in the error correction model – ECM form). It is desirable to model the price means using a cointegration model because it will allow us to identify the long-run relationship between the means of the two price series. If two variables are cointegrated, they have a long-run equilibrium relationship and are moving together. Further, the direction of causality and the speed of adjustment to price shocks in either market can be estimated.

In this case, parameter estimation consists of two steps. First, we use maximum likelihood estimation to obtain consistent estimates of the parameters in the mean equation in the presence of GARCH effects; and second the GARCH model is estimated with the parameters in the mean equation as given. If the futures price Granger-causes the cash price in variance, we conduct the two samples t-tests to see whether the increase in speculators’ positions in the futures market leads to an increase or a decrease
in the futures price volatility (and hence cash price volatility).

Cointegration analysis

Consider a futures market and a cash market for the same underlying commodity. It is reasonable to expect the two markets react similarly to new market information. Cointegration models (in the ECM form) have been widely used to test whether this is in fact true. Based on price stationarity tests (reported below), we estimate bi-variate cointegration models for each of the commodity markets to identify whether the futures and cash markets are moving together in the long-run.

The model used to examine the cointegration relations is based on Johansen and Juselius (1990). The ECM specification is:

\[
\Delta X_t = \Gamma_1 \Delta X_{t-1} + \cdots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k}^* + \Phi D_t + \varepsilon_t \quad (t = 1, \ldots, T)
\]

Under this specification, \( \varepsilon_t \) is \( \text{IN}_p \left( 0, \Lambda \right) \); \( X_i \) is a \( p \times 1 \) vector of endogenous variables, \( \Gamma_1, \ldots, \Gamma_{k-1}, \Pi, \Phi \) are matrices of parameters to be estimated, \( X_{t-k+1}, \ldots, X_0 \) are fixed with \( k \) corresponding to the lag length in the VAR(k) model, \( D_t \) contains deterministic variables (i.e. dummies, etc.), and \( \Pi X_{t-k}^* \) is the error correction term where \( X_{t-k}^* \) contains \( X_t \) and constant, trend or dummy variables that belong to the long-run equilibrium.

The test for cointegration depends on the rank of the \( \Pi \) matrix. If \( \Pi \) has full rank (\( r=p \)), then the vector process \( X_t \) is stationary. If the rank of \( \Pi \) is 0, then the ECM corresponds to a traditional differenced vector time series model. If the rank of

\footnote{The error terms are modeled as GARCH (1,1) rather than independent normal distributions, so the cointegration model assumption is violated. However, Mantalos (2001) and Cavaliere, Rahbek and Taylor (2010) showed that the cointegration test with GARCH errors is consistent with a large data set.}
lies between the two extreme cases, then there are \( r \) cointegrating vectors among \( X_t \).

To formally test the rank of \( \Pi \), we use both the likelihood ratio test, often called the trace test or the Johansen test, and the maximum eigenvalue test. The test statistics are:

\[
\tau_{p-r} = -T \sum_{i=r+1}^{p} \ln \left(1 - \hat{\lambda}_i\right), \text{ and } \delta_r = -T \ln \left(1 - \hat{\lambda}_{r+1}\right)
\]

In the trace test statistic formula, \( \hat{\lambda}_i \) is the \( i^{th} \) largest eigenvalue of matrix \( \Pi \). The null hypothesis of the test is that there are \( r \) cointegrating relations (therefore \( p-r \) common stochastic trends). The alternative hypothesis is that there are at least \( r+1 \) cointegrating relations (therefore at most \( p-r-1 \) common stochastic trends). We select the number of cointegrating vectors based on the following criterion:

\[
r = \hat{r} \text{ when } \{ \tau_{p-\hat{r}+1} > C_{p-\hat{r}+1} \text{ and } \tau_{p-\hat{r}} < C_{p-\hat{r}} \}
\]

where \( C_{p-r} \) is the critical value under the null hypothesis that there are \( r \) cointegrating vectors.

In the maximum eigenvalue test statistic formula, \( \hat{\lambda}_{r+1} \) is the \((r+1)^{th}\) largest eigenvalue of matrix \( \Pi \). The null and alternative hypotheses are the same as that for the trace test. The decision rule is given as:

\[
r = \hat{r} \text{ when } \{ \delta_{\hat{r}-1} > C_{\hat{r}-1} \text{ and } \delta_{\hat{r}} \leq C_{\hat{r}} \}
\]

where \( C_{r} \) is the critical value under the null hypothesis that there are \( r \) cointegrating vectors.

**Two samples t-test**
To focus on the period when commodity prices began to exhibit increased volatility, the sample period for the two samples t-test is from the first week of 2007 to the last week of 2011. We use both futures and options position information. Three different position variables are used as measures of speculators’ activities. First, we use the total non-commercial open interest (NonComm) as the measure of the absolute number of speculative positions. Using this measure allows us to test Master’s assertion concerning speculators’ price influence because his argument appears to be based on observing increases in this measure before observing increases in prices.

Second, we use the percentage of non-commercial total open interest relative to total market open interest (PCofNonComm) as a measure of the market share of speculative positions. Witherspoon (1993) argued that when the positions of agents trading exclusively in the futures market (speculators) exceeded those trading in the cash market (hedgers) beyond some boundary level cash prices will become more volatile. PCofNonComm is an appropriate variable to measure the relative speculation suggested by Witherspoon’s theory. If this theory is correct, then it should be the percentage of speculative positions rather than the absolute number of speculative positions that influence cash price volatility.

Third, we use Non-commercial net-long open interest (NonCommNetL) to measure how many more long positions compared to short positions speculators hold. Some scholars argue that the recent increase in speculative positions is mainly reflected by increases in long positions. The argument is that this brings significant buying pressure to the market and leads to an increase in both price levels and price volatility. Using
NonCommNetL allows us to test whether the increase of the speculative trade on the long side makes futures prices more volatile.

We use four statistics to measure futures price volatility to check the sensitivity of the results: weekly variance, weekly realized volatility, absolute weekly return and weekly trading range. Since the COTs report each Tuesday’s positions, we count each week from Wednesday to the next Tuesday. Most of the weeks have five trading days, but some weeks have days without trading and hence contain only four, three or even two trading days.

The weekly variance is the sample variance of the futures price for each week:

\[
\text{Variance}_t = \frac{\sum_{i=1}^{N_t} (P_{i,t}^t - \overline{P}_t)}{N_t},
\]

where \( \text{Variance}_t \) is the sample weekly variance of the \( t^{\text{th}} \) week, \( N_t \) is the number of trading days of this week, \( P_{i,t}^t \) is the futures price of the \( i^{\text{th}} \) trading day of this week, and \( \overline{P}_t \) is the average price of this week.

The realized price volatility is calculated following Merton (1980):

\[
\text{realized volatility}_t = \frac{\sum_{i=1}^{N_t} (r_{i,t}^t)^2}{N_t},
\]

where \( r_{i,t}^t = \ln P_{i,t}^t - \ln P_{i-1,t}^t \) is the \( i^{\text{th}} \) rate of return in week \( t \).

Absolute return is also often used a measurement of price volatility (Halova 2012). It is calculated as:

\[
\text{absolute return}_t = |\ln P_{N,t}^t - \ln P_{1,t}^t|,
\]

where \( P_{N,t}^t \) is the futures price of the last day of week \( t \) and \( P_{1,t}^t \) is the futures price of
the first day of that week.

Using range as another measure of volatility is discussed in Corrado and Truong (2007). It is defined as:

\[
range_t = |P_{t}^{\text{max}} - P_{t}^{\text{min}}|,
\]

where \(P_{t}^{\text{max}}\) and \(P_{t}^{\text{min}}\) are the highest and lowest prices in week \(t\), respectively.

Our interest is in testing whether an increase in speculative positions is associated with an increase in the futures price volatility. Therefore, for each of the three position variables, we take the difference between the adjacent Tuesday’s positions to construct the series of position changes. Thus, we get four groups of volatility measures which correspond to a decrease in the positions and also four groups of volatility measures which correspond to an increase in the positions for each of the position variables.

If the increase in the speculators’ position causes the futures market to become more volatile, we will expect the average futures price volatility in the weeks which experience an increase in the speculators’ position to be greater than the average futures price volatility in the weeks which experience a decrease in speculators’ positions. Then we can formulate a two samples t-test with the hypothesis that the mean in the increased speculator position sample is greater than the mean in the decreased speculator position sample. The test statistic is:

\[
t = \frac{\overline{\text{vol}} \text{ increase in positions} - \overline{\text{vol}} \text{ decrease in positions}}{sd(\overline{\text{vol}} \text{ increase in positions} - \overline{\text{vol}} \text{ decrease in positions})}
\]

The null hypothesis is the negation of the research hypothesis, i.e., the mean weekly volatility when speculative positions increase is less than the mean weekly volatility
when speculator positions decrease.

**Results**

**Unit root tests**

As discussed above, we need to first test whether the price series are stationary to determine which model to use for understanding the relationship between mean prices. If they are non-stationary we need to determine whether each pair of prices are integrated of the same order to decide whether cointegration is appropriate for identifying the relationships between futures and cash price means.

Three types of unit root tests are implemented: Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF), and the Phillips-Perron (PP) tests. Moreover, we use three models for the DF and ADF tests: models without intercepts or trends, models with intercepts, and models with intercepts and trends. We use two models for the PP test: models with intercepts and models with intercepts and trends. The null hypotheses of the unit root tests are that unit roots exist. Table 2.1 gives the results of the unit root tests. We cannot reject the null hypothesis for any of the six price series; however, the first-order differences of the price series are stationary. This means the series are I(1) and thus cointegration is an appropriate test for evaluating price relationships between cash and futures for all three commodities.

**Lag-length determination of the ECM for the mean**

The determination of the optimal lag length of the ECMs is identified based on the Schwartz Bayesian (SB) and Hannan-Quinn (H-Q) information criteria. Because the information criteria are based on different penalties, they do not need to suggest the
same lag length. The SB criterion tends to penalize more for adding variables into the model. However, the decision rules for both criteria are the same: the smaller the value, the better the model. We chose the model with the smallest H-Q or/and the smallest SB. As Table 2.2 shows, we chose lag lengths of 6, 7, and 4 for coffee, oil and wheat, respectively.

**Cointegration tests**

Using the above lag lengths, estimation of the ECMs and tests for cointegration were conducted. In all three bi-variate models, the error-correction term \( X_{t-k}^* \) includes a constant. For coffee and wheat, a dummy variable is used with 1 indicating the rollover date and 0 for others to account for the rollover effect.

The cointegration test results from the trace as well as the maximum eigenvalue tests are shown in Table 2.3. The results confirm our intuition that cash and futures prices move together in the long run. The trace test statistic for coffee is significant at 10\% level. All other statistics are significant at 5\% level.

**Causality in variance**

Table 2.4 gives the results of the parameter estimates in the GARCH model. The parameters used to test for causality in variance from futures price to cash price, \( a_{12} \) and \( g_{12} \), and the ones used to test for causality in variance from cash price to futures price, \( a_{21} \) and \( g_{21} \), are all significantly different from 0. This means there is a bi-directional causal relationship in variance between the futures and cash prices of coffee, oil, and wheat. Thus, if speculative activity is found to result in increased volatility in futures prices, then there will also be volatility spillover to the cash market. This, in
turn, suggests that cash market participants will face increased price risk as a result of futures traders speculative activity.

Two samples t-test

Tables 2.5.1, 2.5.2 and 2.5.3 give the results for the two samples t-tests. Panels a, b and c of each table show the results with the position variables NonCommercial, PCofNonAll and NonCommercialNetLong, respectively. The first half of each panel shows the results for the null hypothesis “Volatility is greater when speculators’ position decreases than when it increases”; while the lower half of each panel shows the results for testing the opposite statement “Volatility is greater when speculators’ position increases than when it decreases”.

The results demonstrate that when we use NonCommercial and PCofNonAll as the position variables, for all three commodities and for all four volatility measures, we cannot reject the first hypothesis that “Volatility is greater when speculators’ positions decrease than when they increase”, and almost all the tests\(^3\) for the second hypothesis that “Volatility is greater when speculators’ positions increase than when they decrease” reject the null hypothesis. This suggests that the statement “Volatility is greater when speculators’ positions decrease than when they increase” is true. Since there is volatility spillover from the futures market to the cash market, then we can further conclude that increased levels of speculative activity in futures markets helps to reduce cash price volatility, or at the very least do not contribute to increased cash price volatility.

\(^3\) Only the test for oil using realized volatility fails to reject the hypothesis that “Volatility is greater when speculators’ position increases than when it decreases”.

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However, when we use NonCommercialNetLong to measure speculator activity, the results are inconsistent. For coffee, we cannot reject any of the two opposite hypotheses using any of the four volatility measures. This means we cannot conclude that the change in the non-commercial net long positions will influence coffee futures price volatility. Oil and wheat are similar except that when absolute weekly return is used as the volatility measure, the hypothesis that “Volatility is greater when speculators’ positions decrease than when they increase” is rejected. However, given that it is rejected for the other measures it is likely that increases in non-commercial net long positions have no effect on oil and wheat futures price volatilities either. Because high futures price volatility will cause high cash price volatility, this also means that the cash markets are likely unaffected when non-commercial net long positions increase.

Speculators in the futures market play an important role in providing liquidity to the market. However, the extent to which their positive market contributions are diminished, or even turn negative, as their market exposure increases has been actively debated in recent years. Based on the results here, we find that from 2007 to 2011, when commodity prices were experiencing increased volatility relative to earlier time periods, increases in the total number of speculative positions or the percentage of speculative positions relative to the overall market size was associated with a decrease in weekly price volatility. Changes in the net long positions of speculators appears to have no effect on price volatility. This indicates, at least for the markets considered here, that speculative participation in futures markets has provided liquidity while not exceeding the boundary identified by Witherspoon (1993). Thus, speculative behavior has not
played a destructive role in commodity price formation. On balance, the results suggest that policies focused on limiting speculative activity will likely be more harmful to the market, as opposed to contributing to an increase in market stability.

Conclusions

This paper examines whether speculators’ activities in crude oil, wheat and coffee futures markets make cash prices of these commodities more volatile. The conclusions are similar across the three different commodities. First, the futures and cash prices of each of the three commodities are cointegrated. Second, there exists bi-directional volatility spillover between the futures and cash prices for all three commodities but no evidence is found to support the hypothesis that increases in speculative positions increase futures price volatility, thus they do not impact cash price volatility. In fact, there is strong evidence suggesting that increases in speculative positions actually contribute to decreased futures price volatility. This might be because speculators, being as the counterpart of the hedgers, provide liquidity to the market. As a result, the CFTC limits on the size of speculative positions for 28 core physical commodities approved in October 2011 is not expected to contribute to the stabilization of commodity prices, either in futures or cash markets. In order for public policy initiatives to impact market volatility in a positive way a more complete understanding of the drivers of recent price volatility is necessary.
References


Table 2.1 Unit root tests: Dickey-Fuller (DF) test, Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test

<table>
<thead>
<tr>
<th></th>
<th>Coffee</th>
<th></th>
<th></th>
<th>Oil</th>
<th></th>
<th></th>
<th>Wheat</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cash Price</td>
<td>∆ Cash price</td>
<td>Futures price</td>
<td>∆ Futures price</td>
<td>Cash Price</td>
<td>∆ Cash price</td>
<td>Futures price</td>
<td>∆ Futures price</td>
<td>Cash Price</td>
</tr>
<tr>
<td>No intercept/trend</td>
<td>0.05</td>
<td>-73.11</td>
<td>-0.27</td>
<td>-73.43</td>
<td>0.98</td>
<td>-68.24</td>
<td>0.69</td>
<td>-68.56</td>
<td>-0.62</td>
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<tr>
<td>DF With intercept</td>
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<td>-73.11</td>
<td>-1.97</td>
<td>-73.43</td>
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<td>-68.26</td>
<td>-0.37</td>
<td>-68.59</td>
<td>-2.51</td>
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<tr>
<td>With intercept/trend</td>
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<td>-73.11</td>
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<td>-73.42</td>
<td>-1.93</td>
<td>-68.31</td>
<td>-0.22</td>
<td>-68.63</td>
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<tr>
<td>No intercept/trend</td>
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<td>-2.14</td>
<td>-68.70</td>
<td>-3.13</td>
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</table>

Note: The Dickey-Fuller test, Augmented Dickey-Fuller test and Phillips-Perron test share the same 5% critical value for the model without intercept or trend, model with intercept and model with intercept and trend. These are -1.939, -2.863, and -3.413 respectively. The three tests consistently show that the cash and futures prices of the three commodities are not stationary. However, the first-order differences of all the price series show strong stationarity. Therefore, all the price series are I(1) series.
Table 2.2 Lag length determination

<table>
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<tr>
<th>Model</th>
<th>k</th>
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<td>5504</td>
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Table 2.3 Trace and Eigen Value tests of cointegration

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<tr>
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<th>Trace</th>
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<td>16.549**</td>
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</table>

Note: Given by Johansen and Juselius (1990), the 5% critical value for testing the null hypothesis of $r=0$ and $r=1$ are 20.164 and 9.142 in the trace test; and 15.752 and 9.094 in the maximum eigenvalue test.

**: significant at 5% level.
*: significant at 10% level.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coffee</th>
<th>Oil</th>
<th>Wheat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>P-value</td>
<td>Estimate</td>
</tr>
<tr>
<td>$c_{11}$</td>
<td>0.1014</td>
<td>0</td>
<td>0.0377</td>
</tr>
<tr>
<td>$c_{12}$</td>
<td>0.0949</td>
<td>0</td>
<td>0.0401</td>
</tr>
<tr>
<td>$c_{22}$</td>
<td>0.0981</td>
<td>0</td>
<td>-0.01</td>
</tr>
<tr>
<td>$a_{11}$</td>
<td>0.2225</td>
<td>0</td>
<td>0.205</td>
</tr>
<tr>
<td>$a_{12}$</td>
<td>0.0672</td>
<td>0</td>
<td>-0.0494</td>
</tr>
<tr>
<td>$a_{21}$</td>
<td>0.081</td>
<td>0</td>
<td>0.0682</td>
</tr>
<tr>
<td>$a_{22}$</td>
<td>0.2545</td>
<td>0</td>
<td>0.2918</td>
</tr>
<tr>
<td>$g_{11}$</td>
<td>0.9766</td>
<td>0</td>
<td>0.9791</td>
</tr>
<tr>
<td>$g_{12}$</td>
<td>-0.0116</td>
<td>0</td>
<td>0.0102</td>
</tr>
<tr>
<td>$g_{21}$</td>
<td>-0.0208</td>
<td>0</td>
<td>-0.0232</td>
</tr>
<tr>
<td>$g_{22}$</td>
<td>0.9622</td>
<td>0</td>
<td>0.9554</td>
</tr>
</tbody>
</table>
Table 2.5 Results for the two samples t tests (Data: 2007-2011)

### 2.5.1 Coffee

<table>
<thead>
<tr>
<th></th>
<th>T.S.</th>
<th>Pvalue</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. Position data use NonCommercial all</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \geq \text{Var}</em>{\text{Increase in position}}$</td>
<td>2.13</td>
<td>0.983</td>
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</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \geq \text{Range}</em>{\text{Increase in position}}$</td>
<td>2.44</td>
<td>0.992</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \geq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
<td>2.99</td>
<td>0.998</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \geq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>2.76</td>
<td>0.997</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \leq \text{Var}</em>{\text{Increase in position}}$</td>
<td>2.13</td>
<td>0.017</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \leq \text{Range}</em>{\text{Increase in position}}$</td>
<td>2.44</td>
<td>0.008</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \leq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
<td>2.99</td>
<td>0.002</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \leq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>2.76</td>
<td>0.003</td>
<td>Reject</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>T.S.</th>
<th>Pvalue</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>b. Position data use PCofNonAll</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \geq \text{Var}</em>{\text{Increase in position}}$</td>
<td>2.3</td>
<td>0.989</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \geq \text{Range}</em>{\text{Increase in position}}$</td>
<td>2.8</td>
<td>0.997</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \geq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
<td>2.99</td>
<td>0.998</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \geq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>3.33</td>
<td>0.999</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \leq \text{Var}</em>{\text{Increase in position}}$</td>
<td>2.3</td>
<td>0.011</td>
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</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \leq \text{Range}</em>{\text{Increase in position}}$</td>
<td>2.8</td>
<td>0.003</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \leq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
<td>2.99</td>
<td>0.002</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \leq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>3.33</td>
<td>0.001</td>
<td>Reject</td>
</tr>
<tr>
<td>c. Position data use NonCommercialNetLong</td>
<td>T.S.</td>
<td>Pvalue</td>
<td>Conclusion</td>
</tr>
<tr>
<td>--------------------------------------------</td>
<td>------</td>
<td>--------</td>
<td>------------</td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \geq \text{Var}</em>{\text{Increase in position}}$</td>
<td>0.49</td>
<td>0.688</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \geq \text{Range}</em>{\text{Increase in position}}$</td>
<td>-0.16</td>
<td>0.436</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \geq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
<td>-1.24</td>
<td>0.108</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \geq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>0</td>
<td>0.501</td>
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</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \leq \text{Var}</em>{\text{Increase in position}}$</td>
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<td>0.312</td>
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</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \leq \text{Range}</em>{\text{Increase in position}}$</td>
<td>-0.16</td>
<td>0.564</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \leq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
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<td>0.892</td>
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</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \leq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>0</td>
<td>0.499</td>
<td>Fail to reject</td>
</tr>
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</table>
2.5.2 Crude Oil

<table>
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<th>a. Position data use NonCommercial all</th>
<th>T.S.</th>
<th>Pvalue</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0$ : Var$<em>{\text{Decrease in position}}$ $\geq$ Var$</em>{\text{Increase in position}}$</td>
<td>1.47</td>
<td>0.928</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : Range$<em>{\text{Decrease in position}}$ $\geq$ Range$</em>{\text{Increase in position}}$</td>
<td>1.48</td>
<td>0.929</td>
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</tr>
<tr>
<td>$H_0$ : AbsReturn$<em>{\text{Decrease in position}}$ $\geq$ AbsReturn$</em>{\text{Increase in position}}$</td>
<td>0.16</td>
<td>0.564</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : RealizedVol$<em>{\text{Decrease in position}}$ $\geq$ RealizedVol$</em>{\text{Increase in position}}$</td>
<td>2.39</td>
<td>0.991</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : Var$<em>{\text{Decrease in position}}$ $\leq$ Var$</em>{\text{Increase in position}}$</td>
<td>1.47</td>
<td>0.072</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0$ : Range$<em>{\text{Decrease in position}}$ $\leq$ Range$</em>{\text{Increase in position}}$</td>
<td>1.48</td>
<td>0.071</td>
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</tr>
<tr>
<td>$H_0$ : AbsReturn$<em>{\text{Decrease in position}}$ $\leq$ AbsReturn$</em>{\text{Increase in position}}$</td>
<td>0.16</td>
<td>0.436</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : RealizedVol$<em>{\text{Decrease in position}}$ $\leq$ RealizedVol$</em>{\text{Increase in position}}$</td>
<td>2.39</td>
<td>0.009</td>
<td>Reject</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>b. Position data use PCotNonAll</th>
<th>T.S.</th>
<th>Pvalue</th>
<th>Conclusion</th>
</tr>
</thead>
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<tr>
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<td>2.75</td>
<td>0.997</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : Range$<em>{\text{Decrease in position}}$ $\geq$ Range$</em>{\text{Increase in position}}$</td>
<td>2.89</td>
<td>0.998</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : AbsReturn$<em>{\text{Decrease in position}}$ $\geq$ AbsReturn$</em>{\text{Increase in position}}$</td>
<td>0.75</td>
<td>0.772</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : RealizedVol$<em>{\text{Decrease in position}}$ $\geq$ RealizedVol$</em>{\text{Increase in position}}$</td>
<td>2.27</td>
<td>0.988</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0$ : Var$<em>{\text{Decrease in position}}$ $\leq$ Var$</em>{\text{Increase in position}}$</td>
<td>2.75</td>
<td>0.003</td>
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</tr>
<tr>
<td>$H_0$ : Range$<em>{\text{Decrease in position}}$ $\leq$ Range$</em>{\text{Increase in position}}$</td>
<td>2.89</td>
<td>0.002</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0$ : AbsReturn$<em>{\text{Decrease in position}}$ $\leq$ AbsReturn$</em>{\text{Increase in position}}$</td>
<td>0.75</td>
<td>0.228</td>
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<tr>
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<td>2.27</td>
<td>0.012</td>
<td>Reject</td>
</tr>
<tr>
<td></td>
<td>T.S.</td>
<td>Pvalue</td>
<td>Conclusion</td>
</tr>
<tr>
<td>----------------</td>
<td>------</td>
<td>--------</td>
<td>--------------</td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \geq \text{Var}</em>{\text{Increase in position}}$</td>
<td>-0.42</td>
<td>0.336</td>
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<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \geq \text{Range}</em>{\text{Increase in position}}$</td>
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<td>0.423</td>
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<td>-1.55</td>
<td>0.062</td>
<td>Reject</td>
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<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \geq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
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<td>0.135</td>
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<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \leq \text{Var}</em>{\text{Increase in position}}$</td>
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<td>0.664</td>
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<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \leq \text{Range}</em>{\text{Increase in position}}$</td>
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<td>0.577</td>
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</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \leq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
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<td>0.938</td>
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</tr>
<tr>
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<td>0.865</td>
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</table>
2.5.3 Wheat

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<th>Pvalue</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0 : \text{Dec}\downarrow \geq \text{Var}$</td>
<td>2.68</td>
<td>0.996</td>
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</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \geq \text{Range}$</td>
<td>3.07</td>
<td>0.999</td>
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<tr>
<td>$H_0 : \text{Dec}\downarrow \geq \text{AbsReturn}$</td>
<td>1.33</td>
<td>0.908</td>
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</tr>
<tr>
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<td>2.36</td>
<td>0.998</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \leq \text{Var}$</td>
<td>2.68</td>
<td>0.004</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \leq \text{Range}$</td>
<td>3.07</td>
<td>0.007</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \leq \text{AbsReturn}$</td>
<td>1.33</td>
<td>0.092</td>
<td>Reject</td>
</tr>
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<td>$H_0 : \text{Dec}\downarrow \leq \text{RealizedVol}$</td>
<td>2.36</td>
<td>0.01</td>
<td>Reject</td>
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</table>

<table>
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<tr>
<th>b. Position data use PCofNonAll</th>
<th>T.S.</th>
<th>Pvalue</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0 : \text{Dec}\downarrow \geq \text{Var}$</td>
<td>1.58</td>
<td>0.942</td>
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</tr>
<tr>
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<td>2.46</td>
<td>0.993</td>
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</tr>
<tr>
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<td>0.999</td>
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</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \geq \text{RealizedVol}$</td>
<td>2.84</td>
<td>0.998</td>
<td>Fail to reject</td>
</tr>
<tr>
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<td>1.58</td>
<td>0.058</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \leq \text{Range}$</td>
<td>2.46</td>
<td>0.007</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \leq \text{AbsReturn}$</td>
<td>3.03</td>
<td>0.001</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{Dec}\downarrow \leq \text{RealizedVol}$</td>
<td>2.84</td>
<td>0.002</td>
<td>Reject</td>
</tr>
<tr>
<td>c. Position data use NonCommercialNetLong</td>
<td>T.S.</td>
<td>Pvalue</td>
<td>Conclusion</td>
</tr>
<tr>
<td>------------------------------------------</td>
<td>------</td>
<td>--------</td>
<td>------------</td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \geq \text{Var}</em>{\text{Increase in position}}$</td>
<td>-0.26</td>
<td>0.397</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \geq \text{Range}</em>{\text{Increase in position}}$</td>
<td>-0.64</td>
<td>0.262</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \geq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
<td>-1.71</td>
<td>0.044</td>
<td>Reject</td>
</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \geq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>-1</td>
<td>0.159</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Var}<em>{\text{Decrease in position}} \leq \text{Var}</em>{\text{Increase in position}}$</td>
<td>-0.26</td>
<td>0.603</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{Range}<em>{\text{Decrease in position}} \leq \text{Range}</em>{\text{Increase in position}}$</td>
<td>-0.64</td>
<td>0.738</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{AbsReturn}<em>{\text{Decrease in position}} \leq \text{AbsReturn}</em>{\text{Increase in position}}$</td>
<td>-1.71</td>
<td>0.956</td>
<td>Fail to reject</td>
</tr>
<tr>
<td>$H_0 : \text{RealizedVol}<em>{\text{Decrease in position}} \leq \text{RealizedVol}</em>{\text{Increase in position}}$</td>
<td>-1</td>
<td>0.841</td>
<td>Fail to reject</td>
</tr>
</tbody>
</table>

Note: 10% significance level is used for tests in Tables 2.5.1, 2.5.2 and 2.5.3.
Figure 2.1 Annual food price index and crude oil price from 1990 Jan to 2011 Dec

Food price index


Crude oil

Data source: Commodity Research Bureau
CHAPTER 3 HAVE COMMODITY CASH MARKET

INVENTORY HOLDERS PAID RISK PREMIUM?

——WITH SOYBEANS AS AN EXAMPLE

Abstract
This study investigates the existence of futures market risk premiums from the perspective of the commodity cash market. We argue that since the futures market risk premium is paid to the futures market speculators by cash market inventory holders, then if it exists we should find evidence from the behavior of the cash market storers. By analyzing the behavior of two types of soybean cash market inventory holders, producers and commercial elevators, we do not find evidence that the cash market storers have paid risk premiums. Moreover, we separate our analysis for the period before and after the fourth quarter of 2007 with the commodity markets characterized with increased price levels and volatility in the latter sub-period. We find that both types of cash market stores changed their risk preferences between the two sub-periods. However, no evidence suggests that they have paid risk premiums in either period.

Key words: risk premium, futures market, cash market, price volatility, inventory, soybeans
**Introduction and literature review**

Risk premiums in commodity futures markets are defined as the difference between the expected spot price at expiration and the current futures price (Keynes (1930) and Telser (1958), among others). According to Keynes (1930), hedgers in the commodity futures market (producers, commercial elevators) use futures markets to hedge the price risk associated with their physical positions. In order to induce speculators to assume their risk, they are willing to sell products at a discount so that speculators earn the risk premium. Knowing whether investors in commodity futures markets have actually earned risk premiums benefits both speculators and hedgers. On the one hand, the commodity futures price has already encompassed foreseeable trends in the spot market, and the unexpected deviations from the expected future spot price are averaged out to zero for an investor. Therefore the risk premium is the only source of expected return for speculators trading commodity futures (Gorton and Rouwenhorst (2006)). On the other hand, knowing the size of the risk premium could provide information to hedgers concerning the cost is to hedge in commodity futures markets. There is currently no consensus on the existence of the risk premiums in commodity futures markets.

Keynes (1930) first introduced the concept of a risk premium in commodity futures markets in the theory of “normal backwardation”. He implicitly assumed that hedgers were always net-short and speculators were always net-long. Hedgers used the futures market to fix the price of their future sale so that the downward price risk was transferred to speculators. In order to induce speculators to assume the price risk, hedgers needed to lower the futures price relative to the expected final cash price. The difference between the expected spot price at delivery and the futures price was the risk premium earned by the speculators.

Even though the theory has “backwardation” in its name, Keynes did not mean
that the risk premium existed only when the market was in backwardation. “Normal backwardation” meant that because of the existence of a risk premium, backwardation was the normal state of the market. He first argued that:

“If there are no redundant liquid stocks, the spot price may exceed the forward price (i.e. in the language of the market there is a “backwardation”).”

Then he put forth his famous “normal backwardation” to describe that because of the existence of risk premiums, backwardation was the normal state of the market.

“But it is not necessary that there should be an abnormal shortage of supply in order that a backwardation should be established. If supply and demand are balanced, the spot price must exceed the forward price by the amount which the producer is ready to sacrifice in order to ‘hedge’ himself, i.e. to avoid the risk of price fluctuations during his production period. Thus in normal conditions the spot price exceeds the forward price, i.e. there is a backwardation. In other words, the normal supply price on the spot includes remuneration for the risk of price fluctuations during the period of production, whilst the forward price excludes this.”

Then he argued that the risk premium not only existed but also was larger under contango. That is, even though the forward price is above the present spot price under contango, it must fall short of the expected future spot price by at least the amount of the normal backwardation:

“Indeed the existence of surplus stocks must cause the forward price to rise above the spot price, i.e. to establish, in the language of the market, a “contango”; [...] But the existence of a contango does not mean that a producer can hedge himself without paying the usual insurance against price changes. On the contrary, the additional element of uncertainty introduced by the existence of stocks and the additional supply of risk-bearing which they require mean that he must pay more
than usual. In other words, the quoted forward price, though above the present spot price, must fall below the anticipated future spot price by at least the amount of the normal backwardation; and the present spot price, since it is lower than the quoted forward price, must be much lower than the anticipated future spot price.”

The empirical search for risk premiums in commodity futures markets continued nearly 30 years after Keynes’ theoretical support of the existence of such premiums. Telser (1958) was the first to empirically test Keynes’ theoretical assumption. Telser argued that if Keynes was right, then there should be an upward trend in futures prices as they approach maturity. After checking, he found there was no such trend and concluded that the futures price was an unbiased estimator of the expected future spot price, i.e. there was no risk premium in commodity futures. Cootner (1960) challenged Telser’s conclusion by showing that Telser’s assumption (derived from Keynes assumption that hedgers were net-short) that futures prices increase over the entire life of a contract was not correct. He, in line with the Keynesian risk premium, argued that hedging opportunities were valuable and speculators should be compensated for assuming the risk. However, Cootner did not agree that hedgers were always net-short. He claimed that during the accumulation of inventory from the lowest to the peak, hedgers were net-long. To induce speculators to take a short position, hedgers needed to buy at a higher price than the expected price. During this period, prices would be decreasing. After the peak of inventory, hedgers become net-short, and prices start to show an upward trend because of the premium gained by speculators who are net-long. He used a trading strategy where traders held December Wheat futures until the last trading day of November when they rolled over to the May contract (most of the time, differed only in a few months when there was no trading of December or May contracts). He found that the average prices showed the price trend predicted by his assumption.
An important strand of earlier research on futures market risk premiums adopted the Capital Asset Pricing Model (CAPM) as first proposed by Sharpe (1964). Dusak (1973) argued that the search for risk premiums in commodity futures markets should not be based on the change of futures prices, but should be based on how the risk of a futures contract was correlated with the risk of a well-diversified portfolio of assets. She used S&P 500 Common Stocks as a proxy for the return on the well-diversified portfolio, investigated wheat, corn and soybeans over the period of May 15, 1952 to November 15, 1967, and found that both the mean returns and the risk parameter $\beta$s were zero. Based on this she concluded that there was no risk premium in the futures market over the time period studied. Carter, Rausser and Schmitz (1983) pointed out two problems in Dusak (1973): the first was that she implicitly assumed that speculators were net-long throughout the life of the futures contract, and the second was that she used the return on the value-weighted S&P Index of 500 Common Stocks as a proxy variable for the return on the efficient market portfolio, which did not include the price instability of the nation’s stock of agricultural and nonagricultural commodities. This resulted in biased estimates of the degree of systematic risk one should expect for futures contracts. They equally weighted the S&P Index of 500 Common Stocks and the Dow Jones commodity futures index as a proxy for the efficient portfolio, and assumed stochastic systematic risk and non-systematic risk as a function of the net market positions of large speculators. The authors concluded that wheat, corn, and soybeans revealed significant and positive systematic risk for a number of futures contracts. In addition, the “nonmarket” rate of return measure proved to be generally significant. For commodities more closely linked to the general level of economic activity (cotton and live cattle), especially cotton, the results were more striking. Not only did speculators earn excess returns but the degree of systematic risk was
conditioned on whether speculators were net-short or net-long. However, Marcus (1984) argued that Carter, Rausser and Schmitz’s (1983) construction of the market index was inappropriate because commodity returns appeared on both the right and left hand side of the estimated equations, and their empirical results stemmed directly from the use of this index. Baxter, Conine Jr and Tamarkin’s (1985) proxy for the market portfolio was constructed of 93.7% of the S&P 500 Index and 6.3% of the Dow Jones Commodity Cash Index. Their results replicated Dusak’s and confirmed Marcus’ hypothesis that a more proper specification of the market portfolio to include commodities would significantly reduce the size of the estimated systematic coefficients from those of the Carter, Rausser and Schmitz (1983) study. Several others have criticized the search for commodity futures risk premiums using CAPM. Gorton and Rouwenhorst (2006) pointed out that the correlation between commodity futures and equities was so low that the CAPM risk premium (determined by the covariation of commodity futures returns with systematic risk factors) would be hard to find. Fortenbery and Zapata (1993) tested the assumptions underlying CAPM when using OLS estimation (normality, homoscedascity and absence of serial correlation) and found the assumptions were often rejected.

More recent studies look for risk premiums in the commodity futures portfolio. They argue that this method has an advantage because they are studying the “average commodity futures contract” (Gorton and Rouwenhorst (2006)). Gorton and Rouwenhorst (2006) constructed an equally weighted fully-collateralized commodity futures portfolio using 36 commodity futures contracts over the period July 1959 – December 2004. For each month, they first constructed price (or excess returns) on each commodity futures contract by using the nearest contract that did not expire in that month. They rolled into the next nearest futures contract on the last business day of the
month prior to the expiration date of a futures contract. The total returns were calculated under the assumption that the futures position was fully collateralized with 30-day T-bills. Using monthly returns for each commodity futures contract, the index was constructed by adding the monthly returns each month and dividing by the number of commodities in the index that month. They found that this “average commodity futures contract” earned an excess return (risk premium) over T-bills of about 5% a year over what they called the “average time period”. Bodie and Rosansky (1980) also constructed an equally weighted fully-collateralized portfolio of 27 commodity futures contracts, but studied the quarterly returns of this portfolio over the period 1950 – 1976 and found that this portfolio had a return (risk premium) with mean and variance close to that of S&P 500 common stock portfolio. Fama and French (1987) constructed an equally weighted portfolio of 21 commodity futures over the period January 1967 – May 1984, and calculated the monthly returns. They found marginally significant returns (risk premiums) on the portfolio.

Even though the recent portfolio approach seems successful in finding futures risk premiums, some studies questioned the excess returns found in the commodity futures portfolios as actually being risk premiums. Erb and Harvey (2006) pointed out that even though Bodie and Rosansky (1980), Fama and French (1987) and Gorton and Rouwenhorst (2006) all found positive excess returns in their equally weighted commodity futures portfolios, they also all reported insignificant excess returns for individual commodity futures contracts. For example, half of the 36 commodity futures that were encompassed in Gorton and Rouwenhorst’s portfolio had a negative excess return, and 35 out of 36 commodity futures’ excess returns were statistically insignificant. Erb and Harvey explicitly stated that the statistically significant portfolio returns did not prove the existence of commodity futures risk premiums because
rebalancing alone can be a source of statistically significant returns. They showed how the diversification return of a portfolio was generated. In a recent study, Sanders and Irwin (2012) formed two long-only monthly rebalanced commodity futures portfolios – one with 10 commodities which were continuously traded over 1961-2010 and another one with 20 commodities which were continuously traded over 1991-2010 – and found that the excess returns of the portfolios were not significantly different from zero even before excluding the diversification returns (Erb and Harvey 2006).

The research that takes into consideration the relationship between the state of physical inventory and intertemporal commodity prices (which is elaborated in the Supply of Storage theory\(^4\)), and the net hedging position in futures markets seems to be more consistent in finding risk premiums in commodity futures markets. Examples would include Cootner (1960) and Carter, Rausser and Schmitz (1983) cited above. More recently, Gorton, Hayashi and Rouwenhorst (2012) studied how the commodity futures risk premium was related to inventory levels (measured by the inventory level at the end of a month divided by the moving average of inventory levels over the previous 12 months to get rid of the time-trend contained in the inventory time-series). They constructed monthly excess returns for 31 commodity futures over the period January 1971 – December 2010, and showed both from a two-period model and the empirical analysis that the basis decreased and was convex with inventory levels, and that risk premiums also decreased with inventory levels. They also showed that the commodity futures return was higher when 1) the basis was higher; 2) the prior 12-

\(^4\) The theory stated that the intertemporal price relationship in commodity markets was determined by the cost of carry of commodity inventories. Details about the theory can be found in Kaldor (1939), Working (1948, 1949), Brennan (1958). The authors argued that the holding of inventory could generate positive yields. They called this the “convenience yield” because holding inventories could decrease losses caused by shocks such as increased demand for the product or decreased supply for the input. They argued that the convenience yield should be large when the inventory level was low and small when the inventory level was high.
month futures return (futures momentum) was higher; 3) the prior 12-month spot return (spot momentum) was high; 4) return volatilities were higher; and 5) there was higher contemporaneous hedging pressure (measured as hedgers’ net short positions divided by total open interest). Basu and Miffre (2013) studied how commodity futures market risk premiums were related to hedging pressure. They defined hedging pressure as the propensity of market participants to be net long. The hedging pressures of commercial traders or noncommercial traders were calculated as the long open interest in the category divided by the total open interest in that category. The authors constructed portfolios of 27 commodity futures over the Sep, 30 1992 – Mar, 25 2011 period based on hedging pressure strategy. They first sorted cross sections of commodity futures on each contract’s hedging pressure. Using single- and doublesorts, they systematically i) bought the contracts for which hedgers were the shortest and/or speculators were the longest and ii) sold the contracts for which hedgers were the longest and/or speculators were the shortest. They found that the fullycollateralized hedging pressure portfolios present Sharpe ratios that range from 0.27 to 0.93 with an average of 0.51, much higher than a long-only equally-weighted portfolio made of the same commodity futures contracts (presents a Sharpe ratio of 0.08) and the S&P-GSCI (presents a Sharpe ratio of 0.19). They also constructed similar long-short portfolios by sorting commodity futures contracts based on momentum and term structure. The forecasting power of the positions of speculators and the slope of the term structure were found to be the most important drivers of commodity futures returns.

Interestingly, the search for commodity futures risk premiums has been focused on the futures market. Even though some studies like Carter, Rausser and Schmitz (1983) take cash market factors into consideration, they still calculate risk premiums using futures prices. However, if the futures risk premium exists, it is given to
speculators by the hedgers to get rid of risk in their physical positions on the cash market. Therefore, analyzing cash market players’ willingness to pay to reduce their price risk will provide more insight into the existence of futures risk premiums. Very few studies have looked for futures risk premiums in commodity cash markets. Brennan (1958) decomposed the marginal cost of storage into three parts: 1) the marginal outlay on physical storage which is the increase of the sum of rent for storage space, handling or in-and-out charges, interest, insurance, etc., with an increase of one unit of inventory; 2) the marginal convenience yield measuring the increase of “convenience” (see footnote 4) with one more unit of storage; and 3) the marginal risk premium which is the amount of money the storer needs to be compensated with one more unit of storage. Brennan claimed that the marginal convenience yield is negative and is decreasing in magnitude with inventory levels with 0 as its maximum. When the inventory level is small, the large negative marginal convenience yield is an incentive for the storers to hold stocks. The marginal risk premium in Brennan’s two periods’ model is positive, and is increasing with the inventory level. He argued that “The reason why he (the owner of stocks, added by the author) may decide to shift the risk is that total risk aversion is approaching the critical level – critical in terms of the firm’s capital resources and credit position … When the marginal risk premium required by any individual firm exceeds that required by speculators, stocks will be hedged”.

Chavas (1988) pointed out one problem in Brennan’s (1958) conclusions: the assumption that the marginal risk premium was positive under risk aversion was in general invalid in a multi-period setting. Chavas used a three-period model and proved that the marginal risk premium could be negative. He claimed that the storer’s marginal risk premium might be positive if the inventory was large. However, the marginal risk premium might be negative when the inventory was small.
More recently, Lin and Fortenbery (2006) constructed a structural model to depict the optimal storage decision of two types of agents who held stocks: producers and commercial elevators. From the agents’ problems of maximizing infinite periods of expected utility of profits, they derived the representation of marginal risk premium as a part of marginal cost. Similar to Brennan (1958) and Chavas (1988), there was also a marginal outlay in the marginal cost. Different from the two previous studies, Lin and Fortenbery adopted the concept of transaction cost in place of the convenience yield, which was firstly developed in Chavas, Despines and Fortenbery (2000). Lin and Fortenbery (2006) found that the marginal risk premium had positive and negative values, but the average marginal risk premium was significantly positive for both the producers and the commercial elevators over 1986 to 2002. Moreover, the mean Arrow-Pratt risk premiums (Arrow 1971 and Pratt 1964) over the same time period were also significantly positive for both the producers and the commercial elevators, indicating that the cash market might pay a risk premium to the futures market during 1986 to 2002.

Similar to Lin and Fortenbery (2006), this study is looking for commodity market risk premium payments from the cash market, i.e., whether the cash market storers are willing to pay to the futures market speculators to lock in the price of their inventories. We use soybeans as an example because there has been less government price influence on soybeans relative to other storable commodities (Lin and Fortenbery 2006). There are two types of storers on the soybean cash market: producers who hold on-farm inventories and commercial elevators who hold off-farm inventories. We analyze the two types of storers separately since they face different storage problems. The time period studied in this paper is from the first quarter of 1986 to the fourth quarter of 2012. Therefore this paper extends the study period in Lin and Fortenbery (2006) from
2002 to 2012. However, the contribution is not only an extension of time. Starting from late 2007, most commodity markets, including the soybean market, experienced an increase in average price levels, accompanied by higher volatility (Figure 3.1). This was a historic event in the commodity markets and attracted a lot of attention (Li and Fortenbery (2013); Masters (2008, 2010); Singleton (2012); Irwin and Sanders (2012); among others). This paper does not only search for futures risk premiums that storers might be willing to pay to speculators, but also looks for any changes in the futures risk premium characteristics after the 4th quarter of 2007 when the commodity markets were experiencing high price levels and high price volatility.

**The producers’ problem**

Soybean producers are defined in this paper as those who grow, store and sell soybeans. By definition, the producers never buy stocks in our analysis. Let $x_t$, $y_t$, and $q_t$ denote the stocks, output and amount sold in period $t$. Therefore we have $x_t \geq 0$, $y_t \geq 0$, and $q_t \geq 0$. The inventory dynamics of the representative producer can be denoted as:

$$\left(1 - \delta\right)x_{t-1} + y_t = x_t + q_t$$

(1.1)

where $x_{t-1}$ is the inventory level in the end of period $t-1$ brought into period $t$. Since some soybeans deteriorate during storage, only $(1 - \delta)x_{t-1}$ inventories are brought into period $t$, where $\delta$ is the deterioration rate. The inventory dynamics state that in the beginning of period $t$, the total inventory $(1 - \delta)x_{t-1} + y_t$ is allocated into sales in the cash market ($q_t$) and storage for future sales ($x_t$).

Following Chavas, Despins and Fortenbery (2000) and Lin and Fortenbery (2006), the producers incur a transaction cost selling soybeans. Transaction cost is adopted instead of the convenience yield because it can be specified and thus be separated from
the effect of the marginal risk premium. The transaction cost includes the transportation cost (cost for transporting the inventory from the seller to the buyer), and information cost (cost for gathering price information and searching for buyers). Chavas, Despins and Fortenbery (2000) show that when the stock level is low, the marginal transaction cost could be negative and provide incentives for the storers to hold inventory. Thus, the presence of transaction cost can explain the existence of an inverse carrying charge. The more output to be sold, the higher the transportation cost. The larger the producer’s output, the smaller the information cost. This is because compared to a small farm, a big farm has more power to negotiate prices with the buyers, and also finds it easier to locate a buyer. With the above reasoning taken into account, we can assume the unit transaction cost as a fraction of the cash price and a function of the current sale and inventory level:

\[ s_t \left( q_t, x_t \right) = sp_t \frac{q_t}{x_{t-1} + y_t} = sp_t \frac{q_t}{q_t + x_t} \quad (1.2) \]

where \( s \) is a constant and is positive; \( p_t \) is the cash price in period \( t \).

Producers sell soybeans on the spot market or forward to the commercial elevators (Sauer, Smith, and McKenzie 2000; Oklahoma Cooperative Extension Service 2002; Taylor, Tonsor and Dhuyvetter 2013). Even though some producers hedge in the futures market (Sartwelle, O’Brien, Tierney and Eggers 2000), the number of contracts they sell is generally small and included in the non-reportable part of the Commitment of Traders reports (see data section for commercial elevator’s problem). Therefore, the profit function of the representative producer can be expressed as:

\[ \pi_t = \left( p_t - s_t \right) q_t - c_1 \left( y_t \right) - c_2 \left( x_t \right) \quad (1.3) \]

5 Since the data for the forward selling and forward prices are not available, we assume all the sales happen in the cash market at cash prices.
where $c_1(y_t)$ is the production cost and $c_2(x_t)$ is the storage cost in period $t$.

The producer’s objective is to maximize the discounted expected utility of profits over the entire business life. Mathematically it is represented as:

$$\max_{x_t, q_t} \sum_{t=\tau}^{\infty} \beta^{t-\tau} EU(\pi_t)$$

It is assumed the starting period is period $\tau$, and the producer does not know when the business will end. $\beta$ represents the discount factor, $0 < \beta < 1$. $E$ stands for the expectation operator conditional on the information at period $t$. $U(\pi_t)$ is the producer’s utility function, which is assumed to be increasing in $\pi_t$ and differentiable with respect to $\pi_t$. In each period $t$, the producer chooses $x_t$ and $q_t$ to maximize the discounted expected utility of profits based on information available. In each period the producer is active in storage and cash market sales. In other words, $x_t > 0$ and $q_t > 0$. Therefore, there is an interior solution.

The first-order necessary conditions with respect to $x_t$ and $q_t$ are respectively represented as:

$$\frac{\partial u_t}{\partial \pi_t} \left[ - \frac{\partial s_t}{\partial x_t} q_t - \frac{\partial c_1(y_t)}{\partial y_t} \cdot \frac{\partial y_t}{\partial x_t} - \frac{\partial c_2(x_t)}{\partial x_t} \right] + \beta E \frac{\partial u_{t+1}}{\partial \pi_{t+1}} \left[ - \frac{\partial c_1(y_{t+1})}{\partial y_{t+1}} \cdot \frac{\partial y_{t+1}}{\partial x_t} \right] = 0$$

(1.4)

$$\frac{\partial u_t}{\partial \pi_t} \left[ - \frac{\partial s_t}{\partial q_t} q_t + (p_t - s_t) - \frac{\partial c_1(y_t)}{\partial y_t} \cdot \frac{\partial y_t}{\partial q_t} \right] = 0$$

(1.5)

By rearranging the inventory dynamics in equation (1.1) we can get $y_t = x_t + q_t - (1 - \delta)x_{t-1}$. The derivatives of $y_t$ with respect to the control variables $x_t$ and $q_t$ are $\frac{\partial y_t}{\partial x_t} = 1$ and $\frac{\partial y_t}{\partial q_t} = 1$. This means that if the producer wants to have one more unit of stocks while the plan for sales is unchanged in period $t$, he needs to produce one more unit of soybeans. Similarly, if the producer wants to sell one more
unit of soybeans while the stock level is unchanged in period $t$, he also needs to produce one more unit of soybeans. Moreover, the effect of the current period’s stock level on the next period’s production can be represented as $\frac{\partial y_{t+1}}{\partial x_t} = -(1 - \delta)$. This means a one unit increase in stocks will decrease next period’s production by $(1 - \delta)$ units. This may be because that aggregately, a higher inventory level will lower the price level and encourage the representative producer to switch to other grains production, thus soybean production is decreased in the following period.

From equation (1.2) we can get the derivatives of $s_t$ with respect to the control variables. $\frac{\partial s_t}{\partial x_t} = -sp_t q_t/(q_t + x_t)^2$ means that with one more unit of inventory holding, the transaction cost decreases by an amount of $sp_t q_t/(q_t + x_t)^2$. This is because even though the producer does not change the amount of selling, holding more inventories will decrease transaction costs by decreasing the costs faced by buyers of searching for one more unit of inventory. $\frac{\partial s_t}{\partial q_t} = sp_t x_t/(q_t + x_t)^2$ means that with one more unit of sales, the transaction cost increases by an amount of $sp_t q_t/(q_t + x_t)^2$.

Replacing the corresponding items with the above derivatives, equations (1.4) and (1.5) can be written as:

$$\left(\frac{sp_t q_t^2}{(q_t + x_t)^2} - \frac{\partial c_1(y_t)}{\partial y_t} - \frac{\partial c_2(x_t)}{\partial x_t}\right) + \beta E \frac{\partial u_{t+1}}{\partial \pi_{t+1}} \left(1 - \delta\right) \frac{\partial c_1(y_{t+1})}{\partial y_{t+1}} = 0 \quad (1.4')$$

$$\frac{\partial u_t}{\partial \pi_t} \left[- \frac{sp_t x_t q_t}{(q_t + x_t)^2} + \left(p_t - s_t\right) - \frac{\partial c_1(y_t)}{\partial y_t}\right] = 0 \quad (1.5')$$

Since $U(\pi_t)$ is assumed to be increasing in $\pi_t$, we have $\frac{\partial u_t}{\partial \pi_t} > 0$. From equation (1.5’) we get (1.6) and (1.7):
\[
\frac{\partial c_1(y_i)}{\partial y_i} = p_i - s_i - \frac{sp_i q_i}{(q_i + x_i)^2}
\]  
(1.6)

\[
\frac{\partial c_1(y_{t+1})}{\partial y_{t+1}} = p_{t+1} - s_{t+1} - \frac{sp_{t+1} x_{t+1} q_{t+1}}{(q_{t+1} + x_{t+1})^2}
\]  
(1.7)

Substitute equations (1.6) and (1.7) into equation (1.4') and we get:

\[
\frac{\partial u_i}{\partial \pi_t} \left[ \frac{sp_i q_i^2}{(q_i + x_i)^2} (p_i - s_i) + \frac{sp_i x_i q_i}{(q_i + x_i)^2} \frac{\partial c_2(x_i)}{\partial x_i} \right] + \beta (1 - \delta) E\left[ \frac{\partial u_{t+1}^i}{\partial \pi_{t+1}} \left[ p_{t+1} - s_{t+1} - \frac{sp_{t+1} x_{t+1} q_{t+1}}{(q_{t+1} + x_{t+1})^2} \right] \right] = 0
\]  
(1.8)

Further, substitute into equation (1.8) the functions for \( s_t \) and \( s_{t+1} \), and the first order condition is in the following form and will be used to estimate the parameters:

\[
E_i \left[ \beta (1 - \delta) \left( p_{t+1} - sp_{t+1} q_{t+1} + \frac{2x_{t+1}}{q_{t+1} + x_{t+1}} \right) \frac{\partial u_{t+1}^i}{\partial \pi_{t+1}} - \left( p_i - \frac{2sp_i q_i}{q_i + x_i} + \frac{\partial c_2(x_i)}{\partial x_i} \right) \frac{\partial u_i}{\partial \pi_t} \right] = 0
\]  
(1.9)

By rearranging equation (1.9) we can get the arbitrage pricing equation between two periods:

\[
\frac{E \left( p_{t+1} \right)}{u_i} - p_i = \frac{E \left( sp_{t+1} q_{t+1} + \frac{2x_{t+1}}{q_{t+1} + x_{t+1}} \right)}{u_i} - \frac{2sp_i q_i}{q_i + x_i} \frac{\partial c_2(x_i)}{\partial x_i}
\]  
(1.10)

Equation (1.10) is the optimal inventory decision rule of the representative producer, which states that the marginal revenue of storing one more unit of soybeans (left hand side) is equal to the marginal cost (right hand side). There are three parts in the marginal
cost: the marginal transaction cost ($MTC_t$), the marginal risk premium ($MRP_t$) and the marginal storage cost $\partial c_2(x_t)/\partial x_t$.

\[
MTC_t = E \left( sp_{t,t+1} q_{t+1} + 2x_{t+1} \left( q_{t+1} + x_{t+1} \right)^2 \right) \frac{2sp_t q_t}{q_t + x_t} \frac{u_t}{\beta (1-\delta)} E \left( u_{t+1} \right)
\]  \hspace{1cm} (1.11)

\[
MRP_t = -Cov \left( u_{t+1}, p_{t,t+1} - sp_{t,t+1} q_{t+1} \left( q_{t+1} + x_{t+1} \right)^2 \right) \frac{u_t}{\beta (1-\delta)}
\]  \hspace{1cm} (1.12)

Equation (1.11) is the description for the marginal transaction cost. It equals zero if there is no transaction cost ($s=0$). The marginal transaction cost is a component of the marginal cost and determines the inventory level. If it is positive, it means holding one more unit of stocks will increase the transaction cost and thus provides a disincentive for the producer to hold additional inventories; while if it is negative, it provides an incentive for the producer to hold additional inventories by decreasing the transaction cost. The sign of the marginal transaction cost is determined by current and expected inventory levels, current and expected prices, and current and expected marginal utilities of the producer. Therefore, it is in general not possible to conclude whether it is positive or negative in a multi-period and non-risk-neutral agent setting. However, we could gain deeper insight about the marginal transaction cost in a simpler scenario where the producer is assumed to be risk-neutral and prices are stable. Suppose time $t$ is the period just before harvest so that $x_t$ is the lowest storage level in one year and $x_{t+1}$ is the highest storage level. Assume $x_t$ is so low in one year that it is negligible compared to $q_t$, and $x_{t+1}$ is so high that $q_{t+1}$ is negligible. Under risk-
neutral producers and stable prices we have \( MTC_t = \beta (1 - \delta) E \left( \frac{2sp_{t+1}q_{t+1}}{x_{t+1}} \right) - 2sp_t < \beta (1 - \delta) E(2sp_{t+1}) - 2sp_t < 0 \). Therefore, when the current inventory is low, the marginal transaction cost is negative and provides incentives for the producers to hold additional inventories. This is consistent with the results shown in Chavas, Despins and Fortenbery (2000).

Equation (1.12) is the description of the marginal risk premium. If the producer is risk neutral then \( u_{t+1}' \) is a constant and the covariance term is zero, making the marginal risk premium zero. The producer’s risk preference affects both the sign and the magnitude of the marginal risk premium through the covariance term in equation (1.12). The marginal risk premium could be positive or negative, and is a component in the producer’s inventory decision rule.

It is worthwhile to have a little discussion about the marginal risk premium and the risk premium. The marginal risk premium is a component in the producer’s optimal inventory decision rule. The marginal risk premium is the change in the risk premium. A positive marginal risk premium means that the producer gains a higher risk premium by holding one more unit of stocks compared to the lower inventory level and thus is an incentive for holding additional inventories; on the contrary, a negative marginal risk premium means that the producer gains less risk premium by holding one more unit of stocks compared to the lower inventory level, and thus is a disincentive for holding additional inventories. A positive/negative risk premium in period \( t \) does not necessarily mean the marginal risk premium is also positive/negative in period \( t \); also, a positive/negative marginal risk premium does not indicate a positive/negative risk premium. Therefore, the sign of the marginal risk premium does not reflect the producer’s risk attitude (risk-averse or risk-seeking). However, the sign of the risk
premium tells the producer’s risk preferences: a risk-averse agent has a positive risk premium and a risk-seeking agent has a negative risk premium. As defined in Chavas (2004), for a risk-averse agent, the positive risk premium is the sure amount of money a decision-maker would be willing to receive to become indifferent between receiving the risky return versus receiving the sure amount, or equivalently, it is an individual’s willingness to insure (Chavas 2004, p33-35). Alternatively, a decision-maker is risk-seeking if he/she must be compensated when the risk exposure is eliminated (Chavas 2004, p35), and the negative risk premium reflects this compensation. In other words, if a producer is risk-averse, then he/she might want to pay a risk premium as an insurance premium to be able to transfer the price risk to speculators; or he/she might want to earn the risk premium himself/herself. On the other hand, if the producer is risk-seeking, we should not observe risk premiums paid to speculators from producers as compensation for reducing producers’ market risks.

**Empirical analysis for the producers**

**Data**

Quarterly data from the first quarter of 1986 to the last quarter of 2012 were collected because the soybean inventory data are available only on a quarterly basis. The empirical analysis was conducted for two sub-periods: the first sub-period is from the first quarter of 1986 to the third quarter of 2007 and the second sub-period is from the fourth quarter of 2007 to the fourth quarter of 2012. This was done to identify the changes of the producers’ risk preferences due to the changes in commodity market price dynamics starting from late 2007.

The storage cost was assumed to be 0.09 dollars/bushel/quarter, and the depreciation rate $\delta$ was assumed to be 0.03, which were also used in Lin and Fortenbery (2006). The soybean cash prices were obtained from Commodity Research
Bureau (CRB). The production data are from USDA NASS Crop Production Annual Summary reports; the stocks data from the USDA NASS Grain Stocks reports; and the production cost data from USDA ERS commodity costs and returns data. The annual production cost per acre was reported by USDA. The average cost per bushel was calculated and then multiplied by total production to get the annual total cost. As indicated in USDA Field Crops Usual Planting and Harvesting Dates (U.S. Department of Agriculture, 2010), soybeans are planted in the 2nd quarter (April and May) and harvested in the 4th quarter (October, November and December). Therefore, only the fourth quarter of a year has production data with the other three quarters’ production being zero. The annual total cost was divided by three to obtain the quarterly production cost of the last three quarters with the first quarter’s production cost being zero. The quarterly sales were calculated using equation (1.1). The data are summarized in Table 3.1.

Empirical analysis

The estimation of parameters is based on the first-order condition given in equation (1.9). This is a nonlinear Euler equation and could not be solved for explicit representation of the stochastic equilibrium. The generalized method of moments (GMM) proposed in Hansen and Singleton (1982) and Hansen (1982) does not require a complete, explicit representation of the economic environment. The method constructs nonlinear instrumental variable estimators for the parameters. They have shown that these estimators are consistent and have a limiting normal distribution (Hansen and Singleton 1982).

Specifically, let us write the first-order conditions as \( E(u(x_{t+1}, \beta_0)) = 0 \), where \( u(x_{t+1}, \beta_0) \) is \( k \) first-order conditions; \( x_{t+1} \) is the observed information set and \( \beta_0 \) is the vector of true parameter values. Suppose \( z_t \) is a \( q \) dimensional vector of the
instrumental variables and define a function $f$ as:

$$f(x_{t+1}, z_t, \beta) = u(x_{t+1}, b) \otimes z_t$$  \hfill (1.13)

where $\otimes$ is the Kronecker product meaning to multiply every first-order condition by every instrumental variable; and $f$ is a vector of $k \times q$ equations. Then the $k \times q$ theoretical moment conditions can be represented by:

$$g_0(\beta) = E \left( f(x_{t+1}, z_t, \beta) \right) = 0$$  \hfill (1.14)

The corresponding sample moment conditions for a sample of $T$ observations are:

$$g_T(\beta) = \frac{1}{T} \sum_{t=1}^{T} f(x_{t+1}, z_t, \beta)$$  \hfill (1.15)

The GMM estimator is then:

$$\hat{\beta} = \text{argmin}_{\beta} g_T(\beta)'W_Tg_T(\beta)$$  \hfill (1.16)

where $W_T$ is the weighting matrix. The Gauss-Newton algorithm is used to solve the nonlinear minimization problem, and the parameter estimates are obtained when the estimates become stable. Therefore we have used the iterative GMM estimation. The optimal weighting matrix proposed in Hansen (1982) is $\left[ \text{cov}(n^{-\frac{1}{2}}z'u) \right]^{-1}$, and the sample optimal weighting matrix is:

$$W_T = \left[ \frac{1}{T} \sum_{t=1}^{T} \left( \hat{u}(x_{t+1}, \beta) \otimes z_t \right) \left( \hat{u}(x_{t+1}, \beta) \otimes z_t \right)' \right]^{-1}$$  \hfill (1.17)

The variance-covariance matrix of the estimators is:

$$V(\hat{\beta}) = \frac{1}{T} \left( \frac{\partial g_T(\beta)}{\partial \beta} W_T \frac{\partial g_T(\beta)}{\partial \beta} \right)^{-1}$$  \hfill (1.18)

In the empirical analysis for the producers, there was one first-order condition. The instrumental variables were chosen such that they were uncorrelated with the error terms, the parameters were significant and the overidentifying restrictions were valid.
Hansen and Singleton (1982) suggested that the lagged values of the endogenous variables could serve as the instruments. Also, a time trend and a constant are not correlated with the error terms and thus are good candidates for instruments. We also considered the producers’ price index which was also considered as an instrument in Lin and Fortenbery (2006). For the period before the fourth quarter of 2007, we tested several sets of instruments with different numbers of lagged soybean cash prices, with and without a constant, a time trend and the producers’ price index. We found that the set of nine instrumental variables including the lagged one to six periods’ cash prices, producers’ price index, a time trend and a constant gave significant parameters and the overidentifying restrictions were satisfied. Therefore we used the nine instruments in the estimation of the period before the fourth quarter of 2007 which lead to nine moment conditions for this time period. Similarly, seven instrumental variables were chosen for the period after the fourth quarter of 2007 including the one to four periods’ lagged cash prices, producers’ price index, a time trend and a constant, resulting in seven moment conditions for the second time period. The GMM estimation method allows for more moment conditions than there are parameters, and proposes a procedure to test the validity of the overidentifying restrictions. The test statistic (J-statistic) is:

$$J_T = T \min_{\beta} g_T(\beta)'W_T g_T(\beta)$$

(1.19)

This test statistic follows a $\chi^2$ distribution where the number of degrees of freedom equals the number of moment conditions less the number of parameters.

To make the estimation empirically tractable, a parametric structure for the utility function $U(\pi_t)$ was needed. Saha (1993) proposed the expo-power form of utility which did not impose a priori restrictions on the properties of risk aversion and had been adopted by empirical analysis (Chavas and Holt 1996; Lin and Fortenbery 2006). Following this standard practice, the following functional form of the producer’s period
utility was adopted:

$$u(\pi_t) = \int_0^\pi \exp(az + bz^2)dz$$

(1.20)

\(\pi_t\) was assumed to lie in the domain of \([L, U]\). \(a\) and \(b\) are the parameters in the utility function, and \(z\) is the dummy of the integration. This utility specification has several merits. Firstly, it satisfies non-decreasing marginal utility because \(\partial u(\pi_t)/\partial \pi_t = \exp(a\pi_t + b\pi_t^2) > 0\). Secondly, it allows for risk-averse as well as risk-seeking behavior depending on whether the utility function is concave \((\partial^2 u(\pi_t)/\partial \pi_t^2 \leq 0)\) or convex \((\partial^2 u(\pi_t)/\partial \pi_t^2 \geq 0)\) in \(\pi_t\). Finally, it lets the parameter estimates indicate how the individual’s risk preference changes with \(\pi_t\). The Arrow-Pratt (Pratt 1964; Arrow 1971) coefficient of absolute risk aversion is \(AR = -(\partial^2 u(\pi_t)/\partial \pi_t^2)/(\partial u(\pi_t)/\partial \pi_t) = -(a + 2b\pi_t)\). The individual exhibits constant absolute risk aversion (CARA) if \(\partial AR/\partial \pi_t = -2b = 0\), and decreasing (DARA) or increasing (IARA) absolute risk aversion if \(\partial AR/\partial \pi_t < 0\) and \(\partial AR/\partial \pi_t > 0\) respectively.

Table 3.2 gave the parameter estimates for the producer’s problem. The second and third columns show the parameter estimates and standard errors of the estimates for the period before the fourth quarter of 2007, while the last two columns show those results of the period after the fourth quarter of 2007. The small values of the J-statistics indicate that the instruments are valid and the overall model fit is good for both periods. We can see that the representative producer’s risk preference does change between the two periods. Before the fourth quarter of 2007, on average the producers were risk-averse when the aggregate market loss was larger than 687.2 million dollars (the large loss must be related to bad market conditions where the soybean prices were much lower than the costs for most of the producers) and risk-seeking when the
aggregate market loss was less than 687.2 million dollars or the overall market gained profits (this was related to good market conditions where the soybean prices were attractive). On average the producers exhibit DARA \((\partial AR/\partial \pi_t < 0)\) during the first sub-period. This was consistent with the findings for the producers between 1986 and 2002 in Lin and Fortenbery (2006) where the producers exhibited DARA and were risk-averse (-seeking) when they suffered losses (gained profits). After the fourth quarter of 2007, however, on average the producers were risk-averse when the aggregate market loss was less than 2628.5 million dollars or the overall market gained profits, and risk-seeking when aggregate market loss was larger than 2628.5 million dollars. Also, on average the producers exhibited IARA \((\partial AR/\partial \pi_t > 0)\) after the fourth quarter of 2007.

The parameter estimates show that the producer presented variable risk preferences. The existence of variable risk preferences has been supported by many studies. The concept of the S-shaped utility function was firstly proposed in Kahneman and Tversky (1979) where the authors found risk-seeking behavior in the domain of losses and risk-averse behavior in the domain of gains. However, Pennings and Smidts (2003) assessed the utility function of 332 hog farmers by means of computer-guided interviews and found the existence of both S-shaped (risk-seeking under losses and risk-averse under profits) and reverse S-shaped (risk-seeking under profits and risk-averse under losses) utility functions. Our results further indicate that the producer’s risk preferences not only changed with income levels but also changed with the exposure to risk. As shown in Figure 3.1 and also in the summary statistics of soybean cash prices, commodity markets including soybeans markets have become more volatile in the second time period compared to the first time period. Before the fourth quarter of 2007, soybean prices were relatively stable and the prices changed within a small range around the mean price of $5.996. However, after fourth quarter of 2007, soybeans traded in a larger
range around a mean price of $11.902. When producers made profits under relatively stable prices (small risk), they might have exhibited risk-seeking behavior because they thought that prices would not deteriorate so much that they lost significantly. The national loan rate for soybeans was another possible reason that producers were on average risk-seeking under gains in the first sub-period. According to the definition from USDA’s Economic Research Service (ERS), the loan rate for soybeans is the price per bushel at which the Commodity Credit Corporation provides commodity-secured, non-recourse loans to farmers. The national loan rate for soybeans has been stable at $5.00 per bushel over the whole period studied in this paper (Crowder 1990; Maynard, Harper and Hoffman 1997; FSA-USDA 2003; ERS-USDA 2014). The marketing loans provide a per-unit revenue floor at the loan rate for soybean producers: the producers can always sell at the loan rate if the market price falls below it. This loan rate was very effective during the first sub-period when the average market price was $5.996. The producers appeared risk-seeking under gains because the average market price was only a little higher than the “guaranteed” price. There was little risk for the producers to hold the inventories and hope to sell them when market price increases. However, when they suffered losses under stable prices, they appeared to exhibit risk-averse behavior and preferred to lock in selling prices to avoid further losses. This reverse S-shaped utility function is consistent with the DARA producer’s utility in the first time period. On the other hand, when producers were put under higher risk situations, they became risk-seeking under big losses. We hypothesize this is because under higher price volatility producers believed there was a greater possibility that they could turn losses into profits. However, when they had profits under higher price risk, they became more cautious because it was easy to turn profits into a big loss. The loan rate for soybeans was not working as effectively for producers in the second sub-period compared to the first
because the mean price was much higher than the loan rate.

The marginal transaction costs and the marginal risk premiums were calculated using equations (1.11) and (1.12). Following Arrow (1971) and Pratt (1964), the risk premium at time $t$ can be solved from the equation $EU(\pi_t) = U(E(\pi_t) - RP_t)$. This equation is a mathematical expression of the definition of risk premium (RP): a positive RP is a sure amount of money a risk-averse decision-maker would be willing to receive to become indifferent between receiving the risky return versus receiving the sure amount, while a negative RP is a compensation to a risk-seeking decision maker when the risk is taken away. Therefore, the equation we use to calculate the risk premiums is:

$$
E \left[ \int_0^{\xi_t} \exp(az + bz^2)dz \right] = \int_0^{E(\pi_t) - RP_t} \exp(az + bz^2)dz
$$

(1.21)

Since it is impossible to find an antiderivative that is an elementary function, the integrals were calculated using Simpson's rule for numerical integration.

The marginal transaction costs, marginal risk premiums and risk premiums were calculated separately for the two sub-periods. The expectation and covariance terms in the equations were calculated using simulation. First, we fit auto-regression models for the cash prices of each of the two sub-periods. Second, the two sets of regression errors were saved separately. Third, for each quarter in the first time period, we draw a bootstrapping sample of 1000 observations from the first set of regression errors; and for each quarter in the second period, draw a bootstrapping sample of 1000 observations from the second set of regression errors. Finally, each quarter’s bootstrapping prices were calculated by adding the estimated price of that quarter to the 1000 bootstrapping errors. The estimation results of the auto-regression models are summarized in Table 3.3, and the results for the marginal risk premiums, marginal transaction costs, and risk premiums are summarized in Table 3.4.
There were positive and negative marginal risk premiums in both the sub-periods. As discussed above, positive (negative) marginal risk premium is the gain (loss) to producers from holding one more unit of inventories, and thus is an incentive (disincentive) for producers to increase one more unit of inventory holding. Therefore the results indicate that in both time periods, the marginal risk premium served as an incentive for producers to hold one more unit of inventory in some quarters, and a disincentive in other quarters. The average marginal risk premium, however, was significantly negative in the first time period, while significantly positive in the second time period. This indicates that on average, the producers were compensated more for holding one more unit of inventory in the second period. This might be due to the soybean market, as well as most other commodity markets, becoming more volatile after the fourth quarter of 2007. As such soybean producers required more gains to be willing to hold additional inventories in the second period because of the highly volatile market.

The marginal transaction costs were all negative for the producers in both sub-periods, meaning that the marginal transaction cost served as an incentive for producers to hold additional inventories. The average marginal transaction cost was larger in magnitude in the second period. As discussed before, transaction cost comprises transportation cost, information cost and other costs that occur during transactions. The marginal transaction cost measures the change in transaction costs for holding one more unit of inventory. We hypothesize that the more negative average marginal transaction cost for the producers in the second time period is because transportation cost dominated producers’ transaction cost in that period. As shown in Figure 3.1, the crude oil price increased dramatically after the 4th quarter of 2007 compared to periods before that. Therefore the transportation cost should increase significantly. Holding one more
unit of inventory would result in saving more in the transaction cost, indicating bigger marginal transaction cost in magnitude.

The producers’ risk premiums had positive and negative values in both sub-periods. However, the producers’ average risk premium was significantly negative in the first time period, while significantly positive in the second time period. This indicated that on average producers were risk-seeking before the fourth quarter of 2007 and risk-averse after that. We argue that the change in price risk between the two time periods caused the change in the producers’ average risk preferences. The producers were on average risk-seeking in the first sub-period, meaning that they would not be willing to pay to insure. On the contrary, the producers were on average risk-averse in the second sub-period with a positive average risk premium. The positive risk premium measures the amount that they needed to gain to hold inventories under risk, or equivalently, the amount they were willing to pay to get rid of the risk. Since the producers mostly used forward contracts to manage the price risk (Schroeder, Parcell, Kastens and Dhuyvetter 1998), if they decided to pay to eliminate risk in the second time period, the risk premium was transferred to the commercial elevators. Therefore, to find whether the risk premium was further transferred to the futures market, we need to analyze the commercial elevators’ problem.

**The commercial elevators’ problem**

The other type of agents who hold inventories in the soybean cash market are commercial elevators. They buy soybeans from producers and sell them to processors and wholesalers, or store soybeans for later sale (Lin and Fortenbery 2006). The inventory dynamics of a representative commercial elevator can be denoted as:

\[
(1-\delta)x_{t-1} - q_t = x_t
\]  

(2.1)

where \( x_t \) is the amount of inventories in period \( t \); \((1-\delta)x_{t-1}\) is the part of
inventories brought into period $t$ with $\delta$ being the deterioration rate; $q_t$ is the amount of sale (purchase) in period $t$ if it is positive (negative).

The commercial elevator also incurs transaction costs which can be represented as:

$$s_t(q_t, x_t) = sp_t \frac{q_t}{(1-\delta)x_{t-1}} = sp_t \frac{q_t}{q_t + x_t}$$

(2.2)

The interpretations of the transaction cost are the same as those in the producer’s problem, except that the producer does not buy soybeans, while the commercial elevator can sell as well as buy soybeans. When the commercial elevator buys soybeans, the transaction cost is negative because $q_t$ is negative under purchase.

To manage their price risk, the commercial elevators may hedge in the futures market. According to the definition of US Commodity Futures Trading Commission (CFTC), a hedger is one who “purchases or sells futures as a temporary substitute for a cash transaction that will occur later”. Therefore, we seldom see real delivery against futures contracts. Instead, a hedger will close-out his short positions by purchasing an equal number of contracts of the same delivery month. The purpose of short hedging is to lock the cash price of the spot transaction that will happen later. The commercial elevator is assumed to hedge $\xi_t$ soybeans at period $t$ at the current futures price $f_t$. In the next period, period $t+1$, the commercial elevator will sell $q_{t+1}$ in the cash market at price $p_{t+1}$, while purchasing $\xi_t$ soybeans in the futures market at price $p_{t+1}$. Thus the price of the hedged part ($\xi_t$) of the total period $t+1$ sale $q_{t+1}$ is locked at $f_t$.

The commercial elevator’s total profit is the sum of the cash market profit and the futures market profit, and can be expressed as:

$$\pi_t = (p_t - s_t)q_t - c(x_t) + (p_t - f_{t-1})\xi_{t-1}$$

(2.3)

where $c(x_t)$ is the commercial elevator’s storage cost in period $t$. $s_t$ is positive under a sale, meaning that the real selling price is less than the cash price when the commercial
elevator sells stocks due to the existence of transaction costs; $s_t$ is negative under a purchase, meaning that the real purchasing price is higher than the cash price when the commercial elevator purchases stocks because of the transaction costs. The short hedging $\xi_t$ is negative, so if the cash price at the time when the commercial elevator closes-out their positions is less (greater) than the futures price at the time when the commercial elevator enters into the contract, the commercial elevator earns (loses) money in the futures market.

The commercial elevator’s objective is to maximize the discounted expected utility of profits over the entire business life. Mathematically it is represented as:

$$\max_{s_t, \xi_t} \sum_{t=\tau}^{\infty} \beta^{t-\tau} EU(\pi_t)$$

$\beta$ represents the commercial elevator’s discount factor, $0 < \beta < 1$. $E$ stands for the expectation operator conditional on the information at period $t$. $U(\pi_t)$ is the commercial elevator’s utility function, which is assumed to be increasing in $\pi_t$ and differentiable with respect to $\pi_t$. In each quarter $t$, the commercial elevator chooses $x_t$ and $\xi_t$ to maximize the discounted expected utility of profits based on information available. Assume in each quarter the commercial elevator does not deplete stocks and is active on the futures market, i.e., there is an interior solution.

The first-order necessary conditions with respect to $x_t$ and $\xi_t$ are:

$$\frac{\partial u_t}{\partial x_t} \left[ -s_t + (p_t - s_t) \frac{\partial q_t}{\partial x_t} - \frac{\partial c}{\partial x_t} \right] + \beta E \frac{\partial u_{t+1}}{\partial \pi_{t+1}} \left[ -\frac{\partial s_{t+1}}{\partial x_t} q_{t+1} + (p_{t+1} - s_{t+1}) \frac{\partial q_{t+1}}{\partial x_t} \right] = 0 \quad (2.4)$$

$$\beta E \frac{\partial u_{t+1}}{\partial \pi_{t+1}} (p_{t+1} - f_t) = 0 \quad (2.5)$$

Rearranging the inventory dynamics in equation (2.1) we can get $q_t = (1 - \delta)x_{t-1} - x_t$ and $q_{t+1} = (1 - \delta)x_t - x_{t+1}$. The derivative of $q_t$ with respect to
\( x_t \) is \( \partial q_t / \partial x_t = -1 \), meaning that with \( (1 - \delta)x_{t-1} \) units of soybeans allocated into storage and sale, one more unit of soybeans being put into storage leads to one unit less of soybeans being sold in the cash market in period \( t \). The derivative of \( q_{t+1} \) with respect to \( x_t \) is \( \partial q_{t+1} / \partial x_t = 1 - \delta \), meaning that with one more unit of soybeans put into storage in period \( t \), the commercial elevator will have \( 1 - \delta \) more unit of soybeans to sell in period \( t+1 \) if the next period’s storage plan remains unchanged.

Equation (2.2) gives us the expressions for transaction costs of periods \( t \) and \( t+1 \). The derivative \( \partial s_t / \partial x_t = (sp_t \frac{\partial q_t}{\partial x_t} (q_t + x_t) - sp_t q_t \frac{\partial q_t}{\partial x_t} + 1)) / (q_t + x_t)^2 = -sp_t / (q_t + x_t) \) indicates that the commercial elevator decreases the average transaction cost by \( -sp_t / (q_t + x_t) \) with one more unit of storage holding. The derivative of \( s_{t+1} \) with respect to \( x_t \) \( \partial s_{t+1} / \partial x_t = \frac{\partial q_{t+1}}{\partial x_t} = (1 - \delta)sp_{t+1} x_{t+1} / (q_{t+1} + x_{t+1})^2 \) means that the next period’s average transaction cost will increase \( (1 - \delta)sp_{t+1} x_{t+1} / (q_{t+1} + x_{t+1})^2 \) with one more unit of storage in the current period, if the increased storage goes into next period’s sale.

Replacing the corresponding items with the above derivatives, equation (2.4’) can be derived from equation (2.4). Together with equation (2.5), we get two first-order conditions that will be used in the GMM estimation:

\[
\begin{align*}
& E_t \left[ \beta (1-\delta) \left( p_{r+1} - s_{r+1} - sp_{r+1} x_{r+1} q_{r+1} \right) \frac{\partial u_{r+1}}{\partial \pi_{r+1}} - \left( p_{t} - s_{t} - sp_{t} q_{t} \frac{\partial c(x_{t})}{\partial x_{t}} \right) \frac{\partial u_{t}}{\partial \pi_{t}} \right] = 0 \quad (2.4') \\
& \beta E_t \frac{\partial u_{r+1}}{\partial \pi_{r+1}} (p_{r+1} - f_{r}) = 0
\end{align*}
\]

We can get the arbitrage pricing equation between two periods for the commercial elevator from equation (2.4’):
Equation (2.6) states that the marginal revenue of storing one more unit of soybeans is equal to the marginal cost. Similar as in the producer’s problem, there are three parts in the marginal cost: the marginal transaction cost \( MTC_t \), the marginal risk premium \( MRP_t \) and the marginal storage cost \( \partial c(x_t) / \partial x_t \).

\[
MTC_t = \frac{E\left( p_{t+1}\right) - p_t}{\beta(1-\delta)E(u_{t+1})} - s_t - \frac{sp_tq_t}{q_t + x_t} - \frac{\text{Cov}\left( u_{t+1}, p_{t+1} - s_t - \frac{sp_tq_tx_{t+1}}{(q_t + x_t)^2}\right)}{\beta(1-\delta)}
\]

Equation (2.7) is the description for the marginal transaction cost for the commercial elevator. As in the producer’s case, the marginal transaction cost equals zero if there is no transaction cost \( s=0 \). Also, in general the marginal transaction cost could be positive and negative. However, when the commercial elevator is risk neutral and the prices are stable, we can prove that it is negative when the inventory level is low and thus provides incentive for the commercial elevator to hold inventory. Suppose the commercial elevator decides to deplete all the soybeans at period \( t \), and purchase new soybeans at period \( t+1 \). Therefore \( s_t \) is positive and \( s_{t+1} \) is negative, leading \( MTC_t \) to be negative.

Equation (2.8) is the description of the marginal risk premium. Similar to the
producer, the commercial elevator’s marginal risk premium could be positive or negative, and serves as an incentive for holding additional inventories when it is positive and disincentive for holding additional inventories when it is negative.

**Empirical analysis for the commercial elevators**

**Data**

Quarterly data from the first quarter of 1986 to the last quarter of 2012 are also used for the empirical analysis for the commercial elevator. The analysis is separated into two sub-periods: before and after the fourth quarter of 2007. The storage cost is assumed to be 0.09 dollars/bushel/quarter, and the depreciation rate $\delta$ is assumed to be 0.03 as in Lin and Fortenbery (2006). The soybean cash prices and the stocks data are from the same sources as described in the producer’s problem. The quarterly sales are calculated using equation (2.1).

The soybean futures prices are from Commodity Research Bureau (CRB). There are seven months in which soybean futures contracts mature. They are January, March, May, July, August, September and November. CRB provides quarterly average futures prices for futures that mature in those months. As discussed before, the commercial elevator hedges in the futures market as a temporary substitute for a cash transaction that will occur later and closes-out his short positions by purchasing an equal number of contracts of the same delivery month when the cash transaction occurs. Therefore, to construct quarterly futures market data, the futures trading strategy in Lin and Fortenbery (2006) is adopted here: in the first quarter of each year, the commercial elevator shorts the July contract and closes-out the positions on the March contract that were placed in the fourth quarter of previous year; in the second quarter, the commercial elevator shorts the September contract and closes-out the positions on the July contract; in the third quarter, the commercial elevator shorts the January contract and closes-out
the positions on the September contract; and in the last quarter, the commercial elevator shorts the March contract and closes-out the January contract.

The commercials’ all short positions for soybean futures trading in the U.S. Commodity Futures Trading Commission (CFTC) Commitment of Traders (COT) report were used for the short positions. CFTC requires traders who hold positions equal to or above the reporting levels to report their number of positions. In the COT report, a trader’s reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined by CFTC. Before October 1992, the COT report was released biweekly. After that, the report was released weekly. The quarterly positions are calculated as the quarterly average using the weekly or biweekly data. The descriptive statistics of the data are also included in Table 3.1.

**Empirical analysis**

The estimation of parameters in the first-order conditions of equations (2.4') and (2.5) is also based on the nonlinear iterative GMM method described in the producer’s problem. To find good instruments for the estimations of each of the sub-period, we tested different numbers of lagged soybean cash prices, with and without a constant, a time trend and the producers’ price index. Finally we chose the instruments that give significant parameters with the overidentifying restrictions satisfied. For the period before the fourth quarter of 2007, the instrumental variables include the lagged one- to five-period cash prices, a time trend and a constant, leading to 14 moment conditions. The instruments used for the period after the fourth quarter of 2007 include the lagged one- to four-period cash prices, the producer’s price index, a time trend and a constant, leading to 14 moment conditions. Moreover, the same utility function as described in equation (1.20) is used for the commercial elevator. Table 3.5 shows the parameter
estimates for the commercial elevator’s problem.

The second and third columns show the parameter estimates and standard errors of the estimates for the period before the fourth quarter of 2007, while the last two columns show those results after the fourth quarter of 2007. The insignificant J-statistics indicate that the instruments are valid and the overall model fit is good for both periods. We can see that the commercial elevator’s risk preference does change between the two periods. Before the fourth quarter of 2007, the commercial elevator is risk-averse when the aggregate loss is less than 1725.8 million dollars or on average the commercial elevators gain profits, and risk-seeking when the aggregate loss is greater than 1725.8 million dollars (a bad market condition when the revenue of storing soybeans is less than the cost for most of the commercial elevators). On average the commercial elevators exhibit IARA ($\partial AR/\partial \pi_t > 0$) during the first sub-period. After the fourth quarter of 2007, however, the commercial elevator is risk-averse when the aggregate loss is greater than 10327 million dollars and risk-seeking when the aggregate loss is less than 10327 million dollars or the commercial elevators gain profits. During the second sub-period the commercial elevators on average exhibit DARA ($\partial AR/\partial \pi_t < 0$). These results mirror the inconclusive status of the study on firms’ risk preferences in the management literature. As discussed in the producer’s problem, the notion of variable individual risk preferences has been claimed (Kahneman and Tversky 1979; Pennings and Smidts 2003). Some studies extend the notion and argue that firms also have variable risk preferences and are risk-averse (risk-seeking) when the performance is above (below) a reference level (e.g., Bowman 1982; Fiegenbaum 1990). The commercial elevator’s results before the fourth quarter of 2007 show some empirical evidence for this argument. However, some management studies argue for the existence of a “threat-rigidity response” whereby risk taking decreases under threats to survival
(Staw, Sandelands, and Dutton 1981). There are also disputes about whether firms remain risk averse or become risk seeking as performance rises above the target levels (Miller and Chen 2004). The commercial elevator’s risk-averse attitude under loss after the fourth quarter of 2007 could serve as evidence for the “threat-rigidity response”. When the commercial elevator’s loss is greater than 10327 million dollars, the high price volatility provides the possibility that the soybean cash price could go lower and “threaten” the commercial elevator’s business. However, the higher soybean price levels in the second time period could increase the commercial elevator’s profit above the target level and the commercial elevator becomes risk-seeking under gains.

The marginal transaction costs and marginal risk premiums are calculated using equations (2.7) and (2.8), and the risk premiums are calculated using the same equation (1.21) in the producer’s problem. The same bootstrapping simulation technique is used to calculate the mean and covariance terms in the calculations, and the integrals in the risk premiums are calculated using the Simpson’s rule for numerical integration. The results for the marginal risk premiums, marginal transaction costs, and risk premiums of the commercial elevator are summarized in Table 3.6.

There are positive and negative marginal risk premiums both before and after the fourth quarter of 2007, meaning that the marginal risk premium serves as a disincentive for the commercial elevator to hold one more unit of inventories in some quarters and an incentive for holding additional inventories in others. The mean marginal risk premiums are significantly positive both before and after the fourth quarter of 2007, and the magnitude of the second period’s mean marginal risk premium is bigger than that of the first period. This indicates that on average, the marginal risk premium is an incentive for the commercial elevator to hold additional inventories and the commercial elevator is compensated more to hold additional inventories in the second period. This
might be due to the high volatility of the commodities markets after the fourth quarter of 2007. The high price volatility increases the risk of inventory holding, and the commercial elevator requires more incentive to hold additional stocks. Without the higher incentive, we should expect to observe less stocks being held.

There are positive and negative marginal transaction costs for the commercial elevator, meaning that it serves as a disincentive for the commercial elevator to hold additional inventories in some quarters and an incentive for additional inventory holding in others. However, the average marginal transaction costs are negative both before and after the fourth quarter of 2007, indicating that on average it serves as an incentive for the commercial elevator to hold additional inventories. Moreover, the commercial elevator’s marginal transaction costs are smaller in magnitude than those of the producer’s in both periods. This finding is consistent as in Lin and Fortenbery (2006) who hypothesize the reason to be the existence of economies of scale in storage. If this is so, the average transaction cost of the commercial elevator is lower than that of the producer and the marginal transaction cost for holding one more unit of inventory would be smaller.

The risk premiums of the commercial elevator have positive and negative values both before and after the fourth quarter of 2007, as suggested by the parameter estimates. So the commercial elevator presents variable risk preferences in both time periods. However, the mean risk premiums are significantly negative in both periods, indicating that on average the commercial elevator is risk-seeking in both time periods. So the commercial elevator does not need compensation for bearing risk or is not willing to pay futures market speculators for price insurance. Therefore, no risk premium should be found in commodity futures markets before the fourth quarter of 2007 because both the producer and the commercial elevator are risk-seeking in this period. Moreover,
even though the higher price volatility induces the soybean producer to become risk-averse, and they may be willing to pay a risk premium after the fourth quarter of 2007, the commercial elevators are not willing to pay any risk premium to futures market, indicating that no risk premium should be observed after the fourth quarter of 2007.

**Conclusion and discussion**

The search for the existence of a commodity futures market risk premium has been focused on the futures market and the results are inconclusive. Since the risk premium is defined as the insurance that the cash market inventory holders pay to futures market speculators to transfer price risk in their physical positions, it should emanate from the cash market if it exists. This paper has studied two types of soybeans cash market inventory holders, soybean producers and commercial elevators, to investigate cash market participants’ willingness to pay a risk premium using quarterly data from 1986 to 2012. Because commodity markets, including the soybean market, have experienced increases in both price levels and volatility since the fourth quarter of 2007, we separate the analysis into two sub-periods, before and after the fourth quarter of 2007, and look for any changes in risk preferences on the part of cash market participants.

The utility maximization problems of the representative producer and representative commercial elevator are studied. Three components are specified in the marginal cost of the optimal inventory decision rules: the marginal transaction cost, marginal risk premium and marginal storage cost. The mean marginal transaction cost is negative in both sub-periods for the producer and the commercial elevator indicating that it serves as an incentive for additional inventory holding. The producer’s marginal transaction cost is bigger in magnitude after the fourth quarter of 2007. This may be because the transportation cost dominates the producer’s transaction cost which is expected to increase due to the increase in crude oil price after the fourth quarter of
2007. The mean marginal risk premium of the producer is negative before the fourth quarter of 2007 and positive after that, and is positive for the commercial elevator in both time periods, but is larger in magnitude in the second period. This indicates that on average the cash market inventory holders need more compensation to hold additional inventories after the fourth quarter of 2007 due to the higher market risk.

The producers and the commercial elevators present variable risk preferences within each sub-period as well as between the two periods. On average, the producers are risk-seeking before the fourth quarter of 2007 and risk-averse after that; while the commercial elevators are risk-seeking in both periods. Therefore, no risk premium should be found on the futures market in the first period because the overall cash market is risk-seeking. The producers might be willing to pay a risk premium to remove the risk in the second period, but they transfer the risk to the commercial elevators and the commercial elevators serve as the final representative of the cash market to the futures market. Since the commercial elevators are risk-seeking in the second period, no risk premium should be observed after the fourth quarter of 2007 either.

In conclusion, by analyzing the two primary types of storers in soybean cash markets who might have the need to insure against price risk, we find that the overall soybean cash market does not pay risk premiums over 1986 to 2012 period. This conclusion is consistent with most studies on the existence of risk premiums of a single commodity futures market.

We will improve this paper from two aspects in the next step. First, we will apply other forms of utility functions for the empirical analysis. As we can see, our results are closely related to the utility function that is used in this paper. We have discussed in the body of the paper the merits of this utility functional form and why we chose this utility form. However, we do intend to investigate whether our analysis is robust with other
functional forms.

Second, we will employ rolling time periods in the analysis to investigate the changes of the risk preferences of the inventory holders over time. Due to our knowledge of changes in commodity markets, we separated our analysis for the period before the fourth quarter of 2007 and the period after that. We do find changes in the inventory holders’ risk preferences between the two sub-periods. It would be interesting to do the continuous analysis to determine whether our structural break is in fact the most appropriate break.
References


### Table 3.1 Descriptive statistics of the variables\(^a\)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Error</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soybean cash prices (dollars/bushel):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(P)</td>
<td>5.996</td>
<td>11.902</td>
<td>1.112</td>
<td>9.322</td>
</tr>
<tr>
<td>Soybean futures prices (dollars/bushel)(^d):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(f)</td>
<td>6.138</td>
<td>11.890</td>
<td>1.049</td>
<td>9.097</td>
</tr>
<tr>
<td>Soybean production output (1,000 bushels)(^e):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(y)</td>
<td>2,414,686.905</td>
<td>3,073,473.000</td>
<td>475,940.415</td>
<td>2,677,117.000</td>
</tr>
<tr>
<td>On farm inventory levels (1,000 bushels):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(x)</td>
<td>505,584</td>
<td>517,317</td>
<td>371,264</td>
<td>1,461,000</td>
</tr>
<tr>
<td>Off farm inventory levels (1,000 bushels):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(x)</td>
<td>537,912</td>
<td>634,965</td>
<td>305,772</td>
<td>1,240,366</td>
</tr>
<tr>
<td>Production costs (1,000 cents)(^f):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(c(y))</td>
<td>1,422,905,678</td>
<td>3,449,487,039</td>
<td>380,626,181</td>
<td>447,526,615</td>
</tr>
<tr>
<td>Commercials’ short all positions in futures market (1,000 bushels)(^g):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\xi)</td>
<td>-438,854.079</td>
<td>-1,588,628.158</td>
<td>265,850.041</td>
<td>515,244.615</td>
</tr>
</tbody>
</table>

\(^a\) The number of observations are 87 and 21 for the 1\(^{st}\) and 2\(^{nd}\) periods respectively;
\(^b\) The 1\(^{st}\) period is from the first quarter of 1986 to the third quarter of 2007;
\(^c\) The 2\(^{nd}\) period is from the fourth quarter of 2007 to the fourth quarter of 2012;
\(^d,g\) The lagged one period value is used in each profit equation, so the number of observations in the 2\(^{nd}\) period is 20;
\(^e\) The production is annual data, with all the harvest in the fourth quarter of each year. The 1\(^{st}\) period is from 1986 to 2006 with 21 observations and the 2\(^{nd}\) period is from 2008 to 2012 with 6 observations;
\(^f\) Production activities are in the second, third and fourth quarters of a year. The annual production cost is divided by three to obtain the quarterly production cost series, with the first quarter’s production cost being 0. Descriptive statistics are for the annual production costs. The 1\(^{st}\) period is from 1986 to 2007 with 22 observations and the 2\(^{nd}\) period is from 2008 to 2012 with 5 observations.
Table 3.2 Parameter estimation results for the producer’s problem

<table>
<thead>
<tr>
<th></th>
<th>1st quarter 1986 – 3rd quarter 2007&lt;sup&gt;a&lt;/sup&gt;</th>
<th>4th quarter 2007 – 4th quarter 2012&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.975***&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.0349</td>
</tr>
<tr>
<td>( s )</td>
<td>0.19***</td>
<td>0.068</td>
</tr>
<tr>
<td>( a )</td>
<td>2.5721E-4***&lt;sup&gt;d&lt;/sup&gt;</td>
<td>1.1156E-4</td>
</tr>
<tr>
<td>( b )</td>
<td>1.8677E-6***</td>
<td>5.3233E-7</td>
</tr>
</tbody>
</table>

Overidentifying test \( (J_T) \) | 7.8339 | 1.6845 |
Pr\( (J > J_T) \) | 0.4499 | 0.9463 |

<sup>a</sup> Number of observations = 87;
<sup>b</sup> Number of observations = 21;
<sup>c</sup> Statistically significant at 10% level;
<sup>d</sup> Statistically significant at 5% level;
<sup>e</sup> Statistically significant at 1% level.
Table 3.3 Auto-regressions for soybeans cash prices

Panel A. Auto-regression for soybeans cash prices: 1st quarter, 1986 – 3rd quarter, 2007a

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_{t-1} )</td>
<td>1.3666***c</td>
<td>0.1070</td>
</tr>
<tr>
<td>( P_{t-2} )</td>
<td>-0.6633***</td>
<td>0.1710</td>
</tr>
<tr>
<td>( P_{t-3} )</td>
<td>0.2980***</td>
<td>0.1075</td>
</tr>
<tr>
<td>Centered R² =</td>
<td>0.7239</td>
<td></td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_{t-1} )</td>
<td>0.9456***</td>
<td>0.2598</td>
</tr>
<tr>
<td>( P_{t-2} )</td>
<td>-0.2889</td>
<td>0.4149</td>
</tr>
<tr>
<td>( P_{t-3} )</td>
<td>-0.1390</td>
<td>0.4112</td>
</tr>
<tr>
<td>( P_{t-4} )</td>
<td>0.4996*</td>
<td>0.2682</td>
</tr>
<tr>
<td>Centered R² =</td>
<td>0.6128</td>
<td></td>
</tr>
</tbody>
</table>

a Number of observations: 87;
b Number of observations: 21;
c Statistically significant at 1% level;
d Statistically significant at 10 level.
Table 3.4 Summarized results for the marginal risk premiums (MRP), marginal transaction costs (MTC), and risk premiums (RP) for producers

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std Err</th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
<th>Std Err</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRP</td>
<td>-0.0115***</td>
<td>0.0262</td>
<td>0.0169</td>
<td>-0.1109</td>
<td>0.0355**</td>
<td>0.0612</td>
<td>0.1445</td>
<td>-0.0194</td>
</tr>
<tr>
<td>MTC</td>
<td>-0.5572***</td>
<td>0.3843</td>
<td>-0.0723</td>
<td>-1.4978</td>
<td>-2.861***</td>
<td>1.57</td>
<td>-0.373</td>
<td>-6.722</td>
</tr>
<tr>
<td>RP</td>
<td>-0.947***</td>
<td>1.803</td>
<td>0.341</td>
<td>-6.018</td>
<td>5.7457***</td>
<td>9.1086</td>
<td>23.32</td>
<td>-0.46</td>
</tr>
<tr>
<td>RP/E(π)</td>
<td>0.0037</td>
<td>0.0062</td>
<td>0.0238</td>
<td>2.7E-6</td>
<td>0.0089</td>
<td>0.0128</td>
<td>0.0338</td>
<td>7.52E-5</td>
</tr>
</tbody>
</table>

a Number of observations = 83;
b Number of observations = 16;
c Statistically significant at 1% level;
d Statistically significant at 5% level.
Table 3.5 Parameter estimation results for the commercial elevator’s problem

<table>
<thead>
<tr>
<th>Parameter</th>
<th>1st quarter 1986 – 3rd quarter 2007&lt;sup&gt;a&lt;/sup&gt;</th>
<th>4th quarter 2007 – 4th quarter 2012&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.9845***&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.0142</td>
</tr>
<tr>
<td>( s )</td>
<td>5.0298E-3***</td>
<td>1.5904E-3</td>
</tr>
<tr>
<td>( a )</td>
<td>-1.1394E-3***</td>
<td>2.6288E-4</td>
</tr>
<tr>
<td>( b )</td>
<td>-3.2953E-6***</td>
<td>6.1529E-7</td>
</tr>
<tr>
<td>Overidentifying test ( (J_T) )</td>
<td>14.4101</td>
<td>10.7160</td>
</tr>
<tr>
<td>( \Pr(J &gt; J_T) )</td>
<td>0.1551</td>
<td>0.3801</td>
</tr>
</tbody>
</table>

<sup>a</sup> Number of observations = 86;
<sup>b</sup> Number of observations = 21;
<sup>c</sup> Statistically significant at 1% level.
Table 3.6 Summarized results for the marginal risk premiums (MRP), marginal transaction costs (MTC), and risk premiums (RP) for producers

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std Err</td>
</tr>
<tr>
<td>MRP</td>
<td>0.0102***c</td>
<td>0.0501</td>
</tr>
<tr>
<td>MTC</td>
<td>-0.2529***</td>
<td>0.8401</td>
</tr>
<tr>
<td>RP</td>
<td>-0.892***</td>
<td>2.818</td>
</tr>
<tr>
<td>$RP/E(\pi)$</td>
<td>0.0041***</td>
<td>0.0059</td>
</tr>
</tbody>
</table>

a Number of observations = 83;
b Number of observations = 17;
c Statistically significant at 5% level;
d Statistically significant at 1% level.
Figure 3.1 Annual food price index and crude oil price from 1990 Jan to 2011 Dec.


Data source: Commodity Research Bureau

Data source: Commodity Research Bureau
CHAPTER 4 HOW DOES THE REVELATION OF PREVIOUS BID AFFECT NEW BID?

Abstract

This study investigates the effect of the revelation of posted bids in second-price experimental auctions for apple quality attributes under the experimental design where information is added progressively across rounds. We find that the revelation of posted bids does not bias the following bids and that increased information about the apple increases the accuracy of participants’ following bids. Therefore, the final round bids are used to evaluate consumers’ willingness to pay for the apple attributes of interest in this study. Consumers are found to prefer large, firm, sweet, and crisp apples with fewer defects.

Key words: affiliation, experimental auctions, posted prices, willingness-to-pay, apple attributes
Introduction

Experimental auctions, such as second price auction (Vickrey 1961), are a popular methodology to elicit individuals’ revealed preferences for goods and services. Recent studies include eliciting consumers’ willingness to pay (WTP) for fruits (e.g., Carrillo-Rodriguez, et al. 2013), ornamental plants (e.g., Yue, et al. 2012), and meat (e.g., Feuz, et al. 2004), etc. To help participants understand the market mechanism and improve the accuracy of their bids, the experimental auctions often have multiple rounds and the winning bids are posted for the participants to observe before the next round begins (Shogren 2001).

However, there are controversies as to whether multi-round auctions with postings of the winning bids can reveal consumers’ true valuations of the bidding objects. Some studies have shown that people are more rational after several rounds of bidding with exposure of price feedback (e.g., Cox & Grether 1996; Shogren et al. 2001). Therefore, experimental auctions using multiple rounds with price feedback are mostly used in practice. Scholars have proposed the possibility of price feedback causing bid affiliation when one bidder’s high value increases the values other participants put on the good. Milgrom and Weber (1982) were the first to show that the incentive compatibility property of auctions such as a second-price auction break down if the bids are affiliated. Bid affiliation is a potential problem under repeated rounds and price feedback, which is the standard practice now. There are several studies investigating the existence of bid affiliation in second-price auctions. List and Shogren (1999) found that posted prices influenced the behavior of the median naïve bidder but did not influence the behavior of the experienced bidder or the bidder for familiar goods. They suggested that while affiliation might exist in auctions for new goods, the repeated rounds with non-price information removes the correlation of values and provides the experience that bidders
need to understand the market mechanism. Corrigan and Rousu (2006) designed an experiment that was specifically used to investigate the effects of posted prices on bids in subsequent rounds. They put confederate bidders in some of the sessions whose bids were purposefully much higher than the value of the bidding objects and varied in a small predetermined range. They found that posted bids had a statistically and economically significant impact on bids submitted in subsequent rounds. Therefore they suggested that the repeated-trial second-price auctions should be abandoned and one-round auctions should be used. Corrigan, et al (2012) argued that the reason for disagreement on the effect of posted bids on the following bids was that people’s true valuations on the bidding object were unknown *ex ante*. They designed experiments with goods of observable values. They concluded that posting bids leads to biased following bids and recommended that repeated round auctions without price feedback should be used.

The role of posted bids in multi-round auctions is still an on-going debate. Different studies have reached different conclusions. The common component of the experimental auctions in these studies is that they provide the same non-price information in every round of the auction. In this paper, we design a multi-round second-price experimental auction on apples where participants are given different information in each round. We are interested in the effect of posted winning bids on the bids in the following round. Specifically, we want to address whether the posted bids provide information that would increase participants’ bidding accuracy. Or do the posted bids cause “irrational” participant behavior so that the subsequent bids are biased? Moreover, this study provides valuable information to apple breeding scientists by informing them about consumers’ valuations on apples’ key external appearance and eating quality attributes which are objectively or instrumentally measured.
Experimental design

The sensory taste tests and experimental auctions were conducted during the Fall 2012 in three US locations: Pullman, WA; St. Paul, MN; and Portland, OR. There were 128 participants in each location, divided into 8 sessions with 16 participants per session.

Individuals were compensated for their participation with $40. Following the introduction of the study, there was a practice session with two brands of candy bars to help the participants become familiar with the second-price auction mechanism and understand why it is to their benefit to bid exactly what it is worth to them to obtain the product being auctioned.

After the practice round, three rounds of bids with apples were conducted in each session. To ensure a random distribution of apples with different attributes across participants two orthogonal designs were created. One considered two levels of size (large and small) and two levels of coverage of defects (no defects and defects) for the first round of bids. The second design considered two levels of firmness (lower and higher than 12 lbf), sweetness (lower and higher than 13°Brix) and crispness (crisp ("Honeycrisp"), no crisp ("Gala")) for the second round of bids. Apples harvested at different harvest times, growing locations and storage conditions were procured so we could ensure variability in sweetness and firmness. To obtain variability in crispness two different cultivars were used, “Honeycrisp” and “Gala”. Each apple sample to be tasted was cut into two parts. Sweetness and firmness was measured for each sample before the sensory taste, so we ensured that the distribution of apples followed the orthogonal design.

In the first round, two apple samples were displayed in the front of the room, and participants were asked to visually inspect them. These two samples corresponded to
the same cultivar to avoid cultivar effect on bidding and were differentiated by size and external defects. After viewing the two samples, participants submitted their bids for each of the two samples observed in Round 1 (BID1). Bids were ordered in ascending order. The highest and the second highest prices bid for each sample were posted on a board in front of the room.

In the second round, each participant was given two samples of sliced and peeled apples with different combinations of eating quality attributes (firmness, sweetness, tartness, and crispness). Apples were peeled to prevent cultivar recognition based on skin traits. Each participant tasted half of the apple samples, with the other half sealed in ziplock bags and sent to the laboratory to obtain the scientific measures of sweetness, tartness, and firmness. Participants were requested to respond to a questionnaire about how much they liked and how intense they rated the eating qualities of each apple sample including aroma, overall taste, crispness, firmness, juiciness, flavor, sweetness, and tartness. Next, they submitted the second round of bids (BID2) for each of the two samples based on the eating quality information. Similar to the first round, the highest and the second highest bids for both samples were posted in the board in front of the room.

In the third round, participants were informed that the apples they had tasted corresponded to the same apples they visually inspected in the first round. They were asked to submit the third round of bids for both samples taking into consideration the overall information provided, that is, external appearance and eating quality. Then, the highest and second highest bids for the third round were posted. After the three rounds of auctions, one binding round and one binding sample were randomly chosen, so one individual would win the auction. Finally, the participants completed a questionnaire with questions about their demographic information and consumption habits.
Method

To determine whether revelation of the previous winning bid affects the following bids, we follow three steps. In the first step, we investigate the changes of the variances across rounds. If no differences in bid variances across rounds are detected, then the posted bids do not cause bias in the following bids (see the discussion in the results session). We use Levene’s test (Levene 1960) and Brown-Forsythe’s test (Brown & Forsythe 1974) to detect differences in variances of bids across rounds. Both tests can accommodate a non-normal distribution of the underlying population. Levene’s test performs better when the underlying population is symmetric but with moderately fat tails, while the Brown-Forsythe test performs better when the underlying population follows a heavily skewed distribution.

For these tests, suppose \( t \) is the number of groups whose variances we want to compare; \( y_{ij} \) is the sample observation \( j \) from group \( i \); \( n_i \) is the number of observations from group \( i \); \( N \) is the sum of \( n_i \) which is the total number of combined observations; \( \bar{y}_i \) is the sample mean of group \( i \); \( D_{ij} = |y_{ij} - \bar{y}_i| \) is the absolute deviation of observation \( j \) from the group \( i \) mean; \( \bar{D}_i \) is the average of the \( n_i \) absolute deviations from group \( i \); and \( \bar{D} \) is the average of all \( N \) absolute deviations. The Levene’s statistic is calculated as:

\[
F_{\text{Levene}} = \frac{\sum_{i=1}^{t} n_i (\bar{D}_i - \bar{D})^2 / (t-1)}{\sum_{i=1}^{t} \sum_{j=1}^{n_i} (D_{ij} - \bar{D})^2 / (N-t)}
\]  

(1)

Levene’s test statistic follows an F-distribution, with numerator degrees of freedom \( df_1 = t - 1 \), and the denominator degrees of freedom \( df_2 = N - t \), under the null hypothesis of equal variances. In our analysis, we conduct pairwise comparisons of the three rounds of bids, which means \( t=2 \), \( n_i = 768 \) (384 participants who offer bids for two samples in each round) for \( i = 1, 2, 3 \), and \( N = 2304 \) (total number of bids, \( 768 \times 3 \)).
The Brown-Forsythe’s test is similar except that it is based on the median and not the mean. The test statistic is identical, except that \( D_{ij} = |y_{ij} - \bar{y}_i| \) here stands for the absolute deviation of observation \( j \) from the group \( i \) median, and with corresponding changes in the meanings of \( \bar{D}_i \) and \( \bar{D} \). The Brown-Forsythe test statistic is also distributed with the same F distribution under the null hypothesis of equal variances. Hence for a specified significance level \( \alpha \), both tests have the same decision rule: rejecting the hypothesis of equal variance if \( F \geq F_{\alpha, df_1, df_2} \).

The second step is to look for the informational value of the posted bids. We hypothesize that if the posted bids provide market information to the participants, the posted bids will provide explanatory power in the subsequent bid equation. Typically, a Tobit model is used to analyze auction data, due to a high proportion of zero bids which censor the distribution of the dependent variable. However, we did not observe this phenomenon in our data, as the number of zero bids was less than 2% of the observations in the various rounds. Hence, an Ordinary Least Square (OLS) regression was used to fit the second round bid (BID2) and the third round bid (BID3). Two regressions were used for each bid round, one considering the previously posted bid, and the other without it. For BID2 we have:

\[
BID2^1 = X_2'\alpha^1 + \epsilon
\]

\[
BID2^2 = \alpha^2_{\text{Posted}}BID1 + X_2'\alpha^2 + \epsilon
\]

In both equations (2) and (3), \( X_2' \) includes a vector of the scientific instrumental measures of the attribute levels, a dummy variable for crispness, an intercept, and location dummy variables for St.Paul and Portland.

Similarly, two regressions were used for BID3:
\[ BID3^1 = X'_3 \beta^1 + \epsilon \]  \hfill (4)  
\[ BID3^2 = \beta^2_{\text{Posted}} \cdot BID2 + X'_2 \beta^2 + \epsilon \]  \hfill (5)

In the third or last round of bidding, the participants were told that the apple samples they tasted in the second round were the same as the ones they observed in the first round. Hence their bids should be based on the overall valuation of the attributes that are of interest. Therefore, \( X'_3 \) contains all the variables in \( X'_2 \), plus two dummy variables for the size and defects coverage attributes observed in round 1.

If the \( Post\_BID \) coefficients are significantly different than zero, and the F-tests comparing the full models (models 3 and 5) against the reduced model (models 2 and 4) conclude that the full model is preferred, then we can conclude that the posted bids provide market price information to the participants.

The last step is to compare the variances of the errors from the regression models for each round of bids. As part our experimental design, participants were given an increasing amount of information from the first round to the final round, including the revelation of the winning bid after each round. We expect that the increase of information, in addition to gaining experience after one or two rounds, can make the participants more “rational” – their bids could be better predicted by our control variables. In another words, the variances of the unexplained errors from models for BID1, BID2, and BID3 should be decreasing.

The models for BID2 and BID3 are equations (3) and (5) above. For BID1 we have:
\[ BID1 = X'_1 \gamma + \epsilon \]  \hfill (6)

\( X'_1 \) includes a constant, dummy variables for size, defects coverage, and location of consumers in St.Paul and Portland. There is only one model for BID1 because there was no posted bid for the participants to observe in the first round. After estimating
equations 3, 5, and 6, we compare the variances of the error terms from the models using Bartlett’s test (Bartlett 1937), the most powerful for detecting differences among variances when the underlying populations are normally distributed.

Suppose $t$ is the number of groups whose variances are to be compared; $s_i^2$ is the variance of group $i$; $n_i$ is the number of observations of group $i$; $N$ is the sum of $n_i$ which is the total number of the combined observations; and the pooled variance is defined as $s_p^2 = \sum_{i=1}^{t} (n_i - 1)s_i^2 / (N - t)$. The Bartlett’s test statistic is:

$$
\chi^2_{t-1} = \frac{(N - t)lns_p^2 - \sum_{i=1}^{t}(n_i - 1)s_i^2}{1 + \left(\frac{1}{3(t-1)}\right)((\sum_{i=1}^{t} 1/(n_i - 1)) - 1/(N - t))}
$$

Bartlett’s test statistic follows a $\chi^2$-distribution, with $t-1$ degrees of freedom if the null hypothesis of no difference in variance across groups holds. In our analysis, we conduct pairwise comparison for the errors of the models, which means $t=2$, $n_i = 768$ for $i = 1, 2, 3$, and $N = 2304$.

**Results and discussion**

The attributes of interest in this study and the wording to describe them were based on the recommendations of breeder scientists, industry representatives, and sensory scientists. These attributes are considered to be important factors when apple consumers make purchasing decisions (Miller 2005). Table 4.1 contains a list of the attributes and their categories or range of values. Size, coverage of defects, and crispness are categorical variables. We use 1 to indicate large sizes (larger than 2.9 inches diameter), more coverage of defects (more than 3% per lot), or being crisp; and 0 otherwise. The values for the attributes of firmness, sweetness, and tartness were based on scientific instrumental measures. That is, sweetness is measured as soluble solids concentration in oBrix, with higher values corresponding to sweeter apples; firmness is measured as
the resistance the fruit flesh offers to a penetrometer in lbf; and tartness is measured as
the concentration of malic acid measured in g/ml.

Table 4.2 presents the mean bids across rounds and across locations. Panel A shows
that there is an increasing trend in the mean bid across rounds, with the differences
being statistically different in Pullman and St. Paul, and in the overall data. Panel B
shows that in each round as well as in total, the mean bid in St. Paul is higher than those
in Portland and Pullman. Pullman has the lowest mean bid. The F-tests also show that
the differences across locations in the mean bids are statistically significant.

The significant increase in bids across rounds could be the result of several factors.
First, revelation of the winning or high bid in the previous round makes some
participants who want to win the auction offer a higher bid in the subsequent round.
This will be reflected in changed variances across the rounds. Second, the previous
winning bid might serve as an anchor, meaning that the participants bid toward the
previous winning bid in the following round. In this case, we would observe a
decreasing variance of bids across rounds. If either of these two factors occurs, then
revelation of the previous winning bid causes bias in the following bids. A third possible
explanation for increasing bids across rounds is that the revelation of the previous
winning bid causes a learning effect (Corrigan, et al. 2012). Even though the
participants had been told that their best strategy was to bid on their true valuations of
the apples, the everyday experience that “we will be more satisfied if we pay less than
we are willing to” leads participants to bid lower than their true valuations. However,
after observing a previous winning bid that was higher than their bids but lower than
their true valuation, they might learn that the best strategy is to increase their bids. The
final explanation for increasing in bids is the additional information available in later
rounds. In the first round, participants only observed the size and coverage of defects.
of the apples; in the second round, the participants were allowed to taste the apples and the highest price in the prior round was revealed; and in the third round, the participants were told that the apples they tasted were the ones that they had viewed plus the winning bid in the second round was revealed. The revelation of the previous winning bid provides useful market information to the participants, thereby improve their bidding accuracy, but should not change the variances of the bids across rounds.

The Levene’s and Brown-Forsythe’s tests (results in Table 4.3) show that none of the differences between pairs of bid variances are statistically different from 0. Moreover, the box-and-whisker plots of the distribution of bids shown in Figure 4.1 suggests that bids of the three rounds have similar spreads. We conclude that there are no differences in variances of bids between rounds. Therefore, the revelation of the previous winning bid in our type of experimental design does not appear to cause abnormal bidding behavior, and hence does not bias the bids of following rounds.

To address whether the posted bids provide market information to the participants when they make their bidding decisions in the following rounds, we fit the two models for BID2 and BID3 (Equations 2 – 5), one with the posted bid (full model) and one without it (reduced model). Table 4.4 summarizes the estimation results of the full and reduced models for BID2 and BID3. We have two observations from the results regarding the effect of the revelation of posted bids. The first is that the coefficients for Post_BID1 and Post_BID2 are positive and significant, providing evidence for the information and potential learning effects. The second is that the full models have higher adjusted-$R^2$ values than the reduced models, and the F statistics comparing the two pairs of full models against reduced models show that the full models provide a statistically better fit than the reduced models. In short, the OLS estimations provide evidence that the revelation of previous winning bids offers the bidders market
information, which can help increase bidding accuracy.

A potential problem associated with adding the previous winning bid in the regression of the following bid is endogeneity. We use the Hausman specification test (Hausman 1978) to test for this problem. To find good instruments for Post_BID1 and Post_BID2, we separate the data by location. Since the experimental procedure and treatments (combination of apple attributes) were the same across locations, the bids in the first two locations during the same round can be used as an instrument for the third location. That is, Post_BID1 in session 1 of St.Paul and Portland are potential instruments for Post_BID1 in session 1 of Pullman and are used in the test for endogeneity. As shown in Table 4.5, endogeneity was not detected in the estimations conducted.

An additional question of interest is which bid (BID1, BID2, or BID3) provides the most accurate estimates for apple quality attributes. To evaluate how well each round’s bids are fitted by their models we compare the variances of the component of the bids not explained by their regression models (i.e., the errors in prediction). The smaller the variance, the more accurate the model is for that round of bids. To account for the increasing bid means across rounds, we use the standardized errors which are the errors from the regression divided by the mean of the corresponding round. The variances of the standardized errors from equations 3, 5 and 6 are tested using Bartlett’s test, and the results are summarized in Table 4.6. From panel A of Table 4.6 we can see that the standard deviations of the standardized errors are indeed decreasing from the model of BID1 to the model of BID3. Bartlett’s tests for the three pairs of comparison are all significant at the 1% level, confirming that the model for BID3 is the most accurate in explaining the data. The Box-and-Whisker plots in Figure 4.2 visually confirm the above conclusion. Therefore, the model for BID3 should be used to elicit consumers’
WTP for the apple attributes and will be used here to discuss the results.

The fifth and the seventh columns of Table 4.4 give the estimates of the coefficients for the models for BID3 (Equations 4 and 5). We use equation 4 instead of equation 5 to analyze participants’ WTP for the attributes to avoid the multicollinearity between \textit{Post\_BID2} and the attribute variables. As discussed above, the revelation of posted prices provides market information to the participants. Upon seeing a higher \textit{Post\_BID1}, the participants are more likely to bid higher in the second session. That is, \textit{Post\_BID2} will be higher. Therefore, \textit{Post\_BID2} will be correlated with the first round attributes: size and defects. This conjecture is confirmed by the estimation results for BID3. In the model without \textit{Post\_BID2}, the coefficients of size and defects are significant. However, after adding \textit{Post\_BID2}, they still have the right sign but become insignificant. Therefore, to analyze the WTP for the attributes, we use the model for BID3 without \textit{Post\_BID2}.

Upon examination of the results in the fifth column of Table 4.4, we can find that all the attributes examined, except tartness, significantly affect consumers’ willingness to pay for apples. Moreover, all the significant coefficients have the expected signs. Size, crispness, firmness, and sweetness are significantly positive and defects is significantly negative, meaning that bigger, crisper, firmer, and sweeter apples without defects are preferred. Specifically, with other factors held constant, consumers are willing to pay $0.13/lb more for the large size apples compared to the small ones; $0.23/lb more for crisper apples than not crisp ones; $0.03/lb more for apples with firm flesh than the ones with creamy flesh; $0.07/lb for apples of more sweetness and $0.15/lb less for apples with more coverage of defects. The coefficients of the dummy variables for St.Paul and Portland are significantly positive. This is consistent with the results in panel B of Table 4.2, where St.Paul and Portland have higher mean bids and
the mean bids across locations are statistically different.

To further investigate how well the model for BID3 does in revealing consumers’ valuations on the attributes, we fit two other regressions for BID3 with the rating of the liking (a Likert scale was used with 1=dislike extremely and 9=like extremely) and intensity (a Likert scale was used with 1=lowest intensity and 9=highest intensity) the participants assigned to the taste attributes (sweetness, firmness, and tartness). The three sets of parameter estimates show us the consistency of the results among the models of BID3. Table 4.7 shows that the three regressions have very similar results. The coefficients of the three dummy variables, size, defects, and crispness, are all have the same sign and of similar magnitude across models. In the regressions with the degree of liking and intensity for the taste attributes, the coefficients of firmness and sweetness are positive and significant, indicating consumers are willing to pay more for an apple if they like the degree of firmness and sweetness of the apple, and when they feel the apple is firmer and sweeter. Specifically, the consumers are willing to pay $0.05/lb ($0.07/lb) more for a pound of apples if they like the firmness of the apples (feel the apples are firmer) compared to the ones where they don’t like the degree of firmness (feel the apples are more creamy). Also, they are willing to pay $0.04/lb (0.05/lb) more for a pound of apples if they like the sweetness of the apples (feel the apples are sweeter) compared to the ones where they don’t like the degree of sweetness (feel the apples are less sweet). These results are similar to those when the scientific instrumental measures are used for the taste attributes discussed above. Tartness is only significant (and positive) in the model where the taste attributes are measured with the degree of liking as the explanatory variable. It is expected to be significantly positive because a rational consumer will pay a higher price for apples with the attributes they like. When they like the degree of tartness of an apple, it means that degree of tartness
is close to their ideal level. Tartness is not significant in the models where taste is measured by consumers’ feel of intensity and the scientific instrumental measures, and this suggests that consumers might have heterogeneous preferences on tartness. Some consumers are willing to pay a higher price for the apples that they feel have a tart taste (have a higher number in the scientific instrumental measure for tartness), while some other consumers will pay a lower price for such apples, leading to an insignificant coefficient of tartness. The consistency of the parameter estimates across models suggests that BID3 can accurately reveal consumers valuations on the attributes.

Conclusion
The effect of the revelation of posted winning bids in the second-price experimental auctions for apple quality attributes is studied using an experimental design where information is added progressively across rounds. We find that the revelation of posted bids does not bias the bidding process in the following round. This might be due to consumers’ general familiarity with apples and apple market prices. Also, we find that having increased information about the apple increases the accuracy of the participants’ bids. Therefore, the final round bids were used to analyze consumers’ WTP for the apple attributes.

Size, defects coverage, crispness, firmness, sweetness, and tartness are the attributes of interest. Three regression models for BID3 are fitted which differ in the measures used for the taste attributes (firmness, sweetness, and tartness), while dummy variables are used for size, defects coverage, and crispness. Consumers’ degree of liking of taste attributes, their feeling of the intensity of the taste attributes, and the scientific measure of the taste attributes are used for the three regressions. All three models give significantly positive estimates for size, crispness, firmness and sweetness, and significantly negative estimates for defects. This suggests that BID3 gives accurate
consumers’ valuations on the attributes. The estimates from the regression using scientific measures for the taste attributes show that consumers are willing to pay $0.13 more for big apples relative to small ones; $0.23 more for crisp apples relative to not crisp ones; $0.03 more for apples with firm flesh compared to the ones with creamy flesh; $0.07 for apples of more sweetness; and $0.15 less for apples with more defects coverage. Tartness is only significant in the model where consumers’ degree of liking is used for the taste attributes. The coefficient is positive, meaning the more the consumers like the tartness of an apple, the more they will pay for the apple. The insignificance of tartness in the other two models indicates that consumers have heterogeneous preferences on tartness: consumers who prefer tart (less tart) apples will pay more (less) for an apple when they feel a strong intensity of tartness of the apple, or if the scientific instrumental measure shows a higher level of tartness of the apple.

The proof of the results suffers from several insufficiencies. First, we argued that the homogeneity of bids across rounds showed unbiasedness of the following rounds bids. However, it is not sufficient to reach such a conclusion based only on the bid variances. There might be some causes of bias following bids which will not lead to changes in the bids variances. Second, we argued that the revelation of previous bids added information when the participants gave following bids such that the later round bids were more accurate. However, the positive coefficients before the posted bids were not sufficient to conclude that they had informational value and made the following bids more accurate. Corrigan et al. (2012) also showed that the later round bids were more accurate, but they argued that the improvement was not the result of price revelation. To overcome these issues, in the next step we could design an experiment where some participants are revealed the posted winning bids and the others are not shown the posted winning bids. By comparing bids between the two groups, we could
provide more insight on the problem.
References


Table 4.1 Apple attributes and the attribute categories or values tested for this study

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>Large</td>
</tr>
<tr>
<td></td>
<td>Small</td>
</tr>
<tr>
<td>Coverage of defects</td>
<td>More</td>
</tr>
<tr>
<td></td>
<td>Less</td>
</tr>
<tr>
<td>Crispness</td>
<td>Crisp</td>
</tr>
<tr>
<td></td>
<td>Not crisp</td>
</tr>
<tr>
<td>Firmness</td>
<td>[8.3, 24.5]</td>
</tr>
<tr>
<td>Sweetness</td>
<td>[9.4, 16.8]</td>
</tr>
<tr>
<td>Tartness</td>
<td>[1.8, 6.3]</td>
</tr>
</tbody>
</table>
Table 4.2 Comparison of the average bids (dollars/pound)\(^a\)

Panel A: Comparison across rounds

<table>
<thead>
<tr>
<th>Location</th>
<th>Mean</th>
<th>F-test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Round 1</td>
<td>Round 2</td>
</tr>
<tr>
<td>Pullman</td>
<td>1.0313</td>
<td>1.1091</td>
</tr>
<tr>
<td>St. Paul</td>
<td>2.0366</td>
<td>2.2201</td>
</tr>
<tr>
<td>Portland</td>
<td>1.2705</td>
<td>1.2663</td>
</tr>
<tr>
<td>Total</td>
<td>1.4461</td>
<td>1.5318</td>
</tr>
</tbody>
</table>

Panel B: Comparison across locations

<table>
<thead>
<tr>
<th>Round</th>
<th>Mean</th>
<th>F-test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pullman</td>
<td>St. Paul</td>
</tr>
<tr>
<td>Round 1</td>
<td>1.0313</td>
<td>2.0366</td>
</tr>
<tr>
<td>Round 2</td>
<td>1.1091</td>
<td>2.2201</td>
</tr>
<tr>
<td>Round 3</td>
<td>1.2117</td>
<td>2.3249</td>
</tr>
<tr>
<td>Total</td>
<td>1.1174</td>
<td>2.1938</td>
</tr>
</tbody>
</table>

\(^a\) There are 256 observations in each round per location;  
\(^b\) Statistically significant at 5% level;  
\(^c\) Statistically significant at 1% level.
Table 4.3 Homogeneity tests for bids of different rounds$^a$

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>Leven’s Test</th>
<th></th>
<th>Brown-Forsythe’s Test</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F-value</td>
<td>P-value</td>
<td>F-value</td>
<td>P-value</td>
</tr>
<tr>
<td>Var(BID1) = Var(BID2)</td>
<td>0.20</td>
<td>0.6540</td>
<td>2.18</td>
<td>0.1397</td>
</tr>
<tr>
<td>Var(BID1) = Var(BID3)</td>
<td>0</td>
<td>0.9528</td>
<td>1.29</td>
<td>0.2560</td>
</tr>
<tr>
<td>Var(BID2) = Var(BID3)</td>
<td>0.20</td>
<td>0.6531</td>
<td>0.16</td>
<td>0.6852</td>
</tr>
</tbody>
</table>

$^a$ Number of observations: 1536.
<table>
<thead>
<tr>
<th></th>
<th>BID2 without Post_BID1</th>
<th>BID2 with Post_BID1</th>
<th>BID3 without Post_BID2</th>
<th>BID3 with Post_BID2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Std Err</td>
<td>Estimate</td>
<td>Std Err</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.6051</td>
<td>0.4084</td>
<td>-0.90265**</td>
<td>0.2335***d</td>
</tr>
<tr>
<td>Post_BID1 mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post_BID2 mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>size</td>
<td>0.1267**b</td>
<td>0.0640</td>
<td>0.03101**</td>
<td>0.03194**</td>
</tr>
<tr>
<td>defects</td>
<td>-0.1537***c</td>
<td>0.0632</td>
<td>0.01577</td>
<td>0.03419**</td>
</tr>
<tr>
<td>firmness</td>
<td>0.03447**</td>
<td>0.01615</td>
<td>0.03501**</td>
<td>0.01532</td>
</tr>
<tr>
<td>sweetness</td>
<td>0.05302</td>
<td>0.03748</td>
<td>0.03802</td>
<td>0.03560</td>
</tr>
<tr>
<td>tartness</td>
<td>0.13008*</td>
<td>0.07650</td>
<td>0.09039</td>
<td>0.07271</td>
</tr>
<tr>
<td>crispness</td>
<td>0.24625**</td>
<td>0.07580</td>
<td>0.26339***</td>
<td>0.07194</td>
</tr>
<tr>
<td>St.Paul</td>
<td>1.15355**</td>
<td>0.08092</td>
<td>0.70820***</td>
<td>0.09066</td>
</tr>
<tr>
<td>Portland</td>
<td>0.27140**</td>
<td>0.08420</td>
<td>0.17558**</td>
<td>0.08056</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Adj-R^2</th>
<th>F-statistic</th>
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<td></td>
<td>(Column 1)</td>
<td>(Column 2)</td>
<td>(Column 3)</td>
<td>(Column 4)</td>
</tr>
<tr>
<td></td>
<td>0.2533</td>
<td>0.3278</td>
<td>0.2692</td>
<td>0.3744</td>
</tr>
<tr>
<td></td>
<td>(Column 5)</td>
<td>(Column 6)</td>
<td>(Column 7)</td>
<td>(Column 8)</td>
</tr>
</tbody>
</table>

---

a Number of observations: 768 for each regression.

b significant at 10% level;

c significant at 5% level;

d significant at 1% level.
Table 4.5 Hausman tests for endogeneity of posted bids

A. Hausman tests for endogeneity of Post_BID1 in the regression of BID2

<table>
<thead>
<tr>
<th>Location</th>
<th>Degree of freedom</th>
<th>Test statistic</th>
<th>Pr&gt;ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pullman</td>
<td>8</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>St.Paul</td>
<td>8</td>
<td>1.27</td>
<td>0.9959</td>
</tr>
<tr>
<td>Portland</td>
<td>8</td>
<td>3.77</td>
<td>0.8776</td>
</tr>
</tbody>
</table>

B. Hausman tests for endogeneity of Post_BID2 in the regression of BID3

<table>
<thead>
<tr>
<th>Location</th>
<th>Degree of freedom</th>
<th>Test statistic</th>
<th>Pr&gt;ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pullman</td>
<td>10</td>
<td>5.41</td>
<td>0.8624</td>
</tr>
<tr>
<td>St.Paul</td>
<td>10</td>
<td>0.63</td>
<td>1</td>
</tr>
<tr>
<td>Portland</td>
<td>10</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 4.6 Comparing variances of the standardized error terms for models of bids of different rounds

A. Standard deviation of the standardized errors

<table>
<thead>
<tr>
<th>Standard deviation</th>
<th>Error\textsubscript{BID1}</th>
<th>Error\textsubscript{BID2}</th>
<th>Error\textsubscript{BID3}</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.6268</td>
<td>0.5541</td>
<td>0.4880</td>
</tr>
</tbody>
</table>

B. Bartlett’s tests comparing the variances

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>Chi-Square</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var(\text{Error\textsubscript{BID1}})&gt;Var(\text{Error\textsubscript{BID2}})</td>
<td>11.6074</td>
<td>0.0004</td>
</tr>
<tr>
<td>Var(\text{Error\textsubscript{BID1}})&gt;Var(\text{Error\textsubscript{BID3}})</td>
<td>47.5518</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Var(\text{Error\textsubscript{BID2}})&gt;Var(\text{Error\textsubscript{BID3}})</td>
<td>12.3587</td>
<td>0.0002</td>
</tr>
</tbody>
</table>
Table 4.7 Comparison of regressions of BID3 (eating attributes are measured with participants’ degree of liking, feeling of intensity, and the scientific instruments respectively)\(^a\)

<table>
<thead>
<tr>
<th>Attribute</th>
<th>With Liking</th>
<th>Estimate</th>
<th>Std Err</th>
<th>With Intensity</th>
<th>Estimate</th>
<th>Std Err</th>
<th>With Scientific Measure</th>
<th>Estimate</th>
<th>Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.2704*</td>
<td>0.1533</td>
<td>0.3545***</td>
<td>0.1469</td>
<td>-0.4250</td>
<td>0.1267</td>
<td>-0.4250</td>
<td>0.4012</td>
</tr>
<tr>
<td>size</td>
<td></td>
<td>0.1585**</td>
<td>0.0624</td>
<td>0.1519**</td>
<td>0.0623</td>
<td>0.1267</td>
<td>0.0640</td>
<td>0.1267</td>
<td>0.0640</td>
</tr>
<tr>
<td>defects</td>
<td></td>
<td>-0.1388**</td>
<td>0.0619</td>
<td>-0.1449**</td>
<td>0.0620</td>
<td>-0.1537</td>
<td>0.0632</td>
<td>-0.1537</td>
<td>0.0632</td>
</tr>
<tr>
<td>firmness</td>
<td></td>
<td>0.0465**</td>
<td>0.0200</td>
<td>0.0684****</td>
<td>0.0195</td>
<td>0.03101</td>
<td>0.01577</td>
<td>0.03101</td>
<td>0.01577</td>
</tr>
<tr>
<td>sweetness</td>
<td></td>
<td>0.0433*</td>
<td>0.0221</td>
<td>0.0526***</td>
<td>0.0197</td>
<td>0.06680*</td>
<td>0.03636</td>
<td>0.06680</td>
<td>0.03636</td>
</tr>
<tr>
<td>tartness</td>
<td></td>
<td>0.0460**</td>
<td>0.0221</td>
<td>0.0125</td>
<td>0.0174</td>
<td>0.07474</td>
<td>0.07526</td>
<td>0.07474</td>
<td>0.07526</td>
</tr>
<tr>
<td>crispness</td>
<td></td>
<td>0.1820***</td>
<td>0.0626</td>
<td>0.1609**</td>
<td>0.0630</td>
<td>0.23139*</td>
<td>0.07372</td>
<td>0.23139</td>
<td>0.07372</td>
</tr>
<tr>
<td>St.Paul</td>
<td></td>
<td>1.1526***</td>
<td>0.0760</td>
<td>1.1269***</td>
<td>0.0759</td>
<td>1.15546***</td>
<td>0.07822</td>
<td>1.15546</td>
<td>0.07822</td>
</tr>
<tr>
<td>Portland</td>
<td></td>
<td>0.2136***</td>
<td>0.0770</td>
<td>0.2176***</td>
<td>0.0769</td>
<td>0.24669***</td>
<td>0.08137</td>
<td>0.24669</td>
<td>0.08137</td>
</tr>
<tr>
<td>Adj-R(^2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2902</td>
<td>0.2865</td>
<td>0.2735</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) Number of observations: 768 for each regression.

\(^b\) significant at 10% level;

\(^c\) significant at 5% level;

\(^d\) significant at 1% level.
Figure 4.1 Box-and-Whisker Plot for comparing the variances of bids across rounds
A. Comparing variance of BID1 and BID2

B. Comparing variance of BID1 and BID3

C. Comparing variance of BID2 and BID3
Figure 4.2 Box-and-Whisker Plot for comparing variances of standardized error terms for models of bids of different rounds

A. Comparing variances of the standardized errors from models of BID1 and BID2

B. Comparing variances of the standardized errors from models of BID1 and BID3

C. Comparing variances of the standardized errors from models of BID2 and BID3