THE UNIVERSITY of ADELAIDE

The Role of Information Asymmetry and the Level of Market Trading Activity in Shaping the Time-to-Maturity Pattern of Futures Return Volatility

by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SYNOPSIS

I consider two explanations for the mixed empirical results on the Samuelson effect, which postulates that futures return volatility increases closer to maturity when the futures price becomes more sensitive to information flows. First, I empirically investigate Hong's (2000) theoretical suggestion that information asymmetry has an impact on the time-to-maturity pattern of commodity futures return volatility (the "volatility pattern") by testing the relationships information asymmetry has with the time-to-maturity and return volatility of commodity futures. I find that information asymmetry rises as commodity futures near maturity and that this increases return volatility. Thus, this "speculative effect" amplifies return volatility and can potentially be a more significant driver of the volatility pattern than Samuelson's (1965) price elasticity effect.

Second, I directly examine the time-to-maturity pattern of the sensitivity of futures return volatility to information flows (the "sensitivity pattern") and find that it has an inverted U-shape. I point out that the results for tests of a linear volatility pattern are more significant when the inverted U-shape of the sensitivity pattern tilts more towards maturity. As an example of the practical implication of my findings, I show that a futures price series constructed based on contracts that are closest to the peak of the sensitivity pattern captures higher volatility (9.98% in-sample and 2.63% out-of-sample) than the often used closest-to-maturity series.

DECLARATION

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Phan Hoang Long

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CHAPTER 1

INTRODUCTION

1. INTRODUCTION

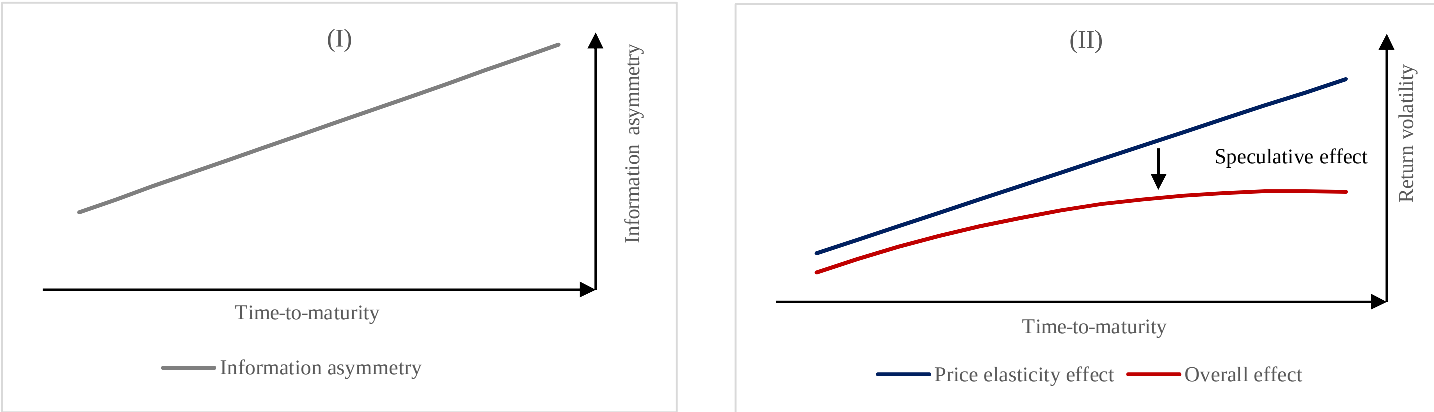
One of the well-known issues in the literature that examines futures markets is the relationship between the return volatility and the time-to-maturity of a futures contract. Samuelson (1965) is the first to propose that futures return volatility should increase closer to maturity (the Samuelson effect). The logic behind this is that the closer a futures contract is to maturity, the more sensitive the price is to information regarding its fundamental value. Evidence for the Samuelson effect is, however, mixed across commodities and over time. For example, Rutledge (1976) finds the Samuelson effect is present for silver and cocoa futures, but not for wheat and soybean oil. Milonas (1986) shows the presence of the Samuelson effect in several commodities futures, but not corn. Bessembinder et al. (1996) document the effect for agricultural futures, crude oil and, to a certain extent, metals. Duong and Kalev (2008) find similar results for agricultural futures but not for crude oil and gold.

Much research has been devoted to investigating the Samuelson effect because the futures return volatility – time-to-maturity relationship has important practical implications. Specifically, this relationship is essential for forming trading strategies, setting margins and pricing options (Board and Sutcliffe, 1990; Chen et al., 1999; Duong and Kalev, 2008). First, the margin required for trading futures is positively related to return volatility, which represents risk. If the Samuelson effect holds, the margin should be raised as the futures contract nears maturity. Second, if return volatility increases closer to maturity, hedgers might want to switch to contracts further from maturity to minimize volatility, since higher volatility entails higher risk premiums (a higher margin is one example). On the other hand, speculators would prefer contracts closer to maturity because higher return volatility can allow them to earn higher short-term profits. Finally, options are priced based on the volatility of the underlying asset. Whether the relationship between return volatility and time-to-maturity is negative or positive should lead to a rise or fall in the price of options on the futures contract as maturity approaches.

The contribution I make in this thesis to the extant literature is that I consider two possible explanations for the previously mixed results on the Samuelson effect (See, among others, Rutledge, 1976; Anderson, 1985; Milonas, 1986; Khoury and Yourougou, 1993; Bessembinder et al., 1996; Galloway and Kolb, 1996; Allen and Cruickshank, 2000; and Duong and Kalev, 2008). First, return volatility arises from the trading activities of investors, whose motivation to trade will be based on the information set they have at hand. This information set is neither likely to be homogenous across all investors nor fixed over the life of the futures contract. However, prior models that attempt to explain the relationship between return volatility and time-to-maturity generally assume investors are symmetrically informed (Samuelson, 1965; Anderson and Danthine, 1983; Bessembinder et al., 1996). The exception is Hong (2000), whose model posits that information asymmetry between investors will be related to time-to-maturity and that this will have a bearing on return volatility. Hong's (2000) model conjectures that the time-to-maturity pattern of futures return volatility is not only shaped by the Samuelson effect (the author coins this the "price elasticity effect"), but also by another effect arising from the presence of information asymmetry in the market (the author coins this the "speculative effect"). This speculative effect results from two important predictions by the model. First, information asymmetry increases closer to maturity. Second, information asymmetry reduces return volatility. Consequently, the speculative effect is expected to have a negative impact on return volatility as the futures contract expires, countering the price elasticity effect (See Figure 1.1 for an illustration)[1]. Hong (2000) suggests that the interaction of the two opposite effects provide a possible explanation for the mixed empirical evidence on the Samuelson effect in previous research. I empirically test Hong's (2000) predictions by examining the impact information asymmetry has on the time-to-maturity pattern of futures return volatility.

[1] A detailed review of the model is provided in Chapter 2 of this thesis.

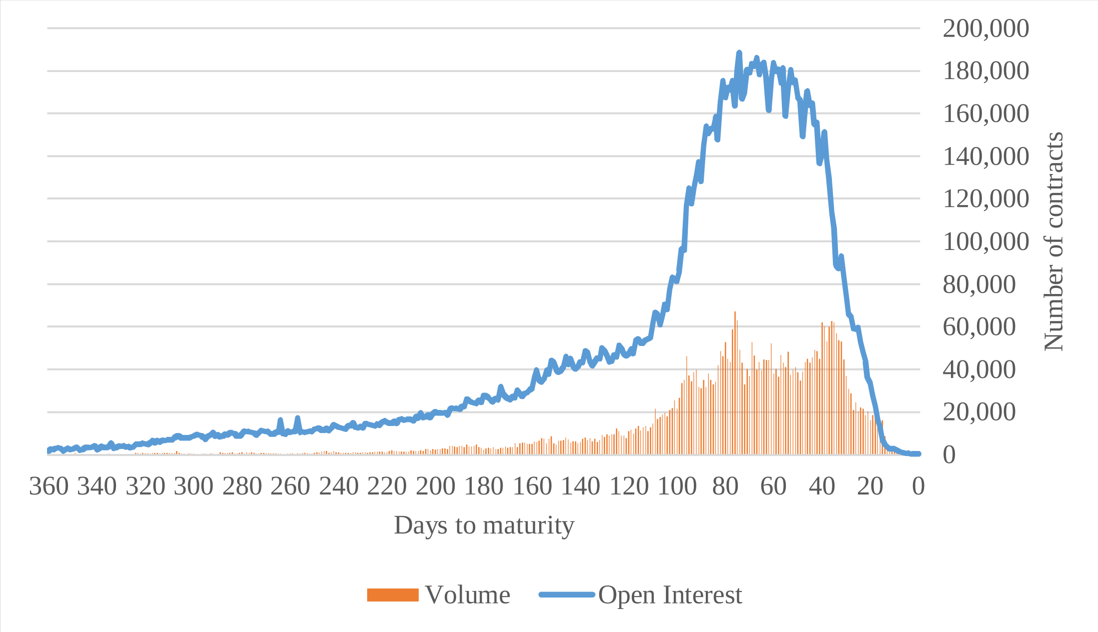
Figure 1.1: Hong's proposal of the time-to-maturity pattern of information asymmetry, the speculative effect (Samuelson effect), the price elasticity effect, and the overall effect.



This figure illustrates Hong's (2000) predictions of (I): the time-to-maturity pattern of information asymmetry, and (II): the time-to-maturity pattern of return volatility (the overall effect), shaped by the price elasticity effect (Samuelson effect) and the speculative effect. Hong (2000) suggests that information asymmetry increases as maturity nears. As he anticipates a negative impact of information asymmetry on return volatility, he predicts that the speculative effect has a negative impact on the upward pattern of return volatility, thereby weakening the price elasticity effect.

Second, prior studies focus on the time-to-maturity pattern of futures return volatility (hereafter the "volatility pattern") rather than the pattern of the sensitivity of futures return volatility to information flows (hereafter the "sensitivity pattern"). However, the Samuelson effect has the underlying assumption that the sensitivity pattern monotonically rises as the contract nears maturity, leading to a similar volatility pattern. This may not be true. In fact, it is more likely that the sensitivity pattern will vary, and be dependent upon, the time-to-maturity pattern of the level of market activity for the contract (see Kyle, 1983; Admati and Pfleiderer, 1988; Bessembinder and Seguin, 1993). In addition, as Anderson and Danthine (1983) highlight, information is not likely to flow uniformly into the market during the life of the futures contract, further leading to changes in the volatility pattern. I hypothesize that the sensitivity pattern will be a quadratic function of time-to-maturity since the market activity of commodity futures contracts generally follows an inverted U-shape pattern (Commodity Exchange Authority, 1960; Powers, 1967; Working, 1970; Leuthold, 1983). As an illustration, Figure 1.2 shows the average trading volume and open interest over the life of September wheat futures contracts traded between 2003 and 2016. Both the levels of trading volume and open interest display an inverted U-shape pattern. I empirically test the sensitivity pattern and also investigate how it affects the result of the test for the linear volatility pattern. Specifically, I conjecture that we are more likely to find stronger (weaker) evidence that volatility increases closer to the maturity date if the inverted U-shape of the sensitivity pattern tilts more (less) towards maturity.

Figure 1.2: Average trading volume and open interest over the contract life for September wheat futures contracts traded during the period 2003-2016.



To examine these issues I start, in Chapter 2 of my thesis, to show and interpret the results from empirical tests of Hong's (2000) prediction on the influence of information asymmetry on the Samuelson effect. To do this I use the twelve most liquid commodity futures traded on the Chicago Mercantile Exchange group of exchanges (CME Group hereafter), including the Chicago Mercantile Exchange (CME), the Chicago Board of Trade (CBOT), the Commodity Exchange (COMEX), and the New York Mercantile Exchange (NYMEX). My data covers an 11-year period from 2006 to 2016. Intraday trading ticks and quotes are collected from Thomson Reuters Tick History (TRTH). I use Madhavan, Richardson, and Roomans' (1997) estimate of the information asymmetry component of the bid-ask spread (hereafter MRR) to measure the daily level of asymmetric information[2]. In examining the relationship this measure has with time-to-maturity, I find that for all futures in the sample, information asymmetry significantly rises closer to maturity. This is consistent with Hong's (2000) prediction.

I then proceed to investigate the impact information asymmetry has on return volatility, which I capture through daily realized volatility (Andersen and Bollerslev, 1998). Hong's (2000) prediction of a negative impact is based on the assumption that uninformed hedgers choose to trade less when facing higher information asymmetry. In reality, however, uninformed hedgers may not have the capability or motivation to learn about their informational disadvantage. As a result, we should expect information asymmetry to instead have a positive impact on return volatility (Admati and Pfleiderer, 1988; Shalen, 1993; Daigler and Wiley, 1999). My empirical results support this expectation and show a strong, positive impact of information asymmetry on return volatility across the twelve futures. My calculation of the speculative and price elasticity effects using a mediation analysis (Judd and Kenny, 1981; Sobel, 1982; Baron and Kenny, 1986) shows that for all futures, the speculative effect significantly raises return volatility as maturity nears instead of dampening it as suggested by Hong (2000). I only find evidence for the price elasticity effect in five of the futures. The result indicates that information asymmetry in fact plays an important role in driving the volatility pattern.

In Chapter 3 I turn my attention to investigating my second hypothesis that the sensitivity pattern is a quadratic function of time-to-maturity. This should be the case as I show that the level of market activity (open interest and trading volume) follows an inverted U-shape over the life of the futures contract. To directly test the sensitivity pattern, I utilize

[2] To reliably estimate the daily MRR measure, a sufficient number of trades and quotes are required. This is the reason why I only include the most liquid futures and only consider the period from 2006 onwards, when the data contains an adequate level of daily trades and quotes.

the Thompson Reuters News Analytics (TRNA) database, which provides comprehensive data on daily commodity news coverage. I measure information flows by the number of daily news items about the commodity, extracted from TRNA. I calculate SENSITIVITY, a measure of the sensitivity of futures return volatility to information flows, as the ratio of return volatility to the number of daily news items. The sample for this empirical test include all contracts traded between January 1st, 2003 and June 30th, 2014 for twelve commodity futures on the CME Group. These include agricultural (grains, oilseeds, and livestock), metals and energy futures.

Both my univariate and multivariate tests support the hypothesis that the sensitivity pattern has an inverted U-shape. To analyse the pattern, I calculate the peak-to-maturity (PTM) for each futures contract. That is the number of days between when the peak of the sensitivity pattern being reached and the maturity date of the contract, measured as the percentage of the contract's life. A smaller PTM indicates that SENSITIVITY peaks later in the life of the contract, and vice versa. This implies that a smaller PTM will more likely lead to the test for the negative relationship between return volatility and time-to-maturity having stronger result, if one is searching for a linear volatility pattern. My analysis shows that PTM is relatively smaller for agricultural and energy futures and but relatively higher for metals futures. As expected, the regression results for a linear volatility pattern show a significant and negative relationship between return volatility and time-to-maturity for energy and agricultural futures, but not for metals. As part of my analysis, I also show that the variation in the tilt of the sensitivity pattern across futures could be attributed to the difference in the relationship between trading volume and open interest across futures.

In Chapter 4 of this thesis I discuss the contributions I make to the extant literature, as well as the limitations of this study and directions for potential future research. This study's first set of results, presented in Chapter 2, indicates that the presence of information asymmetry in the futures markets strengthens the Samuelson effect. To the best of my knowledge, this study is the first to empirically test Hong's (2000) theoretical model which claims that time-varying information asymmetry plays a key role in the relationship between futures return volatility and time-to-maturity. I contribute to the futures market literature by showing a significant and positive impact of information asymmetry, through the speculative effect, on the upward slope of futures return volatility as a contract approaches maturity. I find it is more consistent, in terms of its direction and impact, than the price elasticity effect. My findings can potentially explain why there is such inconsistency in the empirical evidence of previous studies (Rutledge, 1976; Anderson, 1985; Milonas, 1986; Khoury and Yourougou, 1993; Bessembinder et al., 1996; Galloway and Kolb, 1996; Allen and Cruickshank, 2000; and Duong and Kalev, 2008) as they do not account for the mediating impact time-varying information asymmetry has on the time-to-maturity pattern of return volatility. This study is also the first to provide empirical evidence that information asymmetry rises as a futures contract nears its maturity, supporting Hong's (2000) first hypothesis. I also contribute to the literature that looks at the relationship between information asymmetry and return volatility (see Admati and Pfleiderer, 1988; Shalen, 1993; and Daigler and Wiley, 1999) by showing that information asymmetry has a positive impact on futures return volatility. My findings support the premise that uninformed investors may not recognize their informational disadvantage in order to react rationally.

The second set of results of this study, presented in Chapter 3, reveals an inverted U-shape sensitivity pattern. It also shows that the result of the test for a linear volatility pattern depends on the tilt of the sensitivity pattern towards the maturity of the futures contract. My analysis contributes to the extant literature in a number of ways. First, to the best of my knowledge, this work is the first to directly examine the sensitivity pattern. The tilt towards maturity of the inverted U-shape pattern provides an additional explanation for the mixed empirical results on the linear volatility pattern (Rutledge, 1976; Anderson, 1985; Milonas, 1986; Khoury and Yourougou, 1993; Bessembinder et al., 1996; Galloway and Kolb, 1996; Allen and Cruickshank, 2000; and Duong and Kalev, 2008). Second, the results further substantiate previous studies that suggest an inverted U-shape pattern of the level of futures market activity (Commodity Exchange Authority, 1960; Powers, 1967; Working, 1970; Leuthold, 1983), which influences the sensitivity of return volatility to information (Kyle, 1983; Admati and Pfleiderer, 1988; Bessembinder and Seguin, 1993). My findings have an important practical implication. An inverted U-shape sensitivity pattern means that futures prices are more sensitive to information near the peak of the pattern. Thus, market participants should use the distance-to-peak as a better predictor of futures return volatility than the commonly used distance-to-maturity. I show that the closest-to-peak futures price series, constructed by rolling contracts that are closest to the peak of the sensitivity pattern, captures higher average annualized volatility by 9.98% in-sample and 2.63% out-of-sample, than the often used closest-to-maturity series. Using the average maintenance margin (which is determined based on the level of volatility in the market) required to trade the futures in my sample as a proxy for the price of volatility, this amounts to $7,169 (in-sample) and $2,935 (out-of-sample) for an open position of 1000 contracts.

This thesis is organized as follows. Chapter 2 discusses my analysis on the mediating role of information asymmetry in the return volatility – time-to-maturity relationship. In Chapter 3, I investigate the quadratic sensitivity pattern and how it influences the result of the test for a linear volatility pattern. In Chapter 4, I discuss my contributions to the literature, as well as the limitations of this study and potential future research. I conclude this thesis in Chapter 5.

CHAPTER 2

THE IMPACT OF INFORMATION ASYMMETRY ON THE VOLATILITY PATTERN

"…but there are also unknown unknowns. There are things we do not know we don't know."

- Donald Rumsfeld, former US Secretary of Defence, 2002

2. THE IMPACT OF INFORMATION ASYMMETRY ON THE VOLATILITY PATTERN

2.1. Introduction

In this chapter, I examine whether the presence of information asymmetry in the futures market influences the time-to-maturity pattern of futures return volatility. Return volatility arises from the trading activities of investors, whose motivation to trade will be based on the information set they have at hand. This information set is neither likely to be homogenous across all investors nor fixed over the life of the futures contract. However, prior models that attempt to explain the relationship between return volatility and time-to-maturity generally assume investors are symmetrically informed (Samuelson, 1965; Anderson and Danthine, 1983; Bessembinder et al., 1996). The only exception is Hong (2000), whose model posits that information asymmetry between investors will be related to time-to-maturity and that this relationship will have a bearing on return volatility. I empirically test Hong's (2000) predictions by examining how information asymmetry changes over the maturity of futures contracts, and how these changes in information asymmetry affect the time-to-maturity pattern of futures return volatility. Consistent with Hong's (2000) predictions, my results confirm the central role played by time-varying information asymmetry (i.e., the speculative effect). However, I find that the speculative effect has a positive impact on the upward time-to-maturity pattern of futures return volatility instead of a negative one suggested by Hong (2000).

Hong's (2000) model conjectures that the time-to-maturity pattern of futures return volatility is not only shaped by the Samuelson effect (i.e., the price elasticity effect), but also by another effect arising from the presence of information asymmetry in the market (i.e., the speculative effect). This speculative effect results from two underlying hypotheses in Hong's (2000) model regarding the relationship that information asymmetry has with both time-to-maturity and return volatility. Hong's (2000) first hypothesis (H1) is that information asymmetry increases as the futures contract approaches its maturity, and his second hypothesis (H2) is that increases in information asymmetry lead to reductions in return volatility. Consequently, the speculative effect is expected to have a negative impact on return volatility as the futures contract approaches expiration, thus offsetting the price elasticity effect proposed by Samuelson. Hong (2000) suggests that the interaction of these two opposing forces provides a possible explanation for the mixed empirical evidence for the Samuelson effect in previous research.

The logic behind Hong's (2000) hypotheses is as follow. The model proposes two types of investors in the market: perfectly informed speculators and uninformed hedgers. Hedgers trade futures contracts for the sole purpose of hedging their spot positions. In contrast, speculators trade futures contracts for two purposes – to speculate in the market at hand using their private information about the underlying asset's fundamental value and to hedge their positions in other markets (i.e., nonmarketed/noise risk). As maturity nears, the futures price becomes more sensitive to the fundamental (hence, the price elasticity effect) and also to noise risk. In the general case where shocks to the fundamental are more persistent than noise shocks, Hong (2000) theoretically shows that the increase in sensitivity to noise risk outpaces the increase in sensitivity to the underlying fundamentals. Since hedgers are uninformed and only learn about fundamental values by observing futures prices, they find it increasingly difficult to extract fundamental values from futures prices as the contract approaches maturity. Therefore, information asymmetry rises as the futures contract approaches expiration (Hong's H1). Faced with a larger information disadvantage, uninformed hedgers rationally reduce their trading. This decreases the ability of informed speculators, now having fewer counterparties, to trade which then consequently leads to less private information being impounded into the futures price as well as lowering futures return volatility (Hong's H2). Thus, while Samuelson's price elasticity effect will cause a rise in return volatility as futures contracts near maturity, Hong's speculative effect will cause a reduction in return volatility as futures contracts near maturity.

In this study, I simultaneously test both the price elasticity effect and the speculative effect. I utilize a mediation analysis method (see Judd and Kenny, 1981; Sobel, 1982; Baron and Kenny, 1986) to separate the time-to-maturity pattern of return volatility (i.e., the overall effect) into the speculative effect and the price elasticity effect.[3] I treat the price elasticity effect as a direct effect that time-to-maturity has on return volatility, and treat the speculative effect as an indirect effect caused by the mediating role that information asymmetry has on the time-to-maturity – return volatility relationship. The mediation analysis involves three steps. First, I test the relationship between information asymmetry and time-to-maturity (i.e., Hong's H1). Second, I test the impact that information asymmetry has on futures return volatility (i.e., Hong's H2). Using the results of these first two steps, I can then test for the existence of a speculative effect.

[3] I discuss in greater detail the regressions used for the mediation analysis in Section 2.3.

Third, I examine the direct effect (the price elasticity effect) and the overall effect (price elasticity plus speculative effects) of time-to-maturity on futures return volatility.

More specifically, I investigate the relationship between information asymmetry and time-to-maturity by examining transaction-level data for twelve futures contracts traded on the CME Group. The database covers an 11-year period from 2006 to 2016. I use Madhavan, Richardson, and Rooman's (1997) model to estimate the information asymmetry component of the bid-ask spread, and then use this measure as our proxy for the daily level of asymmetric information. My empirical results show that information asymmetry increases significantly as the futures contracts approach maturity, thus confirming Hong's (2000) first hypothesis (H1). For every 10-day period that a futures contract approaches its maturity, its information asymmetry level increases by an average of 3.64%.

Next, I examine the impact of information asymmetry on future return volatility, which I measure using daily realized volatility (Andersen and Bollerslev, 1998). Hong's (2000) prediction of a negative relationship between information asymmetry and return volatility is based on the assumption that uninformed hedgers choose to trade less when facing higher information asymmetry. This leads to less fundamental information being reflected in the futures price (as there are less counterparties for informed traders to trade with), thereby lowering return volatility. In reality, however, uninformed hedgers may not learn about their informational disadvantage (quoted Donald Rumsfeld: "…but there are also unknown unknowns. There are things we do not know we don't know."). First, they may not be able to compare what they derive from observing the futures market with the private information held by speculators, since speculators obviously do not share such information with them. Second, if their motivation to trade is mainly to hedge, then they will have a smaller incentive or capacity to learn about their informational disadvantage. They may, for example, be liquidity traders who are more concerned about addressing liquidity shocks. In fact, Admati and Pfleiderer (1988) theoretically show that uninformed liquidity traders facilitate informed trading, which leads to higher return volatility. Shalen (1993) proposes that when uninformed traders have less accurate expectation about the fundamental, return volatility increases. Daigler and Wiley (1999) document that trading volume by uninformed investors is positively related to return volatility. As a result, I expect that information asymmetry has a positive effect on return volatility, instead of a negative one suggested by Hong (2000).

My empirical test of the second hypothesis (H2) supports my expectation. The results show a strong and positive impact information asymmetry has on return volatility across twelve futures. On average, a one standard deviation increase in information asymmetry leads to a rise by half of a standard deviation in return volatility. Those results, coupled with the results for H1 (information asymmetry increases closer to maturity), suggest that the speculative effect should have a positive impact on return volatility as the futures contract rolls toward maturity instead of a negative impact. My calculation of the speculative effect shows that its positive impact on return volatility is statistically significant to at least the five percent level for all futures. On the other hand, I only find evidence for the price elasticity effect in five of the futures. Economically, I find that the speculative effect raises daily realized volatility by an average of 2.22% for every ten trading days. The results are robust when I control for return volatility autocorrelation, use Huang and Stoll's (1997) adverse selection component of the bid-ask spread as an alternative measure of information asymmetry, or measure the MRR asymmetric information component as percentage of the spread instead of absolute dollar value. Moreover, my subsample analysis shows that while the positive relationship between information asymmetry and return volatility is strong during both the crisis and post-crisis periods, the negative relationship between time-to-maturity and information asymmetry is weaker during the crisis. This is consistent with the notion that noise risks are more persistent during the crisis.

2.2. Related literature

The most widely known explanation for a causal relationship between time-to-maturity and futures return volatility is Samuelson's (1965) argument that futures prices impound more price-sensitive information as the futures contract approaches maturity (i.e., the Samuelson effect). Whilst there is some empirical support for this price elasticity effect, the evidence to date is neither consistent across futures markets, nor is it consistent over time. For example, Rutledge (1976) finds support for the price elasticity effect in silver and cocoa futures, but not in wheat and soybean oil. Milonas (1986) documents the presence of the price elasticity effect in several commodities, but not in corn. Similarly, Khoury and Yourougou (1993) find evidence of price elasticity in some agricultural commodity futures, but not in canola.

To address these empirical shortcomings, Anderson and Danthine (1983) develop an alternative explanation for predictable patterns in futures return volatility over time. Their state variable hypothesis argues that futures return volatility will be higher in periods whenever a relatively large amount of uncertainty about the supply and demand of the underlying asset is resolved. The Samuelson effect then becomes a special case in which the resolution of uncertainty is clustered near the maturity of the futures contract. In effect, Anderson and Danthine (1983) propose a broad seasonality effect in place of

Samuelson's maturity effect. The empirical evidence for this state variable hypothesis (e.g., seasonality effect) is mixed. Whilst Anderson (1985) finds that the seasonality effect is more important than the maturity effect in explaining futures return volatility, Bessembinder et al. (1996) and Duong and Kalev (2008) find strong evidence of the Samuelson effect even after controlling for seasonality.

Bessembinder et al. (1996) examine net-carry-cost effects and propose that the price elasticity effect is more likely to hold in futures markets for real assets, such as commodities, where the covariation between spot price changes and changes in net carry costs is negative. They find support for this negative covariance hypothesis by showing that the price elasticity effect holds for agricultural commodities and crude oil, while it is weaker for metals and non-existent for Treasury bonds and S&P 500 index futures. On the other hand, Duong and Kalev (2008) find the presence of price elasticity effects in agricultural futures but not for metals, energy, or financial futures.

Hong (2000) approaches the issue from a different perspective and points out that previous models which attempt to explain the relationship between time-to-maturity and return volatility assume that investors are symmetrically informed. That may not be the case in practice. For example, Roll (1984) shows that a substantial part of orange juice futures price movement is not explained by public information, which suggests that investors bring their own private information into the market. Lai et al. (2014) document that the average probability of informed trading in 47 equity markets around the world is 27.9%. The reason information asymmetry exists could be due to some market participants having better capability or stronger motivation to acquire private information than others (Grossman and Stiglitz, 1980; Kyle, 1985; Admati and Pfleiderer, 1988; Wang, 1994; He and Wang, 1995). Furthermore, their interpretations of information may not be homogeneous (De Long et al., 1990; Harris and Raviv, 1993; Shalen, 1993; Wang, 1998).

The extant literature shows that the presence of information asymmetry has significant impacts across asset markets. In the stock market, information asymmetry results in discounted equity price due to higher risk premium (Wang, 1993; Chan et al., 2008), higher cost of capital (Admati, 1985; Diamond and Verrecchia, 1991; Easley and O'Hara, 2004; Duarte et al., 2008), higher volatility (Wang, 1994); higher stock returns (Easley et al., 2002), and lower liquidity (Diamond and Verrecchia, 1991). In the bond market, information asymmetry leads to higher yield spread (Lu et al., 2010), higher trading cost (Wittenberg-Moerman, 2008), higher expected returns (Li et al., 2009), and lower price (An et al., 2011). For futures, previous studies mainly focus on the relationship between information asymmetry and futures return volatility (Shalen, 1993; Daigler and Wiley, 1999).

Hong (2000) develops a dynamic model to study the impact of asymmetric information among futures market participants on the Samuelson effect. Hong's (2000) model posits that the time-to-maturity pattern of futures return volatility comprises a price elasticity effect, which is identical to the Samuelson effect, and a speculative effect that arises from the relationships that information asymmetry has with time-to-maturity and with return volatility. The speculative effect exists because the market consists of two types of investors: informed speculators and uninformed hedgers. Hedgers trade futures contracts to hedge their spot positions, while speculators trade futures to take advantage of their private information related to underlying asset fundamentals as well as to hedge their nonmarketed risk (i.e., noise risk).

Since hedgers are uninformed, they try to learn about the fundamentals of underlying asset values by observing futures prices. Hong (2000) argues that under normal conditions, shocks to fundamental values of the underlying assets are more persistent than shocks due to noise. In this case, when the futures contract is far from maturity, price movements are mainly due to shocks to the fundamental, since noise shocks are not persistent and will die away in the near time horizon. Information asymmetry is therefore minimal. As the futures contract rolls towards maturity, its sensitivity to noise shocks increases, making it more difficult for uninformed hedgers to extract fundamental values from observing noisier futures prices. Facing an increase in asymmetric information, hedgers reduce their futures trading activity which, in turn, leads to a reduction in futures return volatility. Following this line of reasoning, Hong's (2000) proposed speculative effect has a downward impact on the time-to-maturity pattern of return volatility.

More specifically, Hong's (2000) speculative effect is based on two central hypotheses. The first hypothesis (H1) is that information asymmetry increases as the time-to-maturity approaches. The second hypothesis (H2) is that higher levels of information asymmetry lead to lower levels of futures return volatility. This second hypothesis (H2) is based on the assumption that uninformed hedgers rationally learn of the widening information gap between themselves and informed speculators. But such knowledge may not be the case. In contrast, I argue that uninformed hedgers are unlikely to know with any degree of certainty how much private information is in the possession of the speculators. Without such knowledge, it would be difficult for hedgers to gauge the size of the information gap between themselves and the speculators at any point in time, or to estimate the changes in this information gap over time.

In addition, hedgers might be at least as concerned about liquidity shocks (which are observable) as they are about changes in asymmetric information (which might not be observable). If hedgers do not observe changes in information asymmetry and simply focus on being liquidity traders, they may not reduce their trading activity as the futures contract approaches its time-to-maturity. If the increase in asymmetric information does not cause hedgers to reduce their trading activity as maturity approaches, then return volatility need not decrease as maturity approaches.

Previous studies provide some theoretical and empirical support to my conjecture that on the positive impact information asymmetry has on return volatility. Admati and Pfleiderer's (1988) theoretical model shows that the trading activity of uninformed liquidity traders (i.e., hedgers) increases with their demand for hedging – a demand that is likely to increase as time-to-maturity decreases. Their model also suggests that increases in hedging demand and uninformed trading activities are facilitated by increasing levels of informed trading, thus leading to lower futures return volatility as maturity approaches. In addition, Shalen (1993) argues that when uninformed traders have less accurate information about underlying asset fundamental values, they trade at a wider price range and adjust their expectation more frequently. As a result, return volatility will increase with higher levels of information asymmetry. Daigler and Wiley (1999) present empirical evidence showing that the trading volume of uninformed traders is positively related to futures return volatility, while the trading volume of informed investors is negatively related to return volatility.

In summary, I argue that uninformed hedgers are unlikely to be able to gauge the level of private information that speculators possess at any point in time. If this "information gap" is unobservable, then it is unlikely to explain uninformed trading behavior – and its proposed impact on return volatility through Hong's (2000) speculative effect – as futures contracts approach their times-to-maturity. In addition, if uninformed traders are more concerned about liquidity shocks than information asymmetry shocks then they are more likely to behave as liquidity traders as futures contracts approach their times-to-maturity. Therefore, I hypothesize that the speculative effect will increase futures return volatility as time-to-maturity approaches.

2.3. Data and methods

To test my hypothesis, I collect data for twelve commodity futures traded on four exchanges of the CME Group, the world's largest futures marketplace. These futures contracts are the most liquid, with the highest trading volumes, for their respective commodity groups.[4] I collect intraday tick-by-tick trades and quotes from Thomson Reuter Tick History (TRTH) between January 1, 2006 and December 31, 2016 for these futures contracts (for feeder cattle the data is from November 1, 2007). Following the literature, I construct a closest-to-maturity time series for each futures by rolling over the front contract (i.e., the contract closest to maturity). When the front contract's trading volume falls below that of the next contract in the maturity cycle, I roll the contract over to obtain a continuous time series.

Using the above time series, I measure the daily level of information asymmetry in each futures market from the information asymmetry component of the bid-ask spread, derived from Madhavan, Richardson, and Rooman's (1997) model (MRR). This is a

[4] Except for feeder cattle, the average daily trading volume for the futures included in my data is well above 10,000 contracts.

commonly-used measure to capture information asymmetry across various asset markets, including equity (Riordan et al., 2013; Armstrong el al., 2011), fixed income (Green, 2004), futures (Huang, 2004). and options (Ahn et al., 2008; Muravyev, 2016). The MRR model also matches well with Hong's (2000) characterization of information asymmetry that is derived from the sequence of trades in the market. Specifically, the MRR model suggests that the effective bid-ask spread can be decomposed into its information asymmetry and liquidity components. The information asymmetry component measures the part of the spread that market makers require compensation for as they must take on the risk of trading with informed traders. Specifically, the MRR model is:

$$p_t - p_{t-1} = (\phi + \theta_{MRR})x_t - (\phi + \rho\theta_{MRR})x_{t-1} + \epsilon_t + \xi_t - \xi_{t-1} \tag{1}$$

where $p_t - p_{t-1}$ is the change in transaction prices between two consecutive trades, θ_{MRR} is the information asymmetry component of the bid-ask spread, ϕ is the liquidity component, ρ is the first-order autocorrelation of the order flow, and x_t is the trade initiation indicator (i.e., $x_t = 1$ if the trade is at the ask, -1 if the trade is at the bid, and 0 if the trade is inside the bid-ask spread), ϵ_t is the error term, and ξ_t is an independent-and-identically distributed random variable with a mean of zero. The set of parameters $(\theta_{MRR}, \phi, \lambda, \rho)$, where λ is the probability of a transaction taking place inside the spread, is estimated using the generalized method of moments (GMM) technique as follows:

$$E\begin{pmatrix} x_t x_{t-1} - x_t^2\rho \\ |x_t| - (1 - \lambda) \\ u_t - \alpha \\ (u_t - \alpha)x_t \\ (u_t - \alpha)x_{t-1} \end{pmatrix} = 0. \tag{2}$$

where $u_t = p_t - p_{t-1} - (\phi + \theta_{MRR})x_t + (\phi + \rho\theta_{MRR})x_{t-1}$, and α is a constant. My proxy for information asymmetry is the asymmetric information component of the bid-ask spread (θ_{MRR}).

For the daily volatility estimates, I use the realized return volatility *(*RV*)* calculated from the daily sum of squared five-minute interval returns, measured in natural logarithm (Andersen and Bollerslev, 1998). The latest quotes available at or prior to each five-minute mark are used to construct the five-minute price series. I use mid-point quotes to calculate the five-minute returns to avoid bid-ask bounce issues (Roll, 1984). The RV measure is defined as follows:

$$RV_t = \ln \sum_{i=1}^{k_t} \left[\ln\left(\frac{Bid_{t,i} + Ask_{t,i}}{2}\right) - \ln\left(\frac{Bid_{t,i-1} + Ask_{t,i-1}}{2}\right) \right]^2 \quad (3)$$

where k_t indicates the number of five-minute intervals throughout the trading day t.

In Table 2.1 I provide details about the futures in my sample, including the type of underlying commodity, the exchange where the futures contract trades, and the related expiration months. Table 2.1 also includes the means and standard deviations of the daily return volatility (RV) and information asymmetry (θ_{MRR}) for each futures time series. I also present information asymmetry as the percentage of the daily bid-ask spread (i.e., $\theta_{MRR}/(\phi + \theta_{MRR})$) to gauge its economic significance. The average daily return volatility ranges from -4.954 to -3.206. The average daily information asymmetry component ranges from 0.0038 cents (soybean oil) to 0.2781 cents (crude oil). On average, information asymmetry appears to account for more than 40% of the daily bid-ask spread. This indicates that information asymmetry has a dominant impact on trading costs.

Table 2.1: Descriptive statistics.

Commodity group	Futures	Futures exchange	Expiration month	Mean (std.) daily return volatility	Mean (std.) daily information asymmetry	
					Absolute value (x10^{-2})	Percentage of the spread
Grains and oilseeds	Corn	CBOT	3,5,7,9,12	-3.438 (0.862)	5.68 (3.18)	40.88% (17.96%)
Grains and oilseeds	Soybean	CBOT	1,3,5,7,8,9,11	-3.844 (0.772)	5.76 (3.61)	49.31% (16.42%)
Grains and oilseeds	Soybean meal	CBOT	1,3,5,7,8,9,10,12	-3.466 (0.722)	3.59 (2.30)	69.64% (17.72%)
Grains and oilseeds	Soybean oil	CBOT	1,3,5,7,8,9,10,12	-3.722 (0.675)	0.38 (0.31)	62.43% (16.52%)
Grains and oilseeds	Wheat	CBOT	3,5,7,9,12	-3.206 (0.749)	10.19 (4.60)	63.30% (13.59%)
Livestock	Feeder cattle	CME	1,3,4,5,8,9,10,11	-4.918 (0.857)	2.56 (1.64)	77.74% (18.16%)
Livestock	Lean hogs	CME	2,4,5,6,7,8,10,12	-4.060 (0.785)	1.23 (1.01)	65.76% (18.71%)
Livestock	Live cattle	CME	2,4,6,8,10,12	-4.954 (0.797)	1.10 (0.92)	62.76% (20.59%)

Return volatility is the natural logarithm of the daily sum of the squared five-minute returns. Information asymmetry is the Madhavan, Richardson and Rooman's (1997) daily information asymmetry component of the bid-ask spread measured in absolute value in US cents (θ_{MRR}) and as the percentage of the spread ($\theta_{MRR}/(\phi + \theta_{MRR})$).

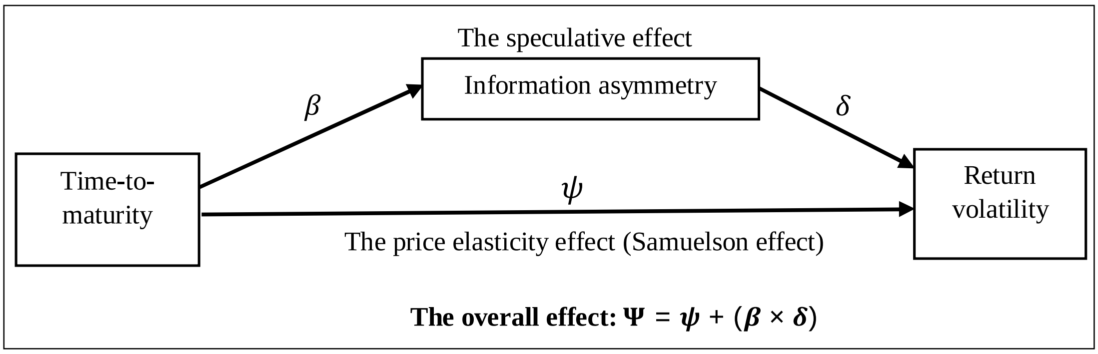
Table 2.1: Descriptive statistics (continued).

Commodity group	Futures	Futures exchange	Expiration month	Mean (std.) daily return volatility	Mean (std.) daily information asymmetry	
					Absolute value (x10^{-2})	Percentage of the spread
Metals	Copper	COMEX	3,5,7,9,12	-3.788 (0.824)	1.95 (2.07)	71.80% (25.38%)
Metals	Gold	COMEX	2,4,6,8,10,12	-4.564 (0.795)	294.58 (156.05)	59.62% (20.56%)
Metals	Silver	COMEX	1,3,5,7,9,12	-3.414 (0.763)	11.68 (11.08)	65.48% (23.21%)
Energy	Crude oil	NYMEX	Every month	-3.434 (0.924)	27.81 (20.19)	49.99% (20.96%)

Return volatility is the natural logarithm of the daily sum of the squared five-minute returns. Information asymmetry is the Madhavan, Richardson and Rooman's (1997) daily information asymmetry component of the bid-ask spread measured in absolute value in US cents (θ_{MRR}) and as the percentage of the spread ($\theta_{MRR} / (\phi + \theta_{MRR})$).

I conduct my empirical analysis based on the mediation regression framework of Judd and Kenny (1981), Sobel (1982), and Baron and Kenny (1986). The mediation framework allows me to investigate how return volatility can be influenced by time-to-maturity via two channels. The first channel represents a direct channel (i.e., the price elasticity effect), and the second channel is an indirect channel (i.e., the speculative effect) with its accompanying mediating variable, information asymmetry. For the indirect channel to work in the manner proposed by Hong (2000), time-to-maturity must affect information asymmetry (i.e., his first hypothesis, or H1) which, in turn, influences return volatility (i.e., his second hypothesis, or H2). The overall effect on return volatility is the sum of the direct and indirect effects. Figure 2.1 provides a conceptual illustration of this mediation model.

Figure 2.1: The mediation framework to separate the speculative effect and the price elasticity effect.



This figure illustrates the mediation framework we use to separate the speculative effect and the price elasticity effect. The return volatility – time-to-maturity relationship materializes from two channels; with one being classified as the direct channel (the price elasticity effect), and the second being an indirect channel (the speculative effect) through a mediating variable (information asymmetry). For the indirect channel to work, time-to-maturity must affect information asymmetry, which then, in turn, influences return volatility. The overall effect on return volatility is the sum of the direct and indirect effects.

The mediation regression framework to test the magnitude and statistical significance of each effect involves three regressions. Time-to-maturity (TTM) is measured by the number of days to maturity. I include dummy variables for each month of the year (MONTH) to address seasonality effects, and the natural logarithm of the number of trades that occur during the day (LN_NT) to account for liquidity. I also include year fixed-effects to account for time trends. The regression models are defined as follows:

$$\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t \tag{4}$$

$$RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t \tag{5}$$

$$RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t \tag{6}$$

Equation (4) is used to establish the time-to-maturity pattern of information asymmetry (coefficient β); Equation (5) is used to separate the impact information asymmetry has on return volatility (coefficient δ) from that of time-to-maturity (the price elasticity effect, or coefficient ψ); and Equation (6) is used to determine the overall effect of time-to-maturity on return volatility (Ψ). The indirect effect (i.e., the speculative effect) can be calculated as either $(\Psi - \psi)$ or $(\beta * \delta)$, since both will produce the same result (Judd and Kenny, 1981; Baron and Kenny, 1986). The significance (t-statistics) for each effect is calculated using the standard errors obtained from the regressions based on Equations (4), (5), and (6) following Sobel (1982) and Baron and Kenny (1986). Specifically, the standard error for the speculative effect is $\sqrt{\beta^2\sigma_\delta^2 + \delta^2\sigma_\beta^2}$; for the direct effect, it is σ_ψ; and for the overall effect, it is σ_Ψ, where σ_β, σ_δ, σ_ψ, and σ_Ψ are the standard errors of β, δ, ψ, and Ψ, respectively.

2.4. Empirical results

2.4.1. The time-to-maturity pattern of information asymmetry

I start my analysis by examining Hong's (2000) prediction that information asymmetry rises as futures contracts approach maturity (i.e., H1). I divide each futures contract into two parts based on the number of days to maturity. The results in Table 2.2 show that, except for Silver and Copper, the average level of information asymmetry is statistically higher for contracts that have less than the median number of days to maturity relative to contracts that have more than the median number of days to maturity. The differences are statistically significant at the 10% level for Live cattle, at the 5% level for Feeder cattle, and at the 1% level for the remaining eight futures contracts. Taking Gold as an example, the average information asymmetry is 284.93 cents for the period far from maturity, and 304 cents for the period close to maturity. The difference represents a 6.69% increase in information asymmetry. Similar analysis for all the futures indicates that, on average, information asymmetry increases by 8.75% as futures move from being more than the median number of days away from maturity to being closer than the median number of days to maturity of the life of the contract.

Table 2.2: Univariate tests of the relationship between information asymmetry and time-to-maturity.

Futures	Information asymmetry (x10^{-2})		
	Far from maturity	Close to maturity	Difference (t-statistic)
Corn	5.32	6.04	0.72*** (6.01)
Soybean	5.21	6.27	1.06*** (7.70)
Soybean meal	3.43	3.75	0.32*** (3.69)
Soybean oil	0.36	0.41	0.05*** (3.90)
Wheat	9.60	10.75	1.15*** (6.58)
Feeder cattle	2.50	2.62	0.12** (1.70)
Lean hogs	1.16	1.29	0.13*** (3.31)
Live cattle	1.07	1.12	0.05* (1.57)
Copper	1.94	1.95	0.01 (0.08)
Gold	284.93	304.00	19.07*** (3.20)
Silver	11.76	11.59	-0.17 (-0.42)
Crude oil	26.22	28.70	2.48*** (3.29)

This table presents the average daily level of information asymmetry estimated from Madhavan, Richardson and Rooman’s (1997) daily information asymmetry component of the bid-ask spread for periods close to, and far from, maturity of each futures based on whether it has less, or more, than the median number of contract days to maturity. *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

To further test this relationship, Table 2.3 and Table 2.4 present the regression results from Equation (4) of regressing the information asymmetry measure, θ_{MRR}, on the number of days to maturity (TTM), both without (Panel A) and with (Panel B) controlling for seasonality (month dummies) and liquidity (LN_NT).[5] I expect a negative coefficient for TTM if information asymmetry increases as maturity nears (i.e., information asymmetry is negatively related to the number of days to maturity). As expected, the coefficients for TTM are negative and statistically significant at the 5% and 1% levels for all futures in both Tables. The proportional increase in information asymmetry over a futures life can be substantial. Using Corn as an illustration, the average level of information asymmetry is 0.0568 cents (see Table 2.1). The coefficient of -0.408×10^{-3} for TTM in Table 2.4 implies that when a Corn futures contract rolls another 10 days towards maturity, information asymmetry will rise by 0.00408 cents $((-10) \times (-0.408 \times 10^{-3}))$, or 7.18% ($0.00408/0.0568$). Similar analyses for the other futures contracts in our sample show that the average 10-day increase in information asymmetry is 3.64%.

[5] Our results are qualitatively similar if we measure time-to-maturity using a squared or logarithmic scale.

Table 2.3: Testing the time-to-maturity pattern of information asymmetry without controlling for seasonality and liquidity.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
TTM (x10^{-3})	-0.272***	-0.208***	-0.024***	-0.006***	-0.420***	-0.038***
	(-14.57)	(-10.24)	(-2.93)	(-6.12)	(-15.04)	(-3.97)
Intercept	0.077***	0.103***	0.072***	0.010***	0.150***	0.067***
	(32.88)	(29.05)	(26.53)	(27.61)	(42.37)	(12.01)
Fixed Effects	Year	Year	Year	Year	Year	Year
Observations	2726	2727	2722	2727	2726	2252
Adjusted R^2	0.558	0.473	0.520	0.581	0.596	0.565
	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
TTM (x10^{-3})	-0.042***	-0.060***	-0.022**	-0.053***	-0.209***	-1.503***
	(-5.37)	(-11.17)	(-2.44)	(-5.90)	(-2.62)	(-3.63)
Intercept	0.032***	0.025***	0.014***	0.007***	0.046***	0.228***
	(24.12)	(35.21)	(9.26)	(7.44)	(6.51)	(12.35)
Fixed Effects	Year	Year	Year	Year	Year	Year
Observations	2728	2723	2728	2730	2725	2726
Adjusted R^2	0.529	0.641	0.816	0.441	0.655	0.360

This table presents the results for testing the time-to-maturity pattern of information asymmetry using the following regression: $\theta_{MRR_t} = \alpha + \beta TTM_t + \varepsilon_t$, where information asymmetry is measured by the daily information asymmetry component of the bid-ask spread calculated using Madhavan, Richardson and Rooman's (1997) model (θ_{MRR}). Time to maturity (TTM) is the number of days until expiration. Year fixed-effect is included. All t-statistics reported in parentheses are based on Newey and West (1987) standard errors. Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.4: Testing the time-to-maturity pattern of information asymmetry with controlling for seasonality and liquidity.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
TTM (x10^{-3})	-0.408***	-0.302***	-0.176***	-0.008***	-0.592***	-0.043**
	(-8.92)	(-7.19)	(-6.84)	(-2.92)	(-9.37)	(-2.22)
LN_NT (x10^{-2})	0.324**	-2.089***	-0.552***	-0.103***	-0.520***	-0.149**
	(2.29)	(-16.84)	(-6.53)	(-9.92)	(-3.42)	(-2.27)
Intercept	0.055***	0.242***	0.087***	0.012***	0.182***	0.075***
	(5.65)	(23.88)	(14.44)	(16.26)	(17.87)	(11.92)
Fixed Effects	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month
Observations	2726	2727	2722	2727	2726	2252
Adjusted R^2	0.654	0.663	0.667	0.737	0.631	0.572
	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
TTM (x10^{-3})	-0.072***	-0.040***	-0.051**	-0.074***	-0.291**	-0.583**
	(-3.85)	(-4.28)	(-2.33)	(-3.39)	(-2.23)	(-2.23)
LN_NT (x10^{-2})	-0.113**	-0.285***	-1.537**	-0.713***	-2.924***	-7.829***
	(-2.44)	(-8.15)	(-2.45)	(-7.42)	(-3.94)	(-18.61)
Intercept	0.036***	0.039***	0.026***	0.059***	0.234***	0.830***
	(16.90)	(19.07)	(7.84)	(8.89)	(4.97)	(20.98)
Fixed Effects	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month
Observations	2728	2723	2728	2730	2725	2726
Adjusted R^2	0.540	0.682	0.826	0.544	0.683	0.550

This table presents the results for testing the time-to-maturity pattern of information asymmetry using the following regression: $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where information asymmetry is measured by the daily information asymmetry component of the bid-ask spread calculated using Madhavan, Richardson and Rooman's (1997) model (θ_{MRR}). Time to maturity (TTM) is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for each month. Year fixed-effect is included. All *t*-statistics reported in parentheses are based on Newey and West (1987) standard errors. Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

2.4.2. The impact of information asymmetry on futures return volatility

Having established the presence of a time-to-maturity pattern of information asymmetry for all of our futures contracts, I proceed to examine the impact of information asymmetry on futures return volatility. I test my argument against Hong's (2000) H2 by estimating Equation (5). I regress return volatility (RV) on both information asymmetry (θ_{MRR}) and time-to-maturity (TTM), whilst controlling for seasonality (MONTH) and liquidity (LN_NT). Table 2.5 shows that, consistent with our expectation, the coefficients for θ_{MRR} are positive and significant at the one percent level across all 12 futures contracts, suggesting that increases in information asymmetry leads to increases in return volatility. Using the wheat contract as an example, we can see that the estimated coefficient for θ_{MRR} is 7.664. When information asymmetry increases by one standard deviation (0.0460, see Table 2.1), return volatility rises by 0.3525 (0.046x7.664), which is approximately half of its standard deviation (0.749, see Table 2.1). The coefficients for TTM, which capture the price elasticity effect, are negative and significant for five futures contracts, and insignificant for seven futures contracts. The coefficients for LN_NT are positive and significant at the one percent level for all futures. This result is consistent with the notion that return volatility is positively related to liquidity.

Table 2.5: Testing the impact of information asymmetry and time-to-maturity on return volatility.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
θ_{MRR}	12.770***	11.885***	30.879***	215.246***	7.664***	23.218***
	(11.36)	(8.99)	(18.95)	(13.78)	(15.83)	(12.35)
TTM (x10^{-3})	1.984	-1.081	-4.664***	-4.267***	-4.709***	-0.178
	(1.40)	(-0.78)	(-3.52)	(-3.20)	(-3.74)	(-0.15)
LN_NT	0.447***	0.450***	0.576***	0.321***	0.343***	0.640***
	(12.54)	(14.07)	(16.78)	(9.03)	(13.25)	(18.96)
Intercept	-6.754***	-7.465***	-8.379***	-6.892***	-6.257***	-8.259***
	(-29.28)	(-23.27)	(-31.73)	(-24.02)	(-32.50)	(-28.19)
Fixed Effects	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month
Observations	2726	2727	2722	2727	2726	2252
Adjusted R^2	0.569	0.457	0.483	0.349	0.491	0.524

This table presents the results for testing the impact of information asymmetry and time-to-maturity on return volatility using the following regression: $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. Information asymmetry is measured by the daily information asymmetry component of the bid-ask spread calculated following Madhavan, Richardson and Rooman's (1997) model (θ_{MRR}). Time to maturity (TTM) is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for each month. Year fixed-effect is included. All *t*-statistics reported in parentheses are based on Newey and West (1987) standard errors. Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.5: Testing the impact of information asymmetry and time-to-maturity on return volatility (continued).

	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
θ_{MRR}	14.334***	80.562***	12.507***	34.651***	3.041***	2.183***
	(4.97)	(14.53)	(5.37)	(16.11)	(13.64)	(16.79)
TTM (x10^{-3})	-0.003	-2.867**	-2.087	0.882	-2.028	-1.854*
	(-0.01)	(-2.26)	(-1.50)	(0.80)	(-1.63)	(-1.66)
LN_NT	0.395***	0.671***	0.257***	0.606***	0.448***	0.269***
	(11.69)	(18.24)	(11.62)	(15.49)	(11.35)	(15.10)
Intercept	-5.724***	-10.382***	-4.957***	-8.833***	-6.127***	-6.369***
	(-33.31)	(-33.72)	(-24.49)	(-33.73)	(-23.98)	(-34.98)
Fixed Effects	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month	Year, Month
Observations	2728	2723	2728	2730	2725	2726
Adjusted R^2	0.392	0.527	0.467	0.579	0.433	0.583

This table presents the results for testing the impact of information asymmetry and time-to-maturity on return volatility using the following regression: $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. Information asymmetry is measured by the daily information asymmetry component of the bid-ask spread calculated following Madhavan, Richardson and Rooman's (1997) model (θ_{MRR}). Time to maturity (TTM) is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for each month. Year fixed-effect is included. All *t*-statistics reported in parentheses are based on Newey and West (1987) standard errors. Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

2.4.3. The speculative effect and the price elasticity effect

After confirming the relationship that information asymmetry has with time-to-maturity (i.e., upward trending as the futures contract expires) and with return volatility (positive), I expect the speculative effect to have a positive and significant impact on return volatility as maturity approaches. To confirm this conjecture, I estimate Equation (6) to get the overall effect of time-to-maturity on return volatility. I then proceed to use these results, along with the results from regressions of Equations (4) and (5), to calculate the coefficients and statistical significance of the speculative and the price elasticity effects.

I report the results of these two effects in Table 2.6. The coefficients for the speculative effect are consistently negative and significant to at least the five percent level for all futures contracts. On the other hand, I find significant price elasticity effects in only five futures contracts. The coefficients for the price elasticity are negative and significant at the ten percent level for crude oil, and to at least the five percent level for soybean meal, soybean oil, wheat, and live cattle. The coefficients are insignificant for the other seven futures contracts.

The economic impact of the speculative effect on return volatility is also significant. Taking soybean as an example, the coefficient of -3.586x10^{-3} for the speculative effect indicates an increase of 0.03586 ($(-10) \times (-3.589 \times 10^{-3})$) in return volatility when the futures contract rolls forward ten days toward its maturity. Since return volatility is measured as a natural logarithm, this means that the speculative effect is responsible for an increase of 3.65% ($e^{0.03586} - 100\%$) in daily realized volatility. Similar analyses for other futures contracts in my sample show that, on average, the speculative effect raises daily realized volatility by 2.22% for every ten days.

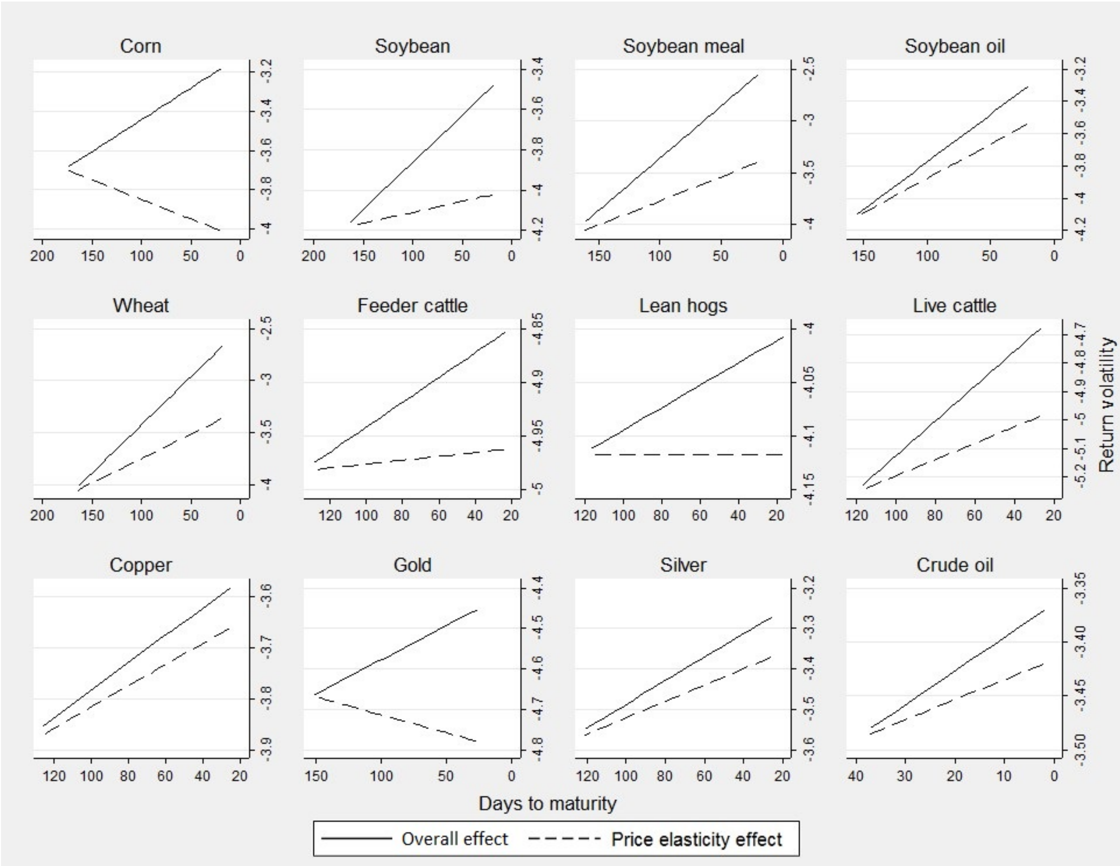
Table 2.6: The speculative effect and the price elasticity effect.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
The speculative effect (x10^{-3})	-5.210***	-3.586***	-5.444***	-1.623***	-4.538***	-0.974**
	(-7.02)	(-5.62)	(-6.43)	(-2.86)	(-8.06)	(-2.18)
The price elasticity effect (x10^{-3})	1.984	-1.081	-4.664***	-4.267***	-4.709***	-0.178
	(1.40)	(-0.78)	(-3.52)	(-3.20)	(-3.74)	(-0.15)
Overall effect (x10^{-3})	-3.226**	-4.667***	-10.108***	-5.890***	-9.247***	-1.152
	(-2.21)	(-3.15)	(-7.18)	(-4.09)	(-7.10)	(-0.88)
Observations	2726	2727	2722	2727	2726	2252
	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
The speculative effect (x10^{-3})	-1.038***	-3.245***	-0.637**	-2.568***	-0.886**	-1.271**
	(-3.04)	(-4.11)	(-2.14)	(-3.32)	(-2.20)	(-2.21)
The price elasticity effect (x10^{-3})	-0.003	-2.867**	-2.087	0.882	-2.028	-1.854*
	(-0.01)	(-2.27)	(-1.50)	(0.80)	(-1.63)	(-1.66)
Overall effect (x10^{-3})	-1.042	-6.112***	-2.724**	-1.686	-2.914**	-3.125**
	(-0.69)	(-4.21)	(-1.96)	(-1.21)	(-2.20)	(-2.41)
Observations	2728	2723	2728	2730	2725	2726

This table presents the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility. We regress (i) $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. θ_{MRR} is the daily information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. TTM is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for every month of the year. Year fixed-effect is included in all regressions. The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is $(\beta \times \delta)$. The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

To provide a visual illustration of these effects, Figure 2.2 shows the impact of the speculative effect on the time-to-maturity pattern of return volatility. We can see that the speculative effect consistently generates an upward pattern of return volatility over the life of a futures contract. In futures markets where the price elasticity effect is significant, the speculative effect strengthens the price elasticity effect. In futures markets where the price elasticity effect is insignificant, the speculative effect alone drives the time-to-maturity pattern of return volatility (the overall effect). The coefficients for the overall effect are negative and significant to at least the five percent level for nine futures contracts, while they are insignificant for feeder cattle, lean hogs, and gold.

Figure 2.2: The impact of the speculative effect on the time-to-maturity pattern of return volatility.



This figure illustrates the impact of the speculative effect on the time-to-maturity pattern of return volatility based on the fitted values of our empirical results. Return volatility is measured by the natural logarithm of the daily sum of the squared five-minute returns. The speculative effect is the difference between the price elasticity effect and overall effect.

There are several points worth discussing from the above results. First, the weak results for the price elasticity effect may be explained by the state variable hypothesis (Anderson and Danthine, 1983). Since the price elasticity effect is driven by the futures market's reaction to information flows, the shape of the time-to-maturity pattern of return volatility directly attributed to this effect depends on when information flows are clustered over the life of a futures contract. If more price-relevant information flows into the market near maturity, then we can see a positive price elasticity effect on the slope of return volatility. Otherwise, if information arrive evenly over the futures contract life or is clustered far from maturity, then the price elasticity effect could be insignificant or even negative.

Second, my results suggest that the time-to-maturity patterns of return volatility observed in previous studies are not only caused by the Samuelson (price elasticity) effect, but rather by the interplay between this effect and the speculative effect; more specifically, by my proposed version of the speculative effect where asymmetric information and return volatility are positively related. Consequently, variations in any factor that influences the speculative effect or the price elasticity effect can lead to a change in the pattern of futures return volatility. These complicating factors are likely to be the reason behind the mixed empirical results found in other studies on the Samuelson effect.

2.5. An illustrative model of return volatility when uninformed liquidity hedgers are unaware of their informational disadvantage

To further support the point that information asymmetry gives rise to return volatility, I develop a simple, illustrative model where uninformed hedgers are unaware of their informational disadvantage, or simply behave as liquidity traders[6]. The model's prediction is consistent with my empirical results that rising information asymmetry positively impact futures return volatility as the contract rolls towards maturity.

We consider two types of traders: a mass λ of uninformed hedgers (denoted by traders H), a mass $(1-\lambda)$ of informed speculators (denoted by traders S), and three periods, indexed as $t = 0$ (far away from maturity), $t = 1$ (close to maturity), and $t = 2$ (maturity).[7] At $t = 0$ and $t = 1$, a trader can enter a futures contract that delivers a commodity at $t = 2$. The commodity delivered at $t = 2$ yields an *ex ante* uncertain payoff of $d \sim N\left(\bar{d}, \sigma_d^2\right)$.

Following Hong (2000), we assume that when the futures contract is far away from maturity, information asymmetry is minimal. In particular, at $t = 0$, all traders have identical prior beliefs that $d \sim N\left(\bar{d}, \sigma_d^2\right)$. When it is close to maturity (i.e., $t = 1$), information asymmetry arises due to traders S receiving a private signal about the uncertain payoff of the commodity: $s = d + \epsilon$, where $\epsilon \sim N(0, \sigma_\epsilon^2)$, whereas traders H do not receive such private information. Similar to Hong (2000), we also assume that traders

[6] I owe a debt of gratitude to Jeffrey Chia-Feng Yu (University of Adelaide) for assisting me in the development of the model.
[7] This is a simplification of the model dynamics considered in Hong (2000).

S also receive nonmarketed income shocks, $z_t \sim N(0, \sigma_z^2)$, $t = 0, 1$, which has an impact on their demand of futures. All uncertainty is resolved at $t = 2$.

Our key departure from Hong (2000) is that we assume that traders H do not learn about their informational disadvantage. It means that the trading behaviour of traders H is motivated by other reasons, not information. In other words, their aggregate demand for futures is represented by $h_t \sim N(0, \sigma_h^2)$, $t = 0, 1$. There can be a multiple number of reasons for this, for example they might simply be liquidity traders (see Grossman and Stiglitz, 1980). This is justifiable if these traders are subject to exogenous liquidity shocks and, due to limited attention, the required time and effort to address liquidity needs dominate all other trading motives and leave them no incentive or capacity to learn about information (see, among others, Peng and Xiong, 2006; Duffie, 2010). Below we will show that this leads to results that are consistent with my empirical results.

For simplicity, we follow Kelsey *et al.* (2011) and restrict our attention to linear trading strategies of speculators.[8] Specifically, at $t = 0$, the trading strategy of traders S is as follows, respectively:

$$D_0^S = \alpha^S[E(d) - p_0 + z_0] \tag{7}$$

where $\alpha^S > 0$ reflects the risk tolerance of traders S, and p_0 is the futures price at $t = 0$. Equation (7) states that the demands of speculators are proportional to the difference between their expectations of the uncertain commodity payoff and the current futures price, plus an additional nonmarketed income shock.

[8] Linear trading strategies can be ensured by assuming a CARA-normal model. Here, we follow Kelsey et al. (2011) and adopt linear trading strategies directly.

At $t = 0$, traders S have identical prior beliefs that $d \sim N(\bar{d}, \sigma_d^2)$. It follows that $E^S(d) = \bar{d}$. The market clearing condition at $t = 0$ requires:

$$(1 - \lambda)D_0^S + \lambda h_0 = 0 \tag{8}$$

Solving for the equilibrium price p_0^* yields:

$$p_0^* = \bar{d} + z_0 + \frac{\lambda h_0}{(1 - \lambda)\alpha^S} \tag{9}$$

At $t = 1$, the trading strategy of traders S, is as follows, respectively:

$$D_1^S = \alpha^S[E(d|s) - p_1 + z_1] \tag{10}$$

where p_1 is the futures price at $t = 1$. Note that, at $t = 1$, traders S update their posterior belief about the uncertain commodity payoff based on the private signals s, and their demand of futures is subject to the nonmarketed income shock at $t = 1$, z_1.

By the Bayesian updating rule, we obtain:

$$E(d|s) = \bar{d} + \frac{\sigma_d^2}{\sigma_d^2 + \sigma_\epsilon^2}(s - \bar{d}) \tag{11}$$

The market clearing condition at $t = 1$ requires:

$$(1 - \lambda)D_1^S + \lambda h_1 = 0 \tag{12}$$

Solving for the equilibrium price p_1^* yields:

$$p_1^* = \bar{d} + \frac{\sigma_d^2}{\sigma_d^2 + \sigma_c^2}\left(s - \bar{d}\right) + \frac{\lambda h_1}{(1-\lambda)\alpha^S} + z_1 \tag{13}$$

After deriving the equilibrium futures prices, p_0^* and p_1^*, we are now ready to demonstrate how futures return volatility changes when moving from $t = 0$ (far away from maturity) to $t = 1$ (close to maturity). The futures return volatility at t is referred to as the variance of the equilibrium futures price at t. From Equations (9) and (13), the difference in futures return volatility between $t = 1$ and $t = 0$, DiV, is given by

$$DiV = \frac{\sigma_d^4}{\sigma_d^2 + \sigma_c^2} \tag{14}$$

which is positive, indicating that futures return volatility is higher the closer the contract is to maturity. This is contrast with Hong (2000), who argues that when futures are closer to maturity, the futures price moves less because uninformed hedgers rationally learn that they are more informationally disadvantaged, and hence less incentivised to trade. We, however, demonstrate that the relationship can potentially be the reverse if the trading behaviour of uninformed hedgers is driven by liquidity concerns and not based on learning about their informational disadvantage. We thus obtain the following result: *If there is no learning by uninformed hedgers about their informational disadvantage, then as information asymmetry arises, futures return volatility increases when the contract is closer to maturity.*

2.6. Robustness tests

I conduct some additional tests for robustness. First, to account for potential autocorrelation in return volatility, I include the previous day's return volatility as a control variable when we run our regressions. Table 2.7 shows that the results remain robust. The coefficients for the speculative effect are negative and significant at the five percent level for eleven futures contracts, and at the ten percent level for copper.

Table 2.7: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship when controlling for autocorrelation in return volatility.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
Time-to-maturity pattern of information asymmetry ($x10^{-3}$)	-0.427***	-0.325***	-0.172***	-0.009***	-0.607***	-0.056**
	(-9.39)	(-8.01)	(-7.11)	(-3.52)	(-10.04)	(-2.46)
Impact of information asymmetry on return volatility	11.040***	10.003***	26.644***	179.900***	6.434***	18.354***
	(9.97)	(8.05)	(15.78)	(12.32)	(13.27)	(10.89)
The speculative effect ($x10^{-3}$)	-4.709***	-3.246***	-4.572***	-1.584***	-3.903***	-1.004**
	(-6.84)	(-5.68)	(-6.48)	(-3.38)	(-6.37)	(-2.40)
The price elasticity effect ($x10^{-3}$)	0.550	-2.414*	-5.213***	-5.475***	-5.637***	-1.660
	(0.40)	(-1.78)	(-4.01)	(-4.21)	(-4.48)	(-1.50)
Overall effect ($x10^{-3}$)	-4.159***	-5.660***	-9.785***	-7.059***	-9.540***	-2.664**
	(-3.02)	(-4.03)	(-7.41)	(-5.17)	(-7.29)	(-2.24)
Observations	2725	2726	2721	2726	2725	2251

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility when controlling for autocorrelation in return volatility. We regress (i) $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + RV_{t-1} + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + RV_{t-1} + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + RV_{t-1} + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. θ_{MRR} is the daily information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. TTM is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for every month of the year. Year fixed-effect is included in all regressions. The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is $(\beta \times \delta)$. The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.7: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship when controlling for autocorrelation in return volatility (continued).

	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
Time-to-maturity pattern of information asymmetry (x10^{-3})	-0.071***	-0.043***	-0.047**	-0.094***	-0.357***	-0.521**
	(-3.84)	(-4.89)	(-2.16)	(-4.84)	(-2.82)	(-2.18)
Impact of information asymmetry on return volatility	13.452***	68.618***	6.999***	26.918***	1.937***	1.101***
	(5.01)	(13.36)	(4.35)	(12.08)	(9.48)	(9.24)
The speculative effect (x10^{-3})	-0.962***	-2.923***	-0.330*	-2.536***	-0.693***	-0.570**
	(-3.05)	(-4.59)	(-1.93)	(-4.49)	(-2.70)	(-2.12)
The price elasticity effect (x10^{-3})	-0.710***	-3.249***	-1.554	-0.623	-3.310***	-2.088**
	(-0.49)	(-2.83)	(-1.60)	(-0.60)	(-3.00)	(-2.40)
Overall effect (x10^{-3})	-1.672	-6.172***	-1.884*	-3.159***	-4.003***	-2.658***
	(-1.16)	(-4.57)	(-1.91)	(-2.61)	(-3.53)	(-2.88)
Observations	2727	2722	2727	2729	2724	2725

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility when controlling for autocorrelation in return volatility. We regress (i) $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + RV_{t-1} + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + RV_{t-1} + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + RV_{t-1} + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. θ_{MRR} is the daily information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. TTM is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for every month of the year. Year fixed-effect is included in all regressions. The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is $(\beta \times \delta)$. The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Second, I use Huang and Stoll's (1997) adverse selection component of the bid-ask spread as an alternative measure of information asymmetry. Huang and Stoll's (1997) three-way decomposition of the bid-ask spread is quite similar to the MRR method, although less commonly-used in the literature. The daily adverse selection component is computed by estimating the two following equations simultaneously using GMM (corresponding to their Equations (25) and (21), respectively) as follows:

$$\Delta P_t = \frac{S}{2} Q_t + (\alpha_{HS} + \beta_{HS} - 1)\frac{S}{2} Q_{t-1} - \alpha_{HS}\frac{S}{2}(1 - 2\pi)Q_{t-2} + e_t \tag{15}$$

$$\mathrm{E}(Q_{t-1} | Q_{t-2}) = (1 - 2\pi)Q_{t-2} \tag{16}$$

where ΔP_t is change in transaction price, S is the constant spread, π is the probability of trade reversals, and Q_t is the trade indicator ($Q_t = 1$ for a buyer-initiated trade and $Q_t = -1$ for a seller-initiated trade). In addition, α_{HS} is the adverse selection component of the spread, β_{HS} is the inventory holding component, and $(1 - \alpha_{HS} - \beta_{HS})$ is the order processing component. I then multiple α_{HS} by the half-spread to get the absolute value of the component, as follows:

$$HS_t = \alpha_{HS_t} \times \frac{\bar{S}_t}{2} \tag{17}$$

where HS_t is our information asymmetry measure on day t, and $\bar{S}_t$ is an estimated value of the constant spread calculated as the average spread of the trading day.

Table 2.8 shows the results of Huang and Stoll's (1997) three-way decomposition. The relationship between information asymmetry and time-to-maturity holds for all futures contracts, except for lean hogs. The impact that information asymmetry has on return volatility remains strong at least at the five percent level of significance across all twelve futures contracts. As a result, the speculative effect is significant at least at the five percent level for nine futures, at the ten percent level for feeder cattle and soybean oil, and insignificant for lean hogs.

I also measure MRR's adverse selection component as a percentage of the spread (i.e., $\frac{\theta_{MRR}}{\phi+\theta_{MRR}}$) to address the potential concern that the absolute bid-ask spread could correlate with return volatility. Table 2.9 indicates that the results for the time-to-maturity pattern of information asymmetry and the speculative effect remain highly significant for all futures contracts.

Table 2.8: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship using Huang and Stoll's (1997) adverse selection component of the bid-ask spread.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
Time-to-maturity pattern of information asymmetry (x10^{-3})	-0.214***	-0.122***	-0.029***	-0.318**	-0.180**	-0.022*
	(-4.59)	(-4.23)	(-3.33)	(-2.23)	(-2.34)	(-1.81)
Impact of information asymmetry on return volatility	6.485***	10.307***	23.651***	0.736**	2.721***	23.957***
	(8.62)	(6.52)	(4.59)	(2.44)	(7.65)	(7.11)
The speculative effect (x10^{-3})	-1.388***	-1.259***	-0.675***	-0.235*	-0.491**	-0.517*
	(-4.05)	(-3.58)	(-2.70)	(-1.65)	(-2.24)	(-1.75)
The price elasticity effect (x10^{-3})	-1.838	-3.408***	-9.433***	-5.655***	-8.756***	-0.635
	(-1.29)	(-3.66)	(-4.39)	(-3.91)	(-6.81)	(-0.87)
Overall effect (x10^{-3})	-3.226**	-4.667***	-10.108***	-5.890***	-9.247***	-1.152
	(-2.21)	(-3.15)	(-7.18)	(-4.09)	(-7.10)	(-0.88)
Observations	2726	2727	2722	2727	2726	2252

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility using the following regressions (i) $HS_t = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta HS_t + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. Information asymmetry is measured by the daily absolute value of the adverse selection component of the bid-ask spread (HS) calculated following Huang and Stoll's (1997) model. Time to maturity (TTM) is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for each month. Year fixed-effect is included in all regressions. The coefficient and significance (t-statistics) for the time-to-maturity pattern of information asymmetry are that for TTM from equation (i). The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is ($\beta \times \delta$). The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.8: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship using Huang and Stoll's (1997) adverse selection component of the bid-ask spread (continued).

	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
Time-to-maturity pattern of information asymmetry (x10^{-3})	-0.114	-0.733***	-1.091***	-0.012***	-0.062****	-1.058***
	(-0.93)	(-2.69)	(-3.87)	(-3.15)	(-3.79)	(-4.87)
Impact of information asymmetry on return volatility	0.197***	2.198***	0.709***	50.410***	4.883**	0.658***
	(20.64)	(12.43)	(3.99)	(7.18)	(2.46)	(4.61)
The speculative effect (x10^{-3})	-0.023	-1.607***	-0.774***	-0.584***	-0.304**	-0.697***
	(-0.93)	(-2.63)	(-2.74)	(-2.88)	(-2.06)	(-3.35)
The price elasticity effect (x10^{-3})	-1.019	-4.505***	-1.950	-1.102	-2.610**	-2.428*
	(-1.32)	(-3.54)	(-1.40)	(-0.82)	(-1.98)	(-1.86)
Overall effect (x10^{-3})	-1.042	-6.112***	-2.724**	-1.686	-2.914**	-3.125**
	(-0.69)	(-4.21)	(-1.96)	(-1.21)	(-2.20)	(-2.41)
Observations	2728	2723	2728	2730	2725	2726

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility using the following regressions (i) $HS_t = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta HS_t + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. Information asymmetry is measured by the daily absolute value of the adverse selection component of the bid-ask spread (HS) calculated following Huang and Stoll's (1997) model. Time to maturity (TTM) is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for each month. Year fixed-effect is included in all regressions. The coefficient and significance (t-statistics) for the time-to-maturity pattern of information asymmetry are that for TTM from equation (i). The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is ($\beta \times \delta$). The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.9: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship using the Madhavan, Richardson and Rooman's (1997) information asymmetry component measured as percentage of the bid-ask spread.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
Time-to-maturity pattern of information asymmetry (x10^{-3})	-2.255***	-1.332***	-0.926***	-0.895***	-1.667***	-1.051***
	(-9.61)	(-5.21)	(-2.98)	(-3.31)	(-6.93)	(-2.86)
Impact of information asymmetry on return volatility	2.336***	2.001***	1.474***	1.508***	1.429***	0.797***
	(19.11)	(14.93)	(14.86)	(12.72)	(-5.32)	(8.87)
The speculative effect (x10^{-3})	-5.268***	-2.666***	-1.363***	-1.351***	-2.382***	-0.807***
	(-8.59)	(-4.92)	(-2.92)	(-3.20)	(-4.22)	(-2.72)
The price elasticity effect (x10^{-3})	2.042	-2.001	-8.745***	-4.539***	-6.865***	-0.345
	(1.49)	(-1.41)	(-10.22)	(-3.26)	(-5.32)	(-0.27)
Overall effect (x10^{-3})	-3.226**	-4.667***	-10.108***	-5.890***	-9.247***	-1.152
	(-2.21)	(-3.15)	(-7.18)	(-4.09)	(-7.10)	(-0.88)
Observations	2726	2727	2722	2727	2726	2252

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility using the following regressions (i) $\theta\%_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta\%_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. Information asymmetry is the daily information asymmetry component measured as the percentage of the bid-ask spread ($\theta\%_{MRR}$), estimated using the Madhavan, Richardson and Rooman's (1997) model. Time to maturity (TTM) is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. $MONTH$ represents a vector of dummy variables for each month. Year fixed-effect is included in all regressions. The coefficient and significance (t-statistics) for the time-to-maturity pattern of information asymmetry are that for TTM from equation (i). The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is ($\beta \times \delta$). The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.9: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship using the Madhavan, Richardson and Rooman's (1997) information asymmetry component measured as percentage of the bid-ask spread (continued).

	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
Time-to-maturity pattern of information asymmetry (x10^{-3})	-2.917***	-1.279***	-1.336***	-0.656***	-0.934***	-1.128***
	(-6.96)	(-4.18)	(-4.23)	(-2.82)	(-3.24)	(-3.43)
Impact of information asymmetry on return volatility	0.505***	2.180***	0.952***	1.699***	1.259***	1.347***
	(5.03)	(16.39)	(6.31)	(6.65)	(8.09)	(14.66)
The speculative effect (x10^{-3})	-1.471***	-2.781***	-1.272***	-1.114***	-1.178***	-1.520***
	(-4.08)	(4.05)	(-3.51)	(-2.60)	(-3.01)	(-3.34)
The price elasticity effect (x10^{-3})	0.429	-3.331***	-1.452	-0.572	-1.736	-1.605
	(0.19)	(-2.68)	(-1.06)	(-0.44)	(-1.35)	(-1.29)
Overall effect (x10^{-3})	-1.042	-6.112***	-2.724**	-1.686	-2.914**	-3.125**
	(-0.69)	(-4.21)	(-1.96)	(-1.21)	(-2.20)	(-2.41)
Observations	2728	2723	2728	2730	2725	2726

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility using the following regressions (i) $\theta\%_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta\%_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. Information asymmetry is the daily information asymmetry component measured as the percentage of the bid-ask spread ($\theta\%_{MRR}$), estimated using the Madhavan, Richardson and Rooman's (1997) model. Time to maturity (TTM) is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. $MONTH$ represents a vector of dummy variables for each month. Year fixed-effect is included in all regressions. The coefficient and significance (t-statistics) for the time-to-maturity pattern of information asymmetry are that for TTM from equation (i). The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is ($\beta \times \delta$). The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Finally, I conduct sub-sample analyses by investigating the 2007-2009 crisis period and post-crisis period separately. Table 2.10 shows the result for the crisis period and Table 2.11 shows the result for the post-crisis period. During the crisis, the relationship between information asymmetry and time-to-maturity is generally weaker than our full-sample results. The reason could be that investors increasingly look to hedge their investments using commodity futures during the crisis. As a result, shocks from other markets (noise shocks) become more persistent. On the other hand, fundamental shocks are not directly affected by the crisis. Consequently, the increase in information asymmetry when the futures contract matures is not as significant, hence the weaker results. In contrast, the impact that information asymmetry has on return volatility remains strong in both periods.

Table 2.10: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship during the 2007-2009 crisis period.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
Time-to-maturity pattern of information asymmetry (x10^{-3})	-0.574***	-0.268*	-0.210**	-0.018	-0.637***	-0.020
	(-3.36)	(-1.88)	(-2.47)	(-1.43)	(-3.43)	(-0.37)
Impact of information asymmetry on return volatility	13.147***	15.262***	24.020***	166.403***	10.074***	10.437***
	(6.70)	(13.01)	(9.55)	(8.27)	(10.27)	(5.96)
The speculative effect (x10^{-3})	-7.546***	-4.095*	-5.036**	-3.060	-6.415***	-0.370
	(-2.94)	(-1.86)	(-2.39)	(-1.41)	(-3.25)	(-0.37)
The price elasticity effect (x10^{-3})	2.086	-4.999	-0.126	-2.082	-0.921	-4.470***
	(0.53)	(-1.42)	(-0.04)	(-0.64)	(-0.33)	(-2.91)
Overall effect (x10^{-3})	-5.460	-9.094**	-5.162	-5.142	-7.336**	-4.840***
	(-1.42)	(-2.16)	(-1.41)	(-1.40)	(-2.21)	(-2.88)
Observations	397	397	397	397	397	367

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility during the 2007-2009 crisis period (from 01/10/2007 to 30/06/2009) using the following regressions (i) $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. θ_{MRR} is the daily information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. TTM is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for every month of the year. Year fixed-effect is included in all regressions. The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is $(\beta \times \delta)$. The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.10: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship during the 2007-2009 crisis period (continued).

	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
Time-to-maturity pattern of information asymmetry (x10^{-3})	-0.035	-0.067***	-0.034	-0.082*	-0.215	-0.595
	(-1.34)	(-2.71)	(-0.75)	(-1.85)	(-0.65)	(-0.67)
Impact of information asymmetry on return volatility	48.316***	57.016***	30.703***	33.282***	7.291***	0.965***
	(8.92)	(9.43)	(10.51)	(11.15)	(20.20)	(6.59)
The speculative effect (x10^{-3})	-1.679	-3.792***	-1.037	-2.722*	-1.566	-0.570
	(-1.33)	(-2.60)	(-0.75)	(-1.83)	(-0.65)	(-0.67)
The price elasticity effect (x10^{-3})	2.396	-6.051**	-0.737	1.036	-0.262	-6.075***
	(0.96)	(-2.28)	(-0.44)	(0.75)	(-0.11)	(-3.37)
Overall effect (x10^{-3})	0.717***	-9.843***	-1.774	-1.686	-1.828	-6.645***
	(0.26)	(-3.28)	(-0.81)	(-0.81)	(-0.53)	(-3.59)
Observations	397	396	399	400	399	400

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility during the 2007-2009 crisis period (from 01/10/2007 to 30/06/2009) using the following regressions (i) $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. θ_{MRR} is the daily information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. TTM is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for every month of the year. Year fixed-effect is included in all regressions. The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is $(\beta \times \delta)$. The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.11: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship after the 2007-2009 crisis period.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Feeder cattle
Time-to-maturity pattern of information asymmetry (x10^{-3})	-0.444*** (-10.48)	-0.255*** (-6.90)	-0.212*** (-9.49)	-0.008*** (-4.00)	-0.359*** (-6.35)	-0.046*** (-3.43)
Impact of information asymmetry on return volatility	17.531*** (24.46)	22.298*** (17.71)	36.179*** (14.71)	351.539*** (9.74)	11.568** (-2.36)	61.376*** (26.18)
The speculative effect (x10^{-3})	-7.784*** (-9.63)	-5.681*** (-6.43)	-7.737*** (-7.97)	-2.716*** (-3.70)	-4.161** (-2.21)	-2.822*** (-3.40)
The price elasticity effect (x10^{-3})	0.126 (0.09)	-1.984 (-1.39)	-4.755*** (3.48)	-3.177** (-2.17)	-3.392** (-2.36)	0.648 (0.58)
Overall effect (x10^{-3})	-7.658*** (-4.89)	-7.665*** (-4.62)	-12.429*** (-7.87)	-5.893*** (-3.60)	-7.553*** (-4.67)	-2.174* (-1.65)
Observations	1891	1892	1892	1892	1891	1885

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility for the period after the 2007-2009 crisis (after 30/06/2009) using the following regressions (i) ${\theta_{MRR}}_t = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta {\theta_{MRR}}_t + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. θ_{MRR} is the daily information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. TTM is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for every month of the year. Year fixed-effect is included in all regressions. The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is $(\beta \times \delta)$. The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 2.11: Testing the mediating role of information asymmetry on the return volatility – time-to-maturity relationship after the 2007-2009 crisis period (continued).

	Lean hogs	Live cattle	Copper	Gold	Silver	Crude oil
Time-to-maturity pattern of information asymmetry (x10^{-3})	-0.047***	-0.034***	-0.017***	-0.044**	-1.366***	-0.833**
	(-9.21)	(-4.51)	(-4.91)	(-1.99)	(-4.34)	(-2.16)
Impact of information asymmetry on return volatility	162.952***	194.846***	57.286***	58.369***	2.181***	1.986***
	(23.89)	(21.04)	(16.47)	(45.44)	(22.31)	(-3.09)
The speculative effect (x10^{-3})	-7.740***	-6.622***	-0.950***	-2.577**	-2.979***	-1.752*
	(-8.59)	(-4.41)	(-4.71)	(-1.99)	(-4.26)	(1.77)
The price elasticity effect (x10^{-3})	2.372	0.763	-2.036***	0.520	-1.524	-3.528***
	(1.58)	(0.51)	(-4.51)	(0.57)	(-1.09)	(-3.09)
Overall effect (x10^{-3})	-5.368***	-5.859***	-2.986***	-2.057	-4.503***	-5.280***
	(-3.23)	(-3.45)	(-6.01)	(-1.35)	(-2.91)	(-2.68)
Observations	1891	1891	1892	1892	1888	1849

This table examines the relationships information asymmetry has with time-to-maturity and return volatility, as well as the speculative effect, the price elasticity effect, and the overall effect of time-to-maturity on return volatility for the period after the 2007-2009 crisis (after 30/06/2009) using the following regressions (i) $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where return volatility (RV) is the natural logarithm of the daily five-minute realized volatility. θ_{MRR} is the daily information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. TTM is the number of days until expiration. LN_NT is the natural logarithm of the number of trades during the day. MONTH represents a vector of dummy variables for every month of the year. Year fixed-effect is included in all regressions. The coefficient for the overall effect is Ψ, the coefficient for the direct effect (the price elasticity effect) is ψ, and the coefficient for the indirect effect (the speculative effect) is $(\beta \times \delta)$. The significance (t-statistics) for each effect is calculated following Sobel (1982) and Baron and Kenny (1986). Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

2.7. Conclusion

In this chapter, I show that, consistent with Hong's (2000) first hypothesis, information asymmetry increases as the futures contract rolls towards maturity. But, in contrast to Hong's second hypothesis, I find that information asymmetry increases return volatility. This leads to the mediating impact of information asymmetry on return volatility (the speculative effect) being positive as the futures contract nears maturity. I also present a model to illustrate that my findings could be attributed to uninformed hedgers not learning about their information disadvantage. The results for the price elasticity effect are mixed across futures.

CHAPTER 3

THE LEVEL OF FUTURES MARKET ACTIVITY AND THE SENSITIVITY PATTERN

3. THE LEVEL OF FUTURES MARKET ACTIVITY AND THE SENSITIVITY PATTERN

3.1. Introduction

In this chapter, I provide the second explanation for the mixed results on the Samuelson effect in the literature. Prior studies focus on the time-to-maturity pattern of futures return volatility (the volatility pattern) rather than the pattern of the sensitivity of futures return volatility to information flows (the sensitivity pattern). The Samuelson effect has the underlying assumption that the sensitivity pattern monotonically rises as the contract nears maturity, leading to a similar volatility pattern. This may not be true. In fact, it is more likely that the sensitivity pattern will vary, and be dependent upon, the level of market activity of the contract (see Kyle, 1985; Admati and Pfleiderer, 1988; and Bessembinder and Seguin, 1993). In addition, as Anderson and Danthine (1983) highlight, information is not likely to flow uniformly into the market during the life of the futures contract, further leading to changes in the volatility pattern.

Based on these points, I infer that the sensitivity and volatility patterns will not monotonically rise. Instead, I hypothesize that the sensitivity pattern will be a quadratic function of time-to-maturity. Specifically, I expect to find an inverted U-shape relationship, given that is the general pattern of market activity most contracts experience. Investigations by the Commodity Exchange Authority (1960) and Powers (1967) show that open interest, reflecting hedging demand, rises as commodities are produced and stored. It often peaks right after harvest (for agricultural futures) when stocks are highest, and starts to decrease as hedgers close their positions when stocks move out of storage. Trading volume is expected to follow a similar pattern since trading by speculators generally corresponds to hedging activity (Working, 1970; Powers, 1967; Leuthold, 1983).[9] Figure 1.2 in Chapter 1 shows the average trading volume and open interest over the life of September wheat futures contracts traded between 2003 and 2016. Both the levels of trading volume and open interest display an inverted U-shape pattern. Bessembinder and Seguin (1993) also document that futures return volatility is positively related to expected trading volumes and negatively related to expected open interest. Therefore, if the levels of trading volume and of open interest display a quadratic relationship with time-to-maturity, then I postulate that so too will the sensitivity pattern.

I empirically test my hypothesis on twelve commodity futures trading on four exchanges under the Chicago Mercantile Exchange group of exchanges (CME Group). The futures include agricultural (grains, oilseeds, and livestock), metals and energy futures. I collect all contracts traded between January 1st, 2003 and June 30th, 2014. I represent volatility as the daily realized volatility calculated from the sum of the five-minute squared realized returns (Andersen and Bollerslev, 1998) using intraday data from Thompson Reuters Tick History (TRTH). I measure information flows by the number of daily news items about the commodity, extracted from the Thompson Reuters News Analytics (TRNA) database. The TRNA database provides comprehensive data on daily commodity news coverage and has been used in previous studies examining commodity news flows (see, for example, Smales, 2014). I calculate SENSITIVITY, the measure of the sensitivity of

[9] The literature (see Bessembinder and Seguin, 1993; Daigler and Wiley, 1999) suggests that the absolute value of trading volume and open interest is composed of the "expected" and "unexpected" components. The "unexpected" volume and open interest reflect shocks in information flows, which result in the day-to-day seesaw shape. The "expected" (or "level" or "average") volume and open interest represent the level of market activity related to non-informational factors (i.e., supply and demand), which follow a steady long-term pattern. My focus here is the expected volume and open interest..

return volatility to information flows, as the ratio of return volatility to the number of daily news items.

To formally establish that trading volume and open interest follows an inverted U-shape pattern over the life of a commodity futures contract, I regress each of them on the quadratic function of time-to-maturity. I measure time-to-maturity (TTM) as the squared root of the number of days to maturity. The results show that for both trading volume and open interest, the coefficient for TTM (TTM^2) is positive (negative) and significant for all twelve commodities. This confirms the inverted U-shape pattern of futures trading volume and open interest.[10]

To examine the changes in SENSITIVITY over a futures contract life, I start with a univariate analysis by dividing the sample into four quartiles based on the time-to-maturity of each futures contract. I then examine the differences in the means of SENSITIVITY between the quartiles. The results provide evidence of an inverted U-shape sensitivity pattern for seven of the commodity futures (with the maxima reached in the third quartile for copper and silver, and in the second quartile for the other five futures). This supports the regression results that find the coefficients for TTM (TTM^2) are positive (negative) and significant for all twelve futures. These results are robust when using as my proxy for information flows only news items that reference the commodity in the headline and when using the logarithm of the number of days to maturity to represent time.

[10] Following Bessembinder and Seguin (1993) and Daigler and Wiley (1999), I also use the AR(10) and ARIMA(0,1,10) models to extract the expected daily trading volume and open interest. The results for the quadratic regressions using the expected values also indicate a clear inverted U-shape pattern.

To analyse the inverted U-shape of the time-to-maturity pattern of open interest, trading volume and SENSITIVITY, I calculate peak-to-maturity (PTM). PTM is the number of days between when the pattern peaks and the maturity date of the contract, measured as a percentage of the contract's life. A smaller PTM will indicate that the pattern peaks later in the life of the contract (i.e. the pattern tilts more towards maturity). I find that open interest peaks around the half-life of a contract (the average PTM is 56%). On the other hand, the tilt of the trading volume pattern varies across futures. This suggests that the relationship between speculative trading and open interest suggested by the literature (Working, 1970; Powers, 1967; Leuthold, 1983) is not identical across futures. It will influence the sensitivity pattern as I find the tilt of the sensitivity pattern generally correlates to that of the pattern of trading volume (the correlation coefficient of $\text{PTM}_{\text{Volume}}$ and $\text{PTM}_{\text{SENSITIVITY}}$ is 0.82). The sensitive pattern tilts more towards maturity for energy and agricultural futures and less so for metal futures.

The difference in how the sensitivity pattern tilts towards maturity across futures will affect tests for a linear volatility pattern. This is important to analyse given that most previous research makes this linear assumption. As SENSITIVITY rises, peaks, and falls over the contract life, return volatility generally follows. Thus, we are more likely to find stronger evidence that volatility increases closer to the maturity date if the inverted U-shape of the sensitivity pattern tilts more towards maturity. As expected, my regression results show that while energy and agricultural futures have negative and significant TTM coefficients, this is not the case for metals (TTM is insignificant for silver and is positive and significant, at the one percent level, for gold). My results resemble that of Bessembinder et al. (1996) and Duong and Kalev (2008), who also find weak or insignificant results for metals.

My findings have important practical implications. Futures return volatility is an essential input for forming trading strategies, setting margins and pricing options. Therefore, market participants seeking to determine which contract will likely have the highest return volatility associated with it will want to take into account the inverted U-shape of the sensitivity pattern. This is because the predicted peak of the sensitivity pattern of a futures contract can provide a better indication of the highest level of return volatility the contract is likely to obtain as opposed to how far the contract is away from maturity. As an example, traders who prefer volatility (option buyers, for example) should follow the closest-to-peak futures price series instead of the often used closest-to-maturity series to maximize the return volatility of their positions.

To show the value in using closest-to-peak futures, I construct two types of price series. The first is constructed from a continuous series of closest-to-peak futures for each commodity in my sample, and the second uses closest-to-maturity futures. I then compare their average daily return volatility using the in-sample data (from January 1st, 2003 to June 30th, 2014) as well as for an out-of-sample period from July 1st, 2014 to December 31th, 2016. The in-sample results show that the average daily volatility of the closest-to-peak price series is higher than that of the closest-to-maturity series for five futures. The average annualised increase in return volatility is 9.98%. To estimate the economic significance, I use the maintenance margin required for trading futures as an estimate of the dollar price of volatility because the margin is set based on the level of volatility in the futures market. My calculation suggests that such increase in return volatility is worth $7,169 for an open position of 1000 contracts. The results for the out-of-sample period also show higher volatility for the closest-to-peak series for four futures (2.63% annualized higher volatility, which is worth $2,935 for an open position of 1000 contracts).

3.2. Data and method

My data consists of twelve commodity futures traded on the four exchanges under the CME Group between January 1st, 2003 and June 30th, 2014. The futures are corn and wheat (grains), soybean, soybean meal, and soybean oil (oilseeds) traded on the Chicago Board of Trade (CBOT); lean hogs and live cattle (livestock) on the Chicago Mercantile Exchange (CME); copper, gold, and silver (metals) on the Commodity Exchange (COMEX); and crude oil and natural gas (energy) on the New York Mercantile Exchange (NYMEX). I collect intraday trading data from Thomson Reuter Tick History (TRTH) for these contracts. I exclude the early period of each futures contract when market activity is low. To do this objectively, I run a Wald test to detect a structural break in the open interest of the contract to determine when it starts significantly rising. As an example, the September wheat contracts in Figure 1.2 have structural break point dates ranging from 118 days to 131 days to maturity. I also follow the literature and drop the period when a contract enters its settlement month (Bessembinder et al., 1996; Duong and Kalev, 2008). Furthermore, I exclude illiquid contract months when average daily trading volume is less than two thousand contracts.[11]

I measure the daily sensitivity of futures return volatility to information flows as the natural logarithm of the ratio of return volatility to the number of news items that are recorded for the day about the underlying commodity:

$$\mathrm{SENSITIVITY}_t = ln\left(\frac{\mathrm{VOLATILITY}_t}{\mathrm{NEWS}_t}\right) \tag{18}$$

[11] Namely, May futures contracts for lean hogs, October contracts for gold and January contracts for silver.

where return volatility is the sum of the squared five-minute realized returns (Andersen and Bollerslev, 1998) calculated using intraday data obtained from TRTH. The latest quotes available at or prior to each five-minute mark are used to construct the five-minute price series. I use mid-point quotes to calculate the five-minute returns to avoid bid-ask bounce issues (Roll, 1984). Specifically;

$$\text{VOLATILITY}_t = \sum_{j=1}^{k_t} \left[ln\left(\frac{\text{Bid}_{j,t} + \text{Ask}_{j,t}}{2}\right) - ln\left(\frac{\text{Bid}_{j-1,t} + \text{Ask}_{j-1,t}}{2}\right)\right]^2 \qquad (19)$$

where k_t indicates the number of five-minute intervals throughout the trading day t.

I extract the number of daily news items (NEWS) about each commodity from the Thompson Reuters News Analytics (TRNA) database. The database contains news headlines about commodities and each news item has a reference code indicating the commodity or group of commodities that the news is related to.

I provide in Table 3.1 the summary statistics of the sample, including the type of commodity, the exchange that the futures are traded on, their expiration months, and their TRNA reference codes. Table 3.1 also includes the number of observations and number of contracts, as well as the average daily sensitivity of return volatility to information flows (SENSITIVITY), trading volume, open interest and average contract life.

Table 3.1: Summary statistics.

Commodity futures group	Futures	Futures exchange	Expiration month	TRNA news code	Number of observations	Number of contracts	Average daily SENSITIVITY	Average daily volume	Average daily open interest	Average contract life
Grains	Corn	CBOT	3,5,7,9,12	GRA	6,271	57	-13.627	78,270	332,715	173
Grains	Wheat	CBOT	3,5,7,9,12	GRA	5,597	57	-13.371	30,679	122,109	157
Oilseeds	Soybean	CBOT	1,3,5,7,8,9,11	OILS	6,441	79	-13.557	48,489	134,073	132
Oilseeds	Soybean meal	CBOT	1,3,5,7,8,9,10,12	MEAL	6,557	90	-13.256	18,296	55,144	120
Oilseeds	Soybean oil	CBOT	1,3,5,7,8,9,10,12	OILS	7,184	90	-13.572	21,599	73,222	130
Livestock	Lean hogs	CME	2,4,5[#],6,7,8,10,12	LIV	5,921	80	-13.758	10,372	52,341	122
Livestock	Live cattle	CME	2,4,6,8,10,12	LIV	4,826	68	-14.595	14,838	89,366	133
Metals	Copper	COMEX	3,5,7,9,12	MET	3,952	57	-13.817	20,153	55,504	128
Metals	Gold	COMEX	2,4,6,8,10[#],12	GOL	3,967	57	-13.462	82,367	181,805	128
Metals	Silver	COMEX	1[#],3,5,7,9,12	GOL	3,889	57	-12.303	25,687	56,088	127
Energy	Crude oil	NYMEX	Every month	CRU	9,111	135	-13.682	105,819	152,988	99
Energy	Natural gas	NYMEX	Every month	NGS	9,093	135	-12.315	44,686	96,163	98

SENSITIVITY is the sensitivity of futures return volatility to information flows, calculate as $\text{SENSITIVITY} = ln\left(\frac{\text{VOLATILITY}}{\text{NEWS}}\right)$, where VOLATILITY is the daily five-minute realized volatility (Andersen and Bollerslev, 1998), NEWS is the number of daily news about the commodity, identified using the TRNA news code. The daily trading volume and open interest are measured in number of contracts. Average contract life is measured in number of days. [#] indicates illiquid contract months not used in the sample.

To empirically confirm that trading volume and open interest form an inverted U-shape over the life of a futures contract, I regress trading volume and open interest for each commodity futures on time-to-maturity and its squared value:

$$\mathrm{DV}_{i,t} = \alpha + \beta_1 \mathrm{TTM}_{i,t} + \beta_2 \mathrm{TTM}_{i,t}^2 + \varepsilon_{i,t} \tag{20}$$

where the dependent variable $\mathrm{DV}_{i,t}$ represents either the natural logarithm of the trading volume or open interest for contract i on day t. TTM is the square root of the number of days to maturity. Contract and year fix effects are included. If trading volume and open interest both have an inverted U-shape relationship with time-to-maturity then we should find that the coefficient β_1 is positive and β_2 is negative. To test my hypothesis that SENSITIVITY is a quadratic function of TTM, I also use Equation (20) with the dependent variable, $\mathrm{DV}_{i,t}$, being the daily $\mathrm{SENSITIVITY}_{i,t}$ measure.

To analyse the inverted U-shape patterns of trading volume, open interest and SENSITIVITY across commodity futures, for each commodity futures I measure the distance between the peak of the patterns and maturity, which I call peak-to-maturity (PTM). The distance is calculated using the first derivative of Equation (20) and I take the square of it to get the PTM measure in days (as TTM is the square root of the number of days to maturity):

$$\mathrm{PTM} = \left(\frac{-\beta_1}{2\beta_2}\right)^2 \tag{21}$$

3.3. Empirical results

3.3.1. The time-to-maturity pattern of trading volume and open interest

To confirm the inverted U-shape time-to-maturity pattern of trading volume and open interest, Table 3.2 presents the regression results from Equation (3). Panel A shows the results for trading volume and Panel B shows the results for open interest. In both Panels, the coefficients for TTM (TTM^2) are positive (negative) and are significant, at the one percent level, for all futures. The positive coefficients for TTM and negative ones for TTM^2 indicate an inverted U-shape pattern for both trading volume and open interest over the life of a futures contract. As the levels of trading volume and open interest directly impact SENSITIVITY (Bessembinder and Seguin, 1993), this indicates that SENSITIVITY should be a quadratic function of TTM.

Table 3.2: Testing the time-to-maturity pattern of trading volume and open interest.

Panel A: Trading volume						
	Corn	Wheat	Soybean	Soybean meal	Soybean oil	Lean hogs
TTM	0.133***	0.617***	0.295***	0.174***	0.151***	0.995***
	(11.93)	(33.69)	(20.20)	(14.35)	(11.78)	(49.27)
TTM^2	-0.014***	-0.043***	-0.026***	-0.018***	-0.018***	-0.072***
	(-25.36)	(-42.34)	(-31.58)	(-27.29)	(-25.57)	(-55.24)
Constant	10.474***	8.16***	7.578***	7.720***	9.079***	4.835***
	(47.15)	(30.79)	(29.56)	(32.85)	(35.77)	(27.75)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	6,271	5,597	6,441	6,557	7,184	5,921
Adjusted R^2	0.354	0.271	0.171	0.294	0.326	0.595
	Live cattle	Copper	Gold	Silver	Crude oil	Natural gas
TTM	1.425***	1.483***	1.167***	1.600***	0.433***	0.106***
	(44.25)	(28.94)	(17.23)	(32.57)	(55.65)	(14.49)
TTM^2	-0.085***	-0.096***	-0.084***	-0.108***	-0.060***	-0.029***
	(-46.52)	(-32.25)	(-21.55)	(-38.48)	(-93.26)	(-51.98)
Constant	1.793***	5.361***	2.829***	6.841***	9.395***	9.308***
	(7.39)	(14.88)	(4.98)	(17.82)	(70.84)	(49.84)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	4,826	3,952	3,967	3,889	9,111	9,093
Adjusted R^2	0.462	0.085	0.230	0.017	0.562	0.747

This table presents the results for testing the time-to-maturity pattern of trading volume (Panel A) and open interest (Panel B) using the following regressions: $\mathrm{VOLUME}_{i,t} = \alpha + \beta_1 \mathrm{TTM}_{i,t} + \beta_2 \mathrm{TTM}^2_{i,t} + \varepsilon_{i,t}$ and $\mathrm{OPEN\_INTEREST}_{i,t} = \alpha + \beta_1 \mathrm{TTM}_{i,t} + \beta_2 \mathrm{TTM}^2_{i,t} + \varepsilon_{i,t}$, where $\mathrm{VOLUME}_{i,t}$ and $\mathrm{OPEN\_INTEREST}_{i,t}$ are the natural logarithms of trading volume and open interest for contract i on day t, respectively. Time-to-maturity (TTM) is measured as the square-root of the number of days to maturity. Contract and year fix effects are included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

Table 3.2: Testing the time-to-maturity pattern of trading volume and open interest (continued).

Panel B: Open interest						
	Corn	Wheat	Soybean	Soybean meal	Soybean oil	Lean hogs
TTM	0.545***	1.251***	0.692***	0.597***	0.671***	1.429***
	(59.09)	(82.03)	(59.90)	(65.25)	(65.14)	(118.92)
TTM^2	-0.028***	-0.070***	-0.039***	-0.033***	-0.037***	-0.092***
	(-61.17)	(-83.16)	(-61.17)	(-66.77)	(-66.60)	(-119.35)
Constant	9.032***	5.429***	6.307***	6.683***	6.333***	5.996***
	(49.05)	(24.65)	(31.07)	(37.71)	(31.03)	(57.88)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	6,271	5,597	6,441	6,557	7,184	5,921
Adjusted R^2	0.290	0.500	0.130	0.185	0.211	0.011
	Live cattle	Copper	Gold	Silver	Crude oil	Natural gas
TTM	2.181***	2.540***	2.194***	2.168***	1.030***	0.788***
	(159.41)	(86.67)	(45.07)	(67.26)	(135.50)	(118.70)
TTM^2	-0.123***	-0.143***	-0.127***	-0.122***	-0.091***	-0.058***
	(-157.86)	(-83.89)	(-45.86)	(-66.50)	(-136.35)	(-116.49)
Constant	0.723***	1.546***	-0.758*	2.417***	8.546***	6.984***
	(7.01)	(7.51)	(-1.86)	(9.61)	(72.30)	(41.34)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	4,826	3,952	3,967	3,889	9,111	9,093
Adjusted R^2	0.825	0.001	0.119	0.151	0.583	0.600

This table presents the results for testing the time-to-maturity pattern of trading volume (Panel A) and open interest (Panel B) using the following regressions: $\mathsf{VOLUME}_{i,t} = \alpha + \beta_1 \mathsf{TTM}_{i,t} + \beta_2 \mathsf{TTM}^2_{i,t} + \varepsilon_{i,t}$ and $\mathsf{OPEN\_INTEREST}_{i,t} = \alpha + \beta_1 \mathsf{TTM}_{i,t} + \beta_2 \mathsf{TTM}^2_{i,t} + \varepsilon_{i,t}$, where $\mathsf{VOLUME}_{i,t}$ and $\mathsf{OPEN\_INTEREST}_{i,t}$ are the natural logarithms of trading volume and open interest for contract i on day t, respectively. Time-to-maturity (TTM) is measured as the square-root of the number of days to maturity. Contract and year fix effects are included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

3.3.2. The sensitivity pattern

To empirically test the main hypothesis that the sensitivity pattern has an inverted U-shape, Table 3.3 shows univariate analysis of how SENSITIVITY changes over the life of a futures contract life by dividing its life into four quartiles. When calculating the differences in the mean of SENSITIVITY across the quartiles I find that seven futures show evidence that SENSITIVITY follows an inverted U-shape pattern. For corn, wheat, soybean, lean hogs, and crude oil futures, the mean of SENSITIVITY increases from the fourth to the second quartile, then decreases from the second to the first quartile. The differences in mean are significant to at least the ten percent level. For copper and silver futures, mean SENSITIVITY increases from the fourth to the third quartile, before declining. Soybean meal, soybean oil, and live cattle futures also show a significant increase in the mean of SENSITIVITY between the fourth and third quartiles, but the reversal that is seen in the other futures contracts is not present.

Table 3.3: Univariate test for the change in SENSITIVITY over the futures contract life.

	4th quartile (Far) → 3rd quartile	3rd quartile → 2nd quartile	2nd quartile → 1st quartile (Near)
Corn	0.176***	0.101***	-0.052**
	(5.87)	(3.59)	(-1.85)
Wheat	0.087***	0.130***	-0.048**
	(3.07)	(4.65)	(-1.72)
Soybean	0.116***	0.068***	-0.044**
	(4.49)	(2.67)	(-1.74)
Soybean meal	0.204***	0.001	-0.008
	(7.22)	(0.01)	(-0.31)
Soybean oil	0.149***	0.067***	0.025
	(5.63)	(2.60)	(0.98)
Lean hogs	0.143***	0.039*	-0.059**
	(5.45)	(1.49)	(-2.27)
Live cattle	0.108***	0.028	-0.025
	(3.71)	(0.93)	(-0.85)
Copper	0.107***	-0.099***	-0.276***
	(3.03)	(-2.81)	(-7.18)
Gold	-0.113***	-0.005	-0.057**
	(-3.50)	(-0.16)	(-1.83)
Silver	0.051*	-0.090***	0.019
	(1.42)	(-2.75)	(0.61)
Crude oil	0.075***	0.026*	-0.068**
	(3.39)	(1.28)	(-2.08)
Natural gas	0.161***	0.090***	0.091***
	(7.13)	(3.87)	(3.83)

This table presents the univariate test for the change in the sensitivity of return volatility to information flows (SENSITIVITY) when the futures contract rolls towards maturity. The sample is divided into four quartiles based on the time-to-maturity (TTM) of each contract and the results for the t-test for the difference in means of SENSITIVITY between the quartiles are reported. SENSITIVITY is the daily sensitivity of futures return volatility to information flows, calculated as $\text{SENSITIVITY} = ln\left(\frac{\text{VOLATILITY}}{\text{NEWS}}\right)$, where VOLATILITY is the daily five-minute realized volatility (Andersen and Bollerslev, 1998) and NEWS is the number of daily news about the commodity, identified using the TRNA news code. TTM is measured as the square-root of the number of days to maturity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

In Table 3.4 I test if SENSITIVITY is a quadratic function of time-to-maturity by regressing SENSITIVITY on TTM and TTM^2. The coefficients for TTM are positive and significant for all twelve futures. Also, as expected, the coefficients for TTM^2 are negative and significant. The positive coefficients for TTM and the negative coefficients for TTM^2 indicate that the sensitivity pattern has an inverted U-shape for all futures. To illustrate the results, Figure 3.1 plots the fitted sensitivity pattern from the regression results.

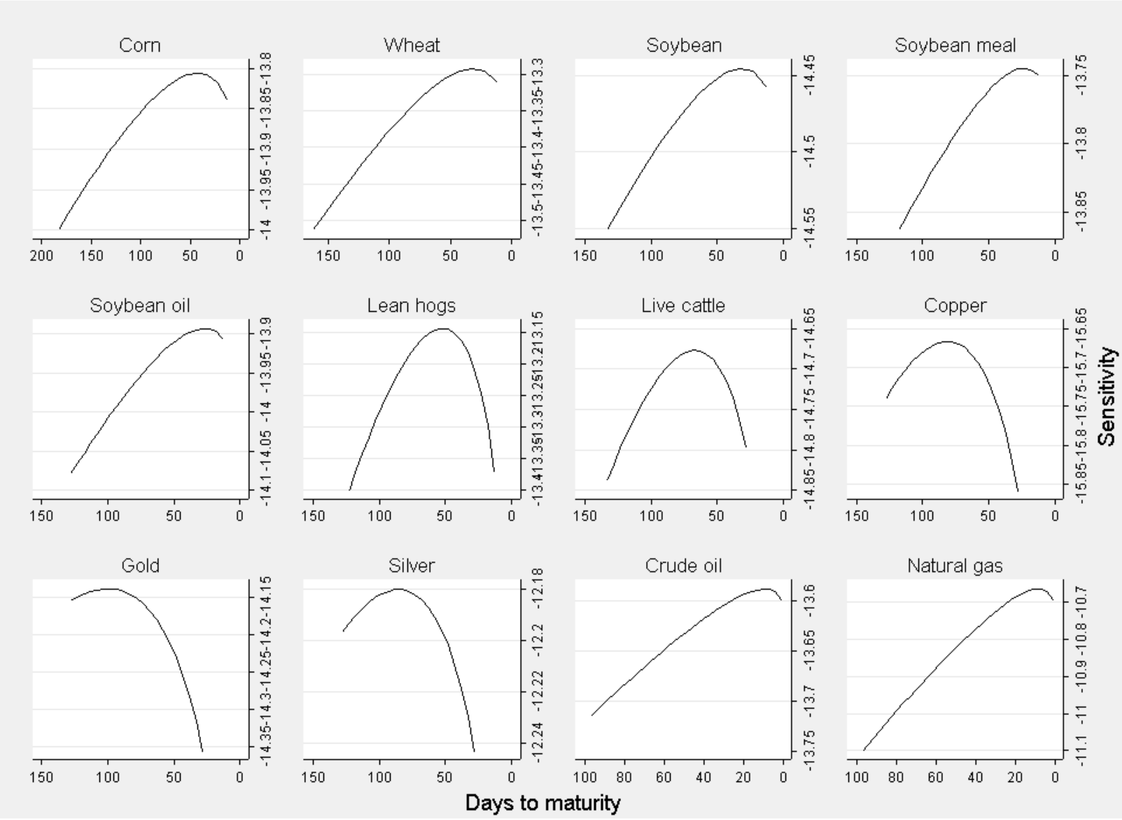
To ensure the results for the main hypothesis are robust, I also use alternative measures for the variables. First, instead of using commodity codes to capture information flows, I only count the news items with the name of the commodity (for example, "corn" for corn futures) in the headline to limit the news counts to those that are specifically related to the commodity. This will exclude peripheral news that the commodity code includes that relates to the commodity group. Table 3.5 shows the results hold for all futures, except for soybean where the coefficient for TTM is now statistically insignificant. The results also hold when I use ten-minute realized volatility or measure TTM as the natural logarithm of the number of days to maturity instead of using the square-root. Table 3 and 4 in the Appendix present the results.

Table 3.4: Testing the sensitivity pattern.

	Corn	Wheat	Soybean	Soybean meal	Soybean oil	Lean hogs
TTM (10^{-2})	5.082***	4.771***	3.364**	3.114**	5.091***	25.026***
	(3.73)	(2.76)	(2.18)	(2.00)	(3.76)	(9.51)
TTM² (10^{-2})	-0.391***	-0.430***	-0.301***	-0.323***	-0.492***	-1.730***
	(-5.85)	(-4.51)	(-3.49)	(-3.87)	(-6.68)	(-10.23)
Constant	-13.971***	-13.424***	-14.539***	-13.820***	-14.025***	-14.048***
	(-51.48)	(-53.76)	(-53.60)	(-45.88)	(-52.31)	(-61.85)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	6,271	5,597	6,441	6,557	7,184	5,921
Adjusted R^2	0.046	0.037	0.071	0.232	0.143	0.078
	Live cattle	Copper	Gold	Silver	Crude oil	Natural gas
TTM (10^{-2})	23.306***	24.846***	19.611***	7.376*	1.620*	4.978***
	(5.17)	(3.77)	(4.73)	(1.87)	(1.94)	(5.87)
TTM² (10^{-2})	-1.425***	-1.378***	-0.980***	-0.398*	-0.271***	-0.882***
	(-5.57)	(-3.26)	(-4.14)	(-1.78)	(-3.94)	(-13.79)
Constant	-15.630***	-16.787***	-15.119***	-12.522***	-13.612***	-10.735***
	(-46.00)	(-7.92)	(-43.53)	(-40.76)	(-95.59)	(-49.66)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	4,826	3,952	3,967	3,889	9,111	9,093
Adjusted R^2	0.156	0.117	0.006	0.005	0.106	0.129

This table presents the results for testing the time-to-maturity pattern of the sensitivity of return volatility to information flows (the sensitivity pattern) using the following regression: $\text{SENSITIVITY}_{i,t} = \alpha + \beta_1 \text{TTM}_{i,t} + \beta_2 \text{TTM}_{i,t}^2 + \varepsilon_{i,t}$, where $\text{SENSITIVITY}_{i,t}$ is the sensitivity of futures return volatility to information flows of contract i on day t, calculated as $\text{SENSITIVITY}_{i,t} = ln\left(\frac{\text{VOLATILITY}_{i,t}}{\text{NEWS}_{i,t}}\right)$, $\text{VOLATILITY}_{i,t}$ is the daily five-minute realized volatility (Andersen and Bollerslev, 1998) and $\text{NEWS}_{i,t}$ is the number of daily news about the commodity, identified using the TRNA news code. Time-to-maturity (TTM) is measured as the square-root of the number of days to maturity. Contract and year fix effects are included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

Figure 3.1: The sensitivity pattern.



This figure plots the fitted quadratic sensitivity pattern using the regression results for $\text{SENSITIVITY}_{\text{i,t}} = \alpha + \beta_1 \text{TTM}_{i,t} + \beta_2 \text{TTM}^2_{i,t} + \varepsilon_{i,t}$, where $\text{SENSITIVITY}_{i,t}$ is the sensitivity of futures return volatility to information flows of contract i on day t, calculated as $\text{SENSITIVITY}_{i,t} = ln\left(\frac{\text{VOLATILITY}_{i,t}}{\text{NEWS}_{i,t}}\right)$, $\text{VOLATILITY}_{i,t}$ is the daily five-minute realized volatility (Andersen and Bollerslev, 1998) and $\text{NEWS}_{i,t}$ is the number of daily news about the commodity, identified by the headlines containing the name of the commodity. Time-to-maturity (TTM) is measured as the square-root of the number of days to maturity. Contract and year fix effects are included.

Table 3.5: Testing the sensitivity pattern using only news headlines containing the name of the commodity.

	Corn	Wheat	Soybean	Soybean meal	Soybean oil	Lean hogs
TTM (10^{-2})	4.193***	5.511***	2.080	5.199**	5.642***	24.550***
	(3.22)	(3.15)	(1.28)	(2.11)	(3.60)	(9.59)
TTM^2 (10^{-2})	-0.351***	-0.484***	-0.218**	-0.651***	-0.510***	-1.670***
	(-5.49)	(-5.01)	(-2.41)	(-3.23)	(-5.98)	(-10.16)
Constant	-11.835***	-11.798***	-12.369***	-6.976***	-10.957***	-12.674***
	(-45.53)	(-46.67)	(-43.41)	(-32.77)	(-35.20)	(-57.39)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	6,271	5,597	6,441	6,557	7,184	5,921
Adjusted R^2	0.062	0.024	0.088	0.002	0.012	0.263
	Live cattle	Copper	Gold	Silver	Crude oil	Natural gas
TTM (10^{-2})	22.023***	20.578***	18.946***	7.706*	1.938**	3.072**
	(4.68)	(2.97)	(4.57)	(1.78)	(2.29)	(2.44)
TTM^2 (10^{-2})	-1.370***	-1.008**	-0.956***	-0.431*	-0.299***	-0.666***
	(-5.13)	(-2.27)	(-4.04)	(-1.75)	(-4.30)	(-7.01)
Constant	-13.706***	-17.571***	-14.150***	-10.461***	-12.734***	-7.528***
	(-38.66)	(-7.90)	(-40.66)	(-31.02)	(-88.38)	(-20.44)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	4,826	3,952	3,967	3,889	9,111	9,093
Adjusted R^2	0.393	0.037	0.023	0.051	0.132	0.256

This table presents the results for testing the time-to-maturity pattern of the sensitivity of return volatility to information flows (the sensitivity pattern) using the following regression: $\mathsf{SENSITIVITY}_{i,t} = \alpha + \beta_1 \mathsf{TTM}_{i,t} + \beta_2 \mathsf{TTM}^2_{i,t} + \varepsilon_{i,t}$, where $\mathsf{SENSITIVITY}_{i,t}$ is the sensitivity of futures return volatility to information flows of contract i on day t, calculated as $\mathsf{SENSITIVITY}_{i,t} = ln\left(\frac{\mathrm{VOLATILITY}_{i,t}}{\mathrm{NEWS}_{i,t}}\right)$, $\mathsf{VOLATILITY}_{i,t}$ is the daily five-minute realized volatility (Andersen and Bollerslev, 1998) and $\mathsf{NEWS}_{i,t}$ is the number of daily news about the commodity, identified by the headlines containing the name of the commodity. Time-to-maturity (TTM) is measured as the square-root of the number of days to maturity. Contract and year fix effects are included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

3.3.3. Peak-to-maturity

To examine in more detail the inverted U-shape patterns of trading volume, open interest and SENSITIVITY for each futures, I proceed to calculate the PTM for each pattern using Equation (21). A smaller PTM will indicate that the pattern peaks and starts to decline closer to maturity (i.e. the pattern tilts more towards maturity), and vice versa. Table 3.6 presents the PTM for the futures in the sample, measured in days and also as a percentage of the average contract life (obtained from Table 3.1). Take wheat for example, a $\mathsf{PTM}_{\mathrm{Volume}}$ of 32% means that trading volume of wheat futures peaks when the contract has passed 68% of its life. Open interest peaks after 49% of wheat contract life and SENSITIVITY peaks after 80%.

We can see that in general, open interest peaks around the half-life of the contract. $\mathsf{PTM}_{\mathrm{Open\ interest}}$ ranges from 32% (crude oil) to 68% (soybean meal) with an average of 56%. This is consistent with the notion that each futures contract month, at least for the agricultural commodity futures, is seasonally tailored to a harvest or production cycle in order to facilitate hedging (Working, 1970; Hieronymus, 1978). Open interest rises early in the season as stocks build up, then decreases when stocks decline and commodities are shipped out (Commodity Exchange Authority, 1960; Powers, 1967).

Table 3.6: Analysing the shape of the time-to-maturity pattern of trading volume, open interest and SENSITIVITY.

	PTM_{Volume}		$PTM_{Open\ interest}$		$PTM_{SENSITIVITY}$	
	days	% of contract life	days	% of contract life	days	% of contract life
Corn	23	13%	95	55%	42	24%
Wheat	51	32%	80	51%	31	20%
Soybean	32	24%	79	60%	31	23%
Soybean meal	23	19%	82	68%	23	19%
Soybean oil	18	14%	82	63%	27	21%
Lean hogs	48	39%	60	49%	52	43%
Live cattle	70	53%	79	59%	67	50%
Copper	60	47%	79	62%	81	63%
Gold	48	38%	75	59%	100	78%
Silver	55	43%	79	62%	86	68%
Crude oil	13	13%	32	32%	9	9%
Natural gas	3	3%	46	47%	8	8%

This table presents the analysis of how the inverted U-shape of the time-to-maturity pattern of trading volume, open interest and SENSITIVITY tilts towards maturity for each commodity futures. The measure peak-to-maturity (PTM) is the average number of days between the peak of the pattern and maturity, calculated as $\mathrm{PTM} = \left(\frac{-\beta_1}{2\beta_2}\right)^2$, where β_1 and β_2 are the coefficients of TTM and TTM^2 from Table 3.2 (for trading volume and open interest) and Table 3.4 (for SENSITIVITY). The value of PTM as percentage of the contract life is calculated from dividing PTM by the average contract life obtained from Table 3.1.

The analysis of $\mathsf{PTM}_{\text{Volume}}$ indicates that the peak of the pattern of trading volume varies across futures. $\mathsf{PTM}_{\text{Volume}}$ for energy futures is small (3-13%), followed by that for grains and oilseeds futures (13-32%), then for livestock and metal futures (38-53%). This means the pattern of trading volume tilts more towards maturity for energy, grains and oilseeds futures than for livestock and metals futures. I expect that the inverted U-shape of the sensitivity pattern is mainly influenced by the pattern of trading volume. The reason is that the pattern of open interest does not vary much across futures (peaks around the half-life) and also Bessembinder and Seguin (1993) document a bigger impact on return volatility by the level of trading volume than by the level of open interest.

The results for $\mathsf{PTM}_{\text{SENSITIVITY}}$ supports my expectation. $\mathsf{PTM}_{\text{SENSITIVITY}}$ is smallest for energy futures (8-9%), implying that $\mathsf{SENSITIVITY}$ tends to decline only when the futures contract is very close to maturity. The peak of the sensitivity pattern of grains and oilseeds futures is also quite close to maturity ($\mathsf{PTM}_{\text{SENSITIVITY}}$ being 19%-24%). For livestock futures, the peak of the pattern is further from maturity ($\mathsf{PTM}_{\text{SENSITIVITY}}$ being 43%-50%). For metals futures, I observe that $\mathsf{SENSITIVITY}$ peaks early in the contract life, even before the futures contract reaches its half-life. $\mathsf{PTM}_{\text{SENSITIVITY}}$ is 63% for copper futures, 68% for silver futures, and is highest at 78% for gold futures. To further support my point, I also calculate the correlation coefficient of $\mathsf{PTM}_{\text{SENSITIVITY}}$ and $\mathsf{PTM}_{\text{Volume}}$ and find it to be high at 0.82. The correlation coefficient of $\mathsf{PTM}_{\text{SENSITIVITY}}$ and $\mathsf{PTM}_{\text{Open interest}}$ is about half of that, at 0.43.

3.3.4. The tilt of the sensitivity pattern and its impact on the linear test for the volatility pattern

The difference in how the sensitivity pattern tilts towards the maturity date across commodity futures could explain the mixed results when testing for a linear volatility pattern in previous studies. They assume that the sensitivity pattern monotonically increases closer to maturity, and so will the volatility pattern which generally tracks it (Rutledge, 1976; Milonas, 1986; Bessembinder et al., 1996; Duong and Kalev, 2008). Having shown an inverted U-shape for the sensitivity pattern, I expect that if the pattern tilts more (less) towards maturity, we are likely to find stronger (weaker) evidence that volatility increases closer to maturity. To test this for my sample, I test for a linear volatility pattern by regressing futures return volatility on time-to-maturity:

$$\text{VOLATIVITY}_{i,t} = \alpha + \beta\text{TTM}_{i,t} + \varepsilon_{i,t} \tag{22}$$

where $\text{VOLATIVITY}_{i,t}$ is the return volatility of futures contract i on day t, measured in natural logarithm. Year and contract fixed effects are also included. From the analysis of the sensitivity pattern above, we should expect the results for the linear volatility pattern are strongest for energy futures, then grains, oilseeds, livestock, and metal futures, in that order.

Table 3.7 presents the results. Consistent with my expectation, the results are strong for energy, grains, and oilseeds futures. The coefficients for TTM are negative and significant at the one percent level for those futures. The results are also significant at the five percent level for livestock futures. I do not find the same results for metal futures. The coefficient for TTM is negative and significant at the ten percent level for copper futures, and is insignificant for silver futures. For gold futures, it is positive and significant at the one percent level, suggesting that on average gold futures return volatility is actually lower when the contract is closer to maturity. In general, the results resemble that of Bessembinder et al. (1996) and Duong and Kalev (2008). Bessembinder et al. (1996) find weak results for metals and Duong and Kalev's (2008) results for gold futures are similar to my results. The results confirm my conjecture that for commodity futures of which the sensitivity pattern tilts more towards maturity, the test for a linear volatility pattern is more likely to yield stronger results that return volatility increases nearer to maturity.

Table 3.7: Testing the linear volatility pattern.

	Corn	Wheat	Soybean	Soybean meal	Soybean oil	Lean hogs
TTM (10^{-2})	-2.175***	-2.286***	-1.428***	-1.998***	-3.145***	-0.940**
	(-7.47)	(-7.22)	(-4.41)	(-5.94)	(-10.90)	(-2.56)
Constant	-3.531***	-3.227***	-4.724***	-4.121***	-4.059***	-4.287***
	(-13.90)	(-13.68)	(-17.84)	(-14.39)	(-15.69)	(-20.50)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	6,271	5,597	6,441	6,557	7,184	5,921
Adjusted R^2	0.161	0.144	0.011	0.081	0.102	0.012
	Live cattle	Copper	Gold	Silver	Crude oil	Natural gas
TTM (10^{-2})	-0.931**	-0.855*	2.638***	0.637	-1.283***	-5.972***
	(-2.12)	(-1.86)	(5.50)	(1.17)	(-6.32)	(-26.25)
Constant	-5.539***	-4.154***	-5.428***	-3.602***	-3.788***	-1.579***
	(-22.32)	(-16.98)	(-20.84)	(-12.91)	(-26.43)	(-7.83)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	4,826	3,952	3,967	3,889	9,111	9,093
Adjusted R^2	0.001	0.044	0.027	0.073	0.030	0.059

This table presents the results for testing the linear volatility pattern by regressing return volatility on time-to-maturity using the following regression: $\mathrm{VOLATIVITY}_{i,t} = \alpha + \beta \mathrm{TTM}_{i,t} + \varepsilon_{i,t}$, where $\mathrm{VOLATIVITY}_{i,t}$ is the return volatility of contract i on day t, measured in natural logarithm. Time-to-maturity (TTM) is measured as the square-root of the number of days to maturity. Year and contract fixed effects are also included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

3.3.5. Practical implications

The results above indicate that, conditional on information flows, futures return volatility is more likely to be higher (lower) when the contract is near to (far from) the peak of the sensitivity pattern rather than, as previously assumed, near to (far from) the maturity date. This suggests market participants should use the distance-to-peak as a better predictor of futures return volatility. For example, traders who prefer volatility, such as option buyers, are better off choosing the underlying futures contract that is closer to the peak of the sensitivity pattern when seeking contracts with the highest level of return volatility. I test this by constructing a closest-to-peak futures price series (based on a contract's distance-to-peak) and the often used closest-to-maturity series (based on a contract's distance-to-maturity). I then compare the average daily return volatility from these two series and examine if the closest-to-peak price series does have a higher return volatility.

I first test the above for an in-sample period from January 1st, 2003 to June 30th, 2014. I use the peak of the pattern identified using $\mathrm{PTM}_{\mathrm{SENSITIVITY}}$ in Table 3.6 to construct the closest-to-peak price series. For example, $\mathrm{PTM}_{\mathrm{SENSITIVITY}}$ for live cattle is 50%, which implies the sensitivity pattern will, on average, peak around the half-life of live cattle futures contracts. For a live cattle contract that starts trading 120 days from maturity, the peak of the sensitivity pattern will therefore be 60 days from maturity. If that contract is trading 70 (or 50) days from maturity, the distance-to-peak is 10 days. I create a continuous closest-to-peak price series by always switching to the contract with least distance-to-peak. The closest-to-maturity series is composed of contracts that are the nearest to maturity. I exclude gold and silver from this analysis as the results for these contracts indicate that return volatility does not increase closer to maturity.

In Panel A of Table 3.8, I find that the average volatility of the closest-to-peak price series is higher than that of the closest-to-maturity price series for five out of ten futures. As an example, the average daily volatility for lean hogs increases by 2.38% (from $(1.42\%)^2$ to $(1.44\%)^2$) if I use the closest-to-peak series instead of the closest-to-maturity series. To gauge the economic significance, I use the maintenance margin required for trading futures as the measure of the price of futures volatility, obtained from the CME Group.[12] The maintenance margin is set to cover the possible loss of an open position due to price movements. It is set based on the level of volatility in the market and is revised frequently when the level of volatility changes. For lean hogs, the average maintenance margin during the in-sample period is $963. Thus, a 2.38% increase in volatility is worth $22,929 for an open position of 1000 lean hogs contracts ($\$963 \times 2.38\% \times 1000$). Similar analysis indicates that the average increase in daily return volatility across the five futures when using the closet-to-peak series is 0.63% (9.98% annually), which leads to an average value of $7,169 for an open position of 1000 contracts across the futures. For the other five futures, because the peak of the sensitivity pattern is relatively close to maturity, the closest-to-peak and the closest-to-maturity price series are almost identical.

I use data from July 1st, 2014 to December 31st, 2016 for the out-of-sample analysis. I construct the closest-to-peak price series using the historical $\text{PTM}_{\text{SENSITIVITY}}$ (Table 3.6) for each futures. The results for the out-of-sample period, presented in Panel B of Table 3.8, also indicate that in general, the distance-to-peak is a better predictor of futures return volatility than the distance from maturity. The average return volatility of the closest-to-

[12] When the margins are different between contract months and between hedgers and speculators, I use the one for contracts that are closer to maturity and for speculators. Table 6.2 in the Appendix include the maintenance margin requirement for the futures in my sample during the period 2003-2016.

peak price series is higher than that of the closest-to-maturity price series for four out of ten futures. The average annual increase in return volatility when switching between the series is 2.53%. Economic analysis similar to the in-sample period suggests this is worth $2,935 for an open position of 1000 contracts. The two series are almost identical for the other six futures.

Table 3.8: Comparing the volatility of the closest-to-peak and the closest-to-maturity futures price series.

	Average daily volatility (10^{-4})					
	Panel A: In-sample period (01/01/2003 – 30/06/2014)			Panel B: Out-of-sample period (01/07/2014-31/21/2016)		
	Closest-to-peak series	Closest-to - maturity series	Difference	Closest-to-peak series	Closest-to - maturity series	Difference
Corn	3.008	3.008	0	3.398	3.398	0
Wheat	4.976	4.976	0	3.922	3.922	0
Soybean	2.870	2.867	0.003	2.188	2.187	0.001
Soybean meal	4.180	4.180	0	3.335	3.335	0
Soybean oil	2.898	2.897	0.002	2.200	2.200	0
Lean hogs	2.064	2.016	0.048	2.654	2.652	0.002
Live cattle	0.870	0.866	0.004	1.092	1.088	0.004
Copper	3.835	3.829	0.006	1.934	1.931	0.003
Crude oil	4.437	4.437	0	6.540	6.540	0
Natural gas	9.330	9.330	0	7.267	7.267	0

This table presents the comparison of the average daily volatility between the closest-to-peak futures price series and the closest-to-maturity series (furthest-to-maturity series for gold and silver) for the in-sample period (01/01/2003 – 30/06/2014) and out-of-sample period (01/07/2014-31/21/2016). The closest-to-peak price series is constructed using contracts that are closest to the peak of the *sensitivity pattern* obtained from Table 6. The closest-to-maturity series is composed of contracts that are closest to maturity.

3.4. Conclusion

In this chapter, I first empirically confirm that both trading volume and open interest follows an inverted U-shape pattern over the life of a futures contract. Open interest peaks around the half-life of a contract while the tilt of the pattern of trading volume towards maturity varies across futures. I then show, in both my univariate and regression analyses, that the sensitivity pattern also has an inverted U-shape and that the tilt of the pattern generally correlates to that of the time-to-maturity pattern of trading volume. Finally, I show that the test for the linear volatility pattern is significant for agricultural and energy futures where the sensitivity pattern peaks close to maturity but not for metal futures, where the pattern peaks far from maturity.

CHAPTER 4

CONTRIBUTIONS, LIMITATIONS AND POTENTIAL FUTURE RESEARCH

4. CONTRIBUTIONS, LIMITATIONS AND POTENTIAL FUTURE RESEARCH

4.1. Contributions and practical implications

From a broad perspective, this thesis contributes to three important strands of literature. First, it contributes to the literature that investigates the Samuelson effect (Rutledge, 1976; Anderson, 1985; Milonas, 1986; Khoury and Yourougou, 1993; Bessembinder et al., 1996; Galloway and Kolb, 1996; Allen and Cruickshank, 2000; and Duong and Kalev, 2008) by examining factors that can influence the volatility pattern in that they are related to time-to-maturity and also impact return volatility. Namely, I consider information asymmetry and the sensitivity of futures prices to information, which is driven by the level of futures market activity. In doing so, I also contribute to the two bodies of studies that examine information asymmetry and market activity in the futures markets and their impact on futures return volatility (Hong, 2000; Shalen, 1993; Daigler and Wiley, 1999; and Commodity Exchange Authority, 1960; Powers, 1967; Working, 1970; Hieronymus, 1978; Leuthold, 1983; Kyle, 1985; Admati and Pfleiderer, 1988; Bessembinder and Seguin, 1993, respectively).

Specifically, the results of this study provide two explanations for the mixed empirical evidence on the volatility pattern observed in previous studies (Rutledge, 1976; Anderson, 1985; Milonas, 1986; Khoury and Yourougou, 1993; Bessembinder et al., 1996; Galloway and Kolb, 1996; Allen and Cruickshank, 2000; and Duong and Kalev, 2008). In Chapter 2 of this thesis, taking into account the mediation effect information has on the volatility pattern suggested by Hong (2000), I show that the speculative effect consistently supports the upward pattern of return volatility over a futures contract's life. The price elasticity effect, on the other hand, is inconsistent. In the majority of cases, it is the speculative impact that drives return volatility to rise as futures near expiry. Consequently, changes in the level of information asymmetry in the futures market, which are not accounted for in previous studies, can have a tangible impact on the volatility pattern. This provides the first explanation. In Chapter 3, I directly test the sensitivity pattern to take into account any potential clustering in information flows faced by previous research when testing the volatility pattern (Anderson and Danthine, 1983). I show that the sensitivity pattern has an inverted U-shape, influenced by the inverted U-shape pattern of the level of market activity (trading volume and open interest) over the life of a futures contract. This offers the second explanation, as previous studies assume a linear sensitivity pattern that leads to a similar volatility pattern. I show that the test for a linear volatility pattern is more likely to yield significant results for commodity futures where the sensitivity pattern tilts more towards maturity.

I also contribute to the literature that investigates information asymmetry in the futures market. By empirically supporting Hong's (2000) hypothesis that information asymmetry rises closer to maturity, my results corroborate the underlying argument that futures markets are exposed to a greater sensitivity to noise shocks as maturity nears. Furthermore, I provide empirical evidence that information asymmetry has a positive impact on futures return volatility (see Shalen, 1993; and Daigler and Wiley, 1999). This supports the premise that uninformed investors may not recognize their informational disadvantage in order to react rationally.

Finally, this thesis contributes to the literature that investigates futures market activity and its impact on return volatility. My results, which imply that the inverted U-shape pattern of market activity influences the inverted U-shape of the sensitivity pattern, further substantiate Bessembinder and Seguin's (1993) finding that futures return volatility is directly related to futures trading volume and open interest. Moreover, the literature suggests trading volume should track open interest because speculative trading should correlate with hedging activity (Commodity Exchange Authority, 1960; Powers, 1967; Working, 1970; Hieronymus, 1978; Leuthold, 1983). While I find that open interest generally peaks around the half-life of a contract, trading volume peaks differently across futures. This implies that the relationship between speculative trading and hedging is different across futures.

My findings also have important market implications. As an example, time-to-maturity is commonly used as a predictor of return volatility and the closest-to-maturity futures price series is expected to have the highest return volatility, if one assumes a monotonic sensitivity pattern. An inverted U-shape sensitivity pattern suggests otherwise. It means a contract is likely to be more volatile when it is closer to the inverted U-shape peak, so distance-to-peak can be a better predictor of return volatility. I show that traders who prefer volatility and follow the closest-to-peak futures price series, constructed by rolling over contracts that are closest to the peak of the sensitivity pattern, will capture higher average return volatility (9.98% in-sample and 2.53% out-of-sample annually). Using the maintenance margin for futures trading, which is set based on volatility in the market, as an estimate of the price of volatility, I show that such an increase in volatility is worth $7,169 in-sample and $2,935 out-of-sample for a position of 1000 contracts.

My findings can also be beneficial for futures market regulators and futures exchange managers. Regulators can devise policies to decrease the information gap between informed speculators and uninformed hedgers to reduce the risk of higher volatility in the market. Since information asymmetry is likely to arise due to hedgers being more concern about liquidity or having smaller capacity to acquire information, such policies could include providing better liquidity to hedgers or developing a more efficient information system. Exchange managers can improve the margin setting mechanism to account for the inverted U-shape sensitivity pattern.

4.2. Limitations and potential future research

A few issues arise from this study that could be addressed in future research. First, Hong (2000) suggests that the level of information asymmetry within a futures market is related to the proportion of informed speculators versus uninformed hedgers in the market. Testing this relationship could help us to predict the change in the speculative effect when speculators enter or leave the market. However, detailed data on the intraday trading of speculators and hedgers, such as the Liquidity Data Bank used to be provided by the CME, is not currently available[13]. More investigation can be conducted should such data become available in the future.

Second, the upward slope of the time-to-maturity pattern of information asymmetry is hypothesized by Hong (2000) to be dependent upon the relative persistence of shocks from other markets (noise shocks) compared to that of shocks to the fundamental value of the underlying commodity. I support this notion by showing that the negative relationship between information asymmetry and time-to-maturity is generally weaker

[13] The historical Liquidity Data Bank was provided by the CME only until 2011 and is currently not available to be acquired. Aside from this, it only reports trading by market participant groups in aggregate for each commodity futures market without providing a break down by individual trading contracts, which may trade concurrently but have different maturity horizons.

during the 2007-2009 financial crisis (see robustness tests in Chapter 2). During this period, noise shocks are expected to be more persistent as investors increasingly look to hedge their investments using commodity futures. Further research can be conducted to precisely quantify the relationship between the slope of the time-to-maturity pattern of information asymmetry and the relative persistence of noise shocks. This is relevant given that the ongoing financialization of futures markets has led to shocks from other markets having more impact in the commodity futures market (Tang and Xiong, 2012; Henderson et al., 2015; Adams and Gluck, 2015).

Third, my analysis of the time-to-maturity pattern of futures market activity implies that the relationship between speculative trading and hedging is different across futures. Further investigation can be done to determine which characteristics of a commodity futures market (for example harvest season or cost of inventory) affect the trading volume – open interest relationship, which influences the variation in the sensitivity pattern across futures.

Finally, my findings on the inverted U-shape sensitivity pattern suggest that the volatility pattern is likely to also be nonlinear. Since return volatility is an input to other important market activities, such as options pricing, the implications of my findings are worth investigating further.

CHAPTER 5

CONCLUSION

5. CONCLUSION

This thesis investigates two issues that explain the mixed empirical results for the Samuelson effect in the literature (Rutledge, 1976; Anderson, 1985; Milonas, 1986; Khoury and Yourougou, 1993; Bessembinder et al., 1996; and Duong and Kalev, 2008). First, it shows that a significant mediating force on the time-to-maturity pattern of futures return volatility is information asymmetry. By departing from the usual assumption that information is symmetric across investors and static across the life of the contract, I show that an economically significant speculative effect drives the time-to-maturity – return volatility relationship. I provide evidence supporting Hong's (2000) assertion that information asymmetry is negatively related to the life of a futures contract. My empirical results also show this leads to a positive, as opposed to his prediction of a negative relationship, with return volatility. This could be explained by the inability of uninformed hedgers to learn about their informational disadvantage.

Second, this study is the first to empirically test the sensitivity pattern of futures contracts. I argue that the sensitivity pattern should have an inverted U-shape relationship with time-to-maturity. The reason is that the level of market activity (trading volume and open interest), which influences sensitivity (Kyle, 1983; Admati and Pfleiderer, 1988; and Bessembinder and Seguin, 1993), follows an inverted U-shape pattern over the life of a futures contract (Commodity Exchange Authority, 1960; Powers, 1967; Working, 1970; Leuthold, 1983). I document an inverted U-shape sensitivity pattern instead of the linear one assumed in previous studies and show that tests for a linear return volatility relationship will only materialise for those futures where the sensitivity pattern tilts toward the maturity date of the contract.

My findings are economically significant. First, I find that for every ten days that a futures contract moves closer to maturity, information asymmetry increases, on average, by 3.64%. This is equivalent to 0.00258 cents on the bid-ask spread and based on daily average trading volumes in the futures markets implies a rise of $9,546 in daily trading costs. Second, the speculative effect raises daily realized volatility by an average of 2.22% for every ten trading days. Finally, I show that traders who prefer volatility and follow the closest-to-peak futures price series, constructed of contracts that are closest to the peak of the sensitivity pattern, will capture higher average return volatility (9.98% in-sample and 2.53% out-of-sample, annually), which is worth $7,169 and $2,935 for a position of 1000 contracts, respectively, if I use margin to proxy for the cost of futures volatility.

CHAPTER 6

APPENDIX

Appendix Table 1: Specifications of commodity futures contracts.

Commodity group	Futures	Futures exchange	Expiration months	Contract unit	Price quotation	Product code	Settlement method
Grains	Corn	CBOT	3,5,7,9,12	5,000 bushels (~ 127 metric tons)	Cents per bushel	C	Deliverable
Grains	Wheat	CBOT	3,5,7,9,12	5,000 bushels (~ 136 metric tons)	Cents per bushel	W	Deliverable
Oilseeds	Soybean	CBOT	1,3,5,7,8,9,11	5,000 bushels (~ 136 metric tons)	Cents per bushel	S	Deliverable
Oilseeds	Soybean meal	CBOT	1,3,5,7,8,9,10,12	100 short tons (~ 91 metric tons)	Cents per short ton	SM	Deliverable
Oilseeds	Soybean oil	CBOT	1,3,5,7,8,9,10,12	60,000 pounds (~ 27 metric tons)	Cents per pound	BO	Deliverable
Livestock	Feeder cattle	CME	1,3,4,5,8,9,10,11	50,000 pounds (~ 23 metric tons)	Cents per pound	GF	Financially settled
Livestock	Lean hogs	CME	2,4,5,6,7,8,10,12	40,000 pounds (~ 18 metric tons)	Cents per pound	LH	Financially settled
Livestock	Live cattle	CME	2,4,6,8,10,12	40,000 pounds (~ 18 metric tons)	Cents per pound	LE	Deliverable
Metals	Copper	COMEX	3,5,7,9,12	25,000 pounds	Dollars and cents per pound	HG	Deliverable
Metals	Gold	COMEX	2,4,6,8,10,12	100 troy ounces	Dollars and cents per troy ounce	GC	Deliverable
Metals	Silver	COMEX	1,3,5,7,9,12	5,000 troy ounces	Dollars and cents per troy ounce	SI	Deliverable
Energy	Crude oil	NYMEX	Every month	1,000 barrels	Dollars and cents per barrel	CL	Deliverable
Energy	Natural gas	NYMEX	Every month	10,000 million British thermal units (mmBtu)	Dollars and cents per mmBtu	NG	Deliverable

Source: The CME Group

Appendix Table 2: Historical maintenance margin during the period 2003-2016.

	Corn		Wheat		Soybean		Soybean meal
Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)
11/2003	$400	11/2003	$650	11/2003	$1200	11/2003	$700
04/2004	$450	01/2004	$725	01/2004	$1500	01/2004	$900
04/2004	$600	03/2004	$800	04/2004	$1600	02/2004	$1000
06/2004	$625	04/2004	$875	04/2004	$1900	04/2004	$1100
07/2004	$575	07/2004	$675	05/2004	$2300	04/2004	$1300
09/2004	$400	09/2004	$500	04/2004	$1800	05/2004	$1600
09/2004	$350	12/2004	$450	07/2004	$1700	06/2004	$1800
10/2004	$300	02/2005	$550	09/2004	$1900	06/2004	$1400
11/2004	$250	03/2005	$600	09/2004	$1450	07/2004	$1250
01/2005	$325	04/2005	$700	10/2004	$1350	09/2004	$900
03/2005	$325	09/2005	$375	11/2004	$1200	10/2004	$800
07/2005	$500	02/2006	$450	12/2004	$900	11/2004	$700
08/2005	$600	05/2006	$550	02/2005	$1100	11/2004	$550
09/2005	$375	05/2006	$650	03/2005	$1350	02/2005	$750
11/2005	$300	06/2006	$950	07/2005	$1700	03/2005	$825
12/2005	$250	07/2006	$700	08/2005	$1850	07/2005	$1100
04/2006	$350	09/2006	$800	09/2005	$800	09/2005	$525
05/2006	$400	10/2006	$1000	12/2005	$750	12/2005	$600
08/2006	$450	10/2006	$1250	01/2006	$850	01/2006	$750
10/2006	$500	12/2006	$1150	05/2006	$750	05/2006	$600
10/2006	$650	06/2007	$1250	12/2006	$800	08/2006	$500
11/2006	$850	08/2007	$1400	01/2007	$1000	11/2006	$625
12/2006	$750	09/2007	$1500	06/2007	$900	01/2007	$800
01/2007	$900	12/2007	$2000	07/2007	$1350	06/2007	$700
01/2007	$1000	01/2009	$2500	07/2007	$1800	07/2007	$950
09/2007	$800	05/2009	$2000	09/2007	$2000	07/2007	$1350
01/2009	$1500	11/2009	$1750	01/2009	$3500	01/2009	$2000

05/2009	$1200	01/2010	$1500	05/2009	$3000	11/2009	$1500
11/2009	$1100	04/2010	$1200	11/2009	$2750	04/2010	$1200
12/2009	$1000	07/2010	$1000	06/2010	$2250	06/2010	$1000
05/2010	$850	08/2010	$2500	10/2010	$2000	08/2010	$1100
07/2010	$950	03/2011	$3000	10/2010	$2500	10/2010	$1250
10/2010	$1100	09/2011	$2250	11/2010	$2750	10/2010	$1750
10/2010	$1500	07/2012	$2750	11/2010	$3250	11/2010	$2000
04/2011	$1750	01/2013	$2400	01/2011	$3500	06/2011	$1750
06/2012	$2000	08/2013	$2000	06/2011	$3250	08/2011	$1500
08/2013	$1500	11/2013	$1650	08/2011	$2750	09/2011	$1250
08/2013	$1750	02/2014	$1400	09/2011	$2500	05/2012	$1450
05/2014	$1500	05/2014	$1500	07/2012	$3000	06/2012	$1600
09/2014	$1250	10/2014	$1300	07/2012	$3750	07/2012	$2000
11/2014	$1000	06/2015	$1500	01/2013	$3400	08/2013	$2250
07/2015	$1250	07/2015	$1750	08/2013	$3000	09/2013	$2000
12/2015	$1000	01/2016	$1500	08/2013	$3500	10/2013	$2250
03/2016	$900	03/2016	$1200	11/2013	$2900	02/2014	$2000
04/2016	$1050	05/2016	$1400	03/2014	$2500	05/2014	$1800
06/2016	$1250	08/2016	$1200	05/2014	$3000	07/2014	$2000
07/2016	$1400	10/2016	$1000	09/2014	$2500	09/2014	$1500
09/2016	$1150			01/2015	$2250	10/2014	$2000
10/2016	$1050			03/2015	$2000	11/2014	$2500
10/2016	$900			07/2015	$2300	02/2015	$2100
				09/2015	$2600	05/2015	$1900
				01/2016	$2100	07/2015	$2200
				03/2016	$1800	01/2016	$1800
				03/2016	$1500	02/2016	$1500
				04/2016	$1750	03/2016	$1200
				05/2016	$2000	04/2016	$1450
				05/2016	$2300	04/2016	$1600
				06/2016	$2600	05/2016	$2000

				07/2016	$2900	06/2016	$2250
				07/2016	$3100	10/2016	$1800
				09/2016	$2700		
				10/2016	$2400		

	Soybean oil		Lean hogs		Live cattle		Copper
Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)
11/2003	$550	01/2004	$800	01/2003	$550	01/2009	$5750
03/2004	$650	07/2006	$900	03/2003	$650	08/2009	$4500
03/2004	$850	01/2007	$800	10/2003	$700	12/2009	$3500
06/2004	$850	04/2007	$700	10/2003	$900	04/2010	$4250
07/2004	$750	07/2007	$600	10/2003	$1000	06/2010	$5000
09/2004	$650	09/2007	$900	10/2003	$1200	09/2010	$4000
12/2004	$475	01/2009	$1000	10/2003	$1500	12/2010	$4750
02/2005	$600	02/2009	$800	10/2003	$2000	01/2011	$4250
03/2005	$725	03/2009	$900	10/2003	$1200	09/2011	$5000
07/2005	$800	05/2009	$1050	12/2003	$1600	10/2011	$5750
09/2005	$500	07/2010	$950	12/2003	$2000	02/2012	$5000
12/2005	$450	10/2010	$1100	02/2004	$1200	04/2012	$4000
01/2006	$500	02/2011	$1250	03/2004	$1000	11/2012	$3500
05/2006	$400	05/2012	$1050	06/2004	$1200	02/2013	$3100
11/2006	$450	08/2012	$1250	09/2004	$1050	05/2013	$3700
07/2007	$600	11/2012	$1050	04/2005	$900	06/2013	$4000
09/2007	$700	06/2013	$1250	04/2005	$800	09/2013	$3500
01/2009	$1500	08/2013	$1000	10/2005	$700	11/2013	$3000
10/2009	$1000	03/2014	$1200	07/2006	$850	07/2014	$2700
03/2010	$800			01/2007	$700	08/2014	$2600
05/2010	$700			09/2007	$800	12/2014	$2900
10/2010	$1100			10/2008	$1100	01/2015	$3400
11/2010	$1300			10/2008	$1200	04/2015	$3100
11/2010	$1500					02/2016	$2850

06/2011	$1250					04/2016	$2600
09/2011	$1000					05/2016	$2300
04/2012	$900					10/2016	$1900
06/2012	$1000					11/2016	$2300
07/2012	$1250					11/2016	$2750
08/2013	$1000						
10/2013	$1500						
02/2014	$1350						
05/2014	$1150						
09/2014	$700						
12/2014	$800						
08/2015	$950						
02/2016	$800						
04/2016	$750						
10/2016	$650						
11/2016	$715						
12/2016	$825						

	Gold		Silver		Crude oil		Natural gas
Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)	Time (month/year)	Margin (per contract)
01/2009	$4302	01/2009	$6400	01/2009	$6750	01/2009	$6500
02/2009	$3999	02/2009	$6000	01/2009	$6000	02/2009	$5750
09/2009	$3333	08/2009	$4000	02/2009	$5250	03/2009	$5000
01/2010	$4002	12/2009	$4500	04/2009	$5750	09/2009	$4500
03/2010	$4998	02/2010	$5000	09/2009	$5250	10/2009	$5000
06/2010	$4251	05/2010	$4250	09/2009	$4500	04/2010	$4500
11/2010	$4500	07/2010	$5000	11/2009	$4000	07/2010	$4000
02/2011	$5001	11/2010	$7250	04/2010	$3750	01/2011	$3500
06/2011	$4500	01/2011	$7750	02/2011	$4500	04/2011	$3000
08/2011	$5500	02/2011	$8250	03/2011	$5000	08/2011	$2750
08/2011	$7000	03/2011	$8700	05/2011	$6250	10/2011	$2500

09/2011	$8500	04/2011	$9500	09/2011	$6000	01/2012	$2100
02/2012	$7500	04/2011	$10750	12/2011	$5600	07/2012	$2300
05/2012	$6750	05/2011	$14000	02/2012	$5100	08/2012	$2500
01/2013	$6000	05/2011	$16000	06/2012	$4600	11/2012	$2250
03/2013	$5400	09/2011	$18500	07/2012	$5100	02/2013	$2100
04/2013	$6400	02/2012	$16000	01/2013	$4500	05/2013	$2350
06/2013	$8000	04/2012	$14000	04/2013	$4100	09/2013	$2100
11/2013	$7250	08/2012	$12500	11/2013	$3700	01/2014	$2300
04/2014	$6500	12/2012	$11000	11/2013	$3400	01/2014	$4500
05/2014	$6000	02/2013	$9500	03/2014	$3100	02/2014	$5000
07/2014	$5400	04/2013	$11250	04/2014	$2900	02/2014	$5500
09/2014	$4600	11/2013	$10000	08/2014	$2700	02/2014	$4750
10/2014	$4000	04/2014	$9000	10/2014	$3400	03/2014	$4000
05/2015	$3750	05/2014	$8250	11/2014	$3700	03/2017	$3000
02/2016	$4250	07/2014	$7500	12/2014	$3850	04/2014	$2850
03/2016	$4500	08/2014	$6500	12/2014	$4450	06/2014	$2550
06/2016	$5500	10/2014	$5500	02/2015	$4900	06/2014	$2800
07/2016	$6000	12/2014	$6500	05/2015	$4250	10/2014	$2710
08/2016	$5400	02/2015	$7700	07/2015	$4600	11/2014	$3100
11/2016	$6000	06/2015	$7000	12/2015	$4000	11/2014	$3650
		08/2015	$6000	02/2016	$3500	12/2014	$4050
		01/2016	$5200	04/2016	$3400	02/2015	$3200
		04/2016	$4800	08/2016	$3200	03/2015	$2500
		07/2016	$5250	09/2016	$2900	04/2015	$2000
		11/2016	$5800	12/2016	$3200	11/2015	$2250
		12/2016	$6500			02/2016	$1900
						03/2016	$1800
						04/2016	$1650
						07/2016	$1800
						07/2016	$2050
						08/2016	$2200

08/2016	$2350
12/2016	$2850
12/2016	$3100

This table presents the historical maintenance margin requirement for speculators to trade the closest to maturity contracts announced by the CME Group during the period from 2003 to 2016.

Appendix Table 3: Testing the sensitivity pattern using ten-minute realized volatility.

	Corn	Wheat	Soybean	Soybean meal	Soybean oil	Lean hogs
TTM (10^{-2})	5.166***	4.369**	3.321**	3.614**	5.014***	24.275***
	(3.53)	(2.51)	(2.13)	(2.32)	(3.63)	(9.57)
TTM^2 (10^{-2})	-0.388***	-0.412***	-0.306***	-0.348***	-0.494***	-1.674***
	(-5.41)	(-4.30)	(-3.51)	(-4.16)	(-6.58)	(-10.28)
Constant	-14.233***	-13.140***	-14.063***	-13.675**	-13.540***	-14.050***
	(-48.79)	(-52.34)	(-51.35)	(-45.38)	(-49.52)	(-64.22)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	6,271	5,597	6,441	6,557	7,184	5,921
Adjusted R^2	0.040	0.099	0.152	0.296	0.190	0.123
	Live cattle	Copper	Gold	Silver	Crude oil	Natural gas
TTM (10^{-2})	23.885***	6.638	18.754***	7.331*	0.936	4.359***
	(5.27)	(1.34)	(4.57)	(1.82)	(1.09)	(4.93)
TTM^2 (10^{-2})	-1.449***	-0.522*	-0.935***	0.417*	-0.215***	-0.826***
	(-5.62)	(-1.81)	(-4.00)	(1.82)	(-3.05)	(-12.38)
Constant	-15.758***	-12.039***	-14.291***	-11.656***	-13.040***	-10.406***
	(-46.12)	(-34.62)	(-41.57)	(-37.01)	(-89.41)	(-46.02)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	4,826	3,952	3,967	3,889	9,111	9,093
Adjusted R^2	0.152	0.268	0.020	0.004	0.148	0.127

This table presents the results for testing the time-to-maturity pattern of the sensitivity of return volatility to information flows (the sensitivity pattern) using the following regression: $\text{SENSITIVITY}_{i,t} = \alpha + \beta_1 \text{TTM}_{i,t} + \beta_2 \text{TTM}_{i,t}^2 + \varepsilon_{i,t}$, where $\text{SENSITIVITY}_{i,t}$ is the sensitivity of futures return volatility to information flows of contract i on day t, calculated as $\text{SENSITIVITY}_{i,t} = ln\left(\frac{\text{VOLATILITY}_{i,t}}{\text{NEWS}_{i,t}}\right)$, $\text{VOLATILITY}_{i,t}$ is the daily ten-minute realized volatility (Andersen and Bollerslev, 1998) and $\text{NEWS}_{i,t}$ is the number of daily news about the commodity, identified by the headlines containing the name of the commodity. Time-to-maturity (TTM) is measured as the square-root of the number of days to maturity. Contract and year fix effects are included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

Appendix Table 4: Testing the sensitivity pattern using the natural logarithm of the number of days to maturity as time-to-maturity.

	Corn	Wheat	Soybean	Soybean meal	Soybean oil	Lean hogs
TTM	0.699***	0.838***	0.363***	0.440***	0.823***	1.776***
	(6.05)	(6.43)	(2.97)	(3.64)	(7.70)	(10.80)
TTM^2	-0.095***	-0.116***	-0.054***	-0.067***	-0.119***	-0.234***
	(-6.96)	(-7.24)	(-3.54)	(-4.49)	(-8.97)	(-11.06)
Constant	-14.923***	-14.705***	-14.975***	-14.353**	-15.183***	-16.532***
	(-41.27)	(-42.35)	(-42.31)	(-37.91)	(-45.06)	(-45.52)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	6,271	5,597	6,441	6,557	7,184	5,921
Adjusted R^2	0.018	0.016	0.079	0.200	0.134	0.095
	Live cattle	Copper	Gold	Silver	Crude oil	Natural gas
TTM	2.159***	1.003***	0.933***	-0.010	0.061**	0.383***
	(5.77)	(2.62)	(2.68)	(-0.03)	(2.38)	(13.08)
TTM^2	-0.262***	-0.126***	-0.098**	0.004	-0.017***	-0.089***
	(-5.94)	(-2.75)	(-2.35)	(0.09)	(-3.91)	(-18.48)
Constant	-19.115***	-15.073***	-16.316***	-12.262***	-13.548***	-10.735***
	(-22.33)	(-18.71)	(-20.08)	(-16.62)	(-85.24)	(-45.21)
Fixed effects	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year	Contract, Year
Observations	4,826	3,952	3,967	3,889	9,111	9,093
Adjusted R^2	0.156	0.289	0.009	0.006	0.100	0.112

This table presents the results for testing the time-to-maturity pattern of the sensitivity of return volatility to information flows (the sensitivity pattern) using the following regression: $\text{SENSITIVITY}_{i,t} = \alpha + \beta_1 \text{TTM}_{i,t} + \beta_2 \text{TTM}^2_{i,t} + \varepsilon_{i,t}$, where $\text{SENSITIVITY}_{i,t}$ is the sensitivity of futures return volatility to information flows of contract i on day t, calculated as $\text{SENSITIVITY}_{i,t} = ln\left(\frac{\text{VOLATILITY}_{i,t}}{\text{NEWS}_{i,t}}\right)$, $\text{VOLATILITY}_{i,t}$ is the daily five-minute realized volatility (Andersen and Bollerslev, 1998) and $\text{NEWS}_{i,t}$ is the number of daily news about the commodity, identified by the headlines containing the name of the commodity. Time-to-maturity (TTM) is measured as the natural logarithm of the number of days to maturity. Contract and year fix effects are included. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

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