Rise of the uninformed: An analysis of the time-to-maturity pattern of information asymmetry and its impact on futures return volatility

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Abstract

We find robust evidence that information asymmetry rises as commodity futures near maturity and that this significantly impacts the time-to-maturity pattern of return volatility. Theoretically, this "speculative effect" should dampen return volatility under normal market conditions (Hong, 2000). However, we find that it amplifies it and can be of more significance in driving the time-to-maturity pattern than Samuelson's (1965) price elasticity effect. We posit this is due to uninformed traders not observing their informational disadvantage and further moderated by overconfident traders. Supporting this, we show that the speculative effect is exacerbated in the presence of small speculators as futures roll to maturity.

Keywords: Commodity futures; Information asymmetry; Time to maturity; Price elasticity effect; Speculative effect.

JEL classification: C22; G13; G15; Q14

1. Introduction

We examine if the presence of information asymmetry in commodity futures is related to its time-to-maturity and the subsequent effect this may have on 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 traders nor fixed over the period 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), who posits that information asymmetry between investors will be related to time-to-maturity and that this will have a bearing on the return volatility of the futures. To empirically investigate this, we test part of Hong's (2000) predictions by examining the relationship that information asymmetry has with time-to-maturity and whether this has an economically significant impact on the time-to-maturity pattern of futures return volatility.

The most widely known explanation for there to be a relationship between time-to-maturity and futures return volatility is Samuelson's (1965) argument that the closer to maturity a futures contract is, the more sensitive the futures price is to information regarding its fundamental value. For commodity futures, this will be in relation to the relative supply and demand of the underlying asset. Whilst there is some empirical evidence for this "price elasticity effect", it does not seem to be present in all futures markets 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 corn. Khoury and Yourougou (1993) also find it is present in agricultural commodity futures, but not canola.

Anderson and Danthine (1983) develop an alternative, state variable hypothesis, which suggests that futures return volatility will be higher in periods when a relatively greater amount of uncertainty concerning the supply and demand of the underlying asset is resolved. For agricultural futures, this will be positively related to the seasonality effect connected to harvest times. The price elasticity effect then becomes a special case in which the resolution of uncertainty is clustered near the maturity of the futures contract. However, the empirical evidence with regard to the state variable hypothesis 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.

In considering net carry costs, Bessembinder et al. (1996) proposes 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 show support for this negative covariance hypothesis by finding that the price elasticity effect holds for agricultural commodities and crude oil, is weaker for metals, and non-existent for Treasury bonds and S&P 500 index futures. Also, Duong and Kalev (2008) find the presence of the price elasticity effect for 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 investors are symmetrically informed. He 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 of the well-known price elasticity effect and a "speculative effect" that arises from the relationship that information asymmetry has with time-to-maturity, thereby affecting return volatility. The speculative effect exists because the market consists of two types of investors; informed speculators and uninformed hedgers. He argues that if shocks to the fundamental value of the underlying asset are more persistent than noise shocks, then the price impact of noise shocks will fall faster than the price impact of fundamental shocks as a futures contract nears maturity. In other words, the sensitivity of futures prices to noise shocks will increase the closer the contract is to expiration. This will lead to a rise in information asymmetry as it becomes more difficult for the uninformed hedgers to gauge the private information held by the informed speculators based on their observable trading behavior. Thus, they hesitate to trade and futures prices move less, leading to a reduction in return volatility. Therefore, whilst the price elasticity effect will generate a rise in return volatility as a futures nears maturity, the speculative effect reduces it.

To empirically test this, we first investigate the relationship that information asymmetry has with time-to-maturity by examining twelve commodity futures traded on the Chicago Mercantile Exchange group of exchanges. Namely the Chicago Mercantile Exchange (CME), the Chicago Board of Trade (CBOT), the Commodity Exchange (COMEX), and the New York Mercantile Exchange (NYMEX), for a six-year period between 2010 and 2015. We use Madhavan, Richardson, and Rooman's (1997) (hereafter MRR) estimate of the information asymmetry component of the bid-ask spread to measure the daily level of asymmetric information. In examining the relationship this measure has with time-to-maturity, we find that for all the futures in our sample, information asymmetry significantly rises closer to maturity. This is consistent with Hong's (2000) prediction where fundamental shocks are more persistent than noise shocks. We find that for every ten days that a futures contract moves closer to maturity, information asymmetry increases, on average, by 8.25%. This is equivalent to 7.63 cents on the bid-ask spread and based on daily trading volumes implies a rise of $440 in daily trading costs.

We then proceed to investigate the impact that the speculative effect has on return volatility, which we capture through daily realized volatility (Andersen and Bollerslev, 1998). Based on the preceding results, Hong (2000) posits that the speculative effect will dampen return volatility as the futures near maturity. This is premised on uninformed hedgers choosing to trade less because information asymmetry rises, as well as them learning that they are more informationally disadvantaged in relation to the informed speculators.[1]

We question whether these are reasonable assumptions to make. If these uninformed hedgers are uninformed from not receiving private signals about the fundamental value of the underlying asset, then why should they become informed about how relatively uninformed they are? Hong (2000)'s argument assumes that uninformed hedgers are focused at all times on gauging the private information of informed speculators and adjusting their hedging positions accordingly. In reality, most investors are likely to be distracted by other tasks much of the time and thus cannot continually focus their attention on information gauging (see, for example, Peng and Xiong, 2007; Duffie, 2010). In fact, if their motivation to trade is purely 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. As a consequence, the trades of uninformed hedgers will not be related to the level of information asymmetry exhibited by the futures.

In addition, we also consider the impact that small speculators have on the time-to-maturity relationship. Empirically, Odean (1999), Barber and Odean (2000), Barber et al.

[1] We implicitly assume that shocks to the fundamental value of the underlying asset will be more persistent than other noise shocks (Hong's (2000) nonmarketed risks) as this is what we would normally expect to be true in the market and is congruent with our observations, under these assumptions, that information asymmetry rises as the contract rolls to maturity.

(2009) document that individual equity investors are too confident about their information and speculate too aggressively, with their performance suffering as a result. Kuo and Lin (2013) and Chuang and Susmel (2011) arrive at similar conclusions when examining small, individual futures traders. The implication, for us, is that if these small speculators do receive fundamental news, they may miscalibate the precision of the information and trade too aggressively. This will lead to a further rise in return volatility.

We test for the presence of a speculative effect within futures and for whether there is support for Hong's (2000) hypothesis of it having a negative impact on return volatility against our alternative hypothesis that it will have a positive impact. We develop a mediation model (Judd and Kenny, 1981; Sobel, 1982; Baron and Kenny, 1986) to separate the speculative effect from the price elasticity effect. We treat the price elasticity effect as the direct effect that time-to-maturity has on return volatility, whilst we consider the speculative effect as an indirect effect arising from the mediating role that the time-to-maturity / information asymmetry relationship has on return volatility. Our results show that whilst evidence for the price elasticity effect is mixed, we consistently find the speculative effect has a positive impact on the time-to-maturity pattern of return volatility. The impact is statistically significant at the one percent level. We find that the speculative effect raises daily realized volatility by an average of 6.87% for every ten trading days. This supports our alternative hypothesis to Hong's (2000) position. Our results are also robust when we control for return volatility autocorrelation or use Huang and Stoll's (1997) adverse selection component of the bid-ask spread as an alternative measure of information asymmetry.

In addition, given that we also argue the speculative effect may be moderated by overconfident, small speculators trading close to the maturity of the contract, we examine whether there is any evidence of this. We examine trade sizes and open interest of different types of traders, obtained from the Commitments of Traders (COT) report from the Commodity and Futures Trading Commission (CFTC). Apart from finding that daily average trade size does drop closer to maturity, indicative of small speculator activity, we observe that the proportion of open interest held by small speculators is, on average, 18.19% higher in the second half of a futures life relative to the first half. Finally, we also show that the interaction of small trades (as a proxy for small speculators) with information asymmetry increases return volatility.

Our study contributes to the literature in three important ways. To the best of our knowledge, we are the first to provide empirical evidence on the relationship that information asymmetry has with time-to-maturity. By finding support for Hong's (2000) theoretical prediction that information asymmetry rises as a futures contract nears maturity, it also supports the notion that futures markets are exposed to a greater sensitivity to noise shocks as maturity nears.

Furthermore, we contribute to the futures market literature by showing that the mediating role of information asymmetry, through the speculative effect, has a significant, positive effect on the upward slope of futures return volatility as a contract approaches maturity. We find it is more consistent, in terms of its direction and impact, than the price elasticity effect. Indeed, we find in the majority of cases the speculative impact is what drives return volatility to rise as futures near expiry. Our results may therefore explain why there is some inconsistency in the empirical evidence of previous papers[2] as they do not account for the mediating role that the changing level of information asymmetry within the market has on the time-to-maturity pattern of return volatility.

Finally, we contribute to the literature that suggests individual investors are overconfident (Odean, 1999; Barber and Odean, 2000; Barber et al., 2009). By taking into

[2] Rutledge (1976), Anderson (1985), Milonas (1986), Khoury and Yourougou (1993), Bessembinder et al. (1996), and Duong and Kalev (2008).

consideration the impact that overconfident, small speculators may have on return volatility as futures roll to maturity, we show it can further strengthen the positive relationship that the speculative effect has, rather than the negative impact predicted by Hong (2000), on return volatility.

The remainder of this paper is organized as follows. The second section describes our data and provides some descriptive statistics. The third section presents our empirical results, whilst the fourth section provides some robustness tests. The fifth section contains our conclusion.

2. Data and method

Our data consists of twelve futures traded on the four exchanges of the CME Group, the world's largest futures marketplace. The futures we choose are the most liquid, with the highest trading volumes, for their respective commodity group. The futures are Corn, Soybean, Soybean meal, Soybean oil, and Wheat (grains and oilseeds) from the CBOT; Lean hogs, Feeder cattle (livestock), and Live cattle from the CME; Copper, Gold, and Silver from the COMEX; and Crude oil (energy) from the NYMEX.[3] We collect intraday tick-by-tick trades and quotes from Thomson Reuter Tick History (TRTH) between January 4th, 2010 and December 31st, 2015 (1,512 trading days) for these futures. We construct a closest to maturity time series for each futures by rolling over the front contract (the contract closest to maturity). When its trading volume falls below that of the next contract in the maturity cycle, we roll the contract over to obtain a continuous time series.[4]

[3] Except for Feeder cattle, trading volume for the futures included in our data is well above 10,000 contracts per day.
[4] For agricultural and metals futures, this typically happens when the front contract enters its maturity month. For Crude oil, the front contract remains heavily traded until maturity.

Using the above time series, we measure the level of daily level of information asymmetry present within each futures contract from the information asymmetry component of the bid-ask spread derived from Madhavan, Richardson, and Rooman's (1997) model (MRR). This is a popular measure to capture information asymmetry across assets markets, including equity (Riordan et al., 2013, Armstrong el al., 2010), fixed income (Green, 2004), futures (Huang, 2004) and options (Muravyev, 2016). It 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, following MRR:

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

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 ($x_t = 1$ 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 for the population moments:

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

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. Our proxy for information asymmetry is the information asymmetry component of the bid-ask spread (θ_{MRR}).

When we estimate Equation (2), we follow common practice in the microstructure literature of aggregating sequential trades within five seconds of each other if there are no updated quotes (see, for example, Huang and Stoll, 1997; Lai et al., 2014). This is to account for the possibility that large orders are being broken into a series of smaller orders that occur within a short interval. Such small orders are not independent observations and may tamper our analyses as the estimated autocorrelation will appear to be positive.

For our daily volatility estimates, we use realized return volatility *(RV)* calculated from the natural logarithm of the daily sum of squared five-minute interval returns (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. We use mid-point quotes to calculate the five-minute returns to avoid bid-ask bounce issues (Roll, 1984).

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

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

In Table 1 we provide contract details, including the type of commodity, the exchange that the futures are traded in, and their expiration months. Table 1 also includes the means and standard deviations of the daily return volatility (RV) and information asymmetry (θ_{MRR}) for each futures time series. We also present information asymmetry as the percentage of the daily bid-ask spread (calculated as $\theta_{MRR}/(\phi + \theta_{MRR})$) to gauge its economic significance. The average daily return volatility ranges between -5.0 to -3.2, which is close to the statistics reported in previous studies on commodity futures (for example Bessembinder et al. 1996;

Duong and Kalev, 2008). The average daily information asymmetry component ranges from 0.5 cents (Crude oil and Soybean oil) to 19.7 cents (Silver). On average, information asymmetry appears to account for more than half of the daily bid-ask spread for all futures, except for Corn. This suggests that information asymmetry has a dominant impact on trading costs.

[Insert Table 1]

We conduct our empirical analysis based on the mediation regression framework of Judd and Kenny (1981), Sobel (1982) and Baron and Kenny (1986). The mediation framework allows us to investigate how return volatility can be influenced by time-to-maturity via two channels, with one being classified as our 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 total effect on return volatility is the sum of the direct and indirect effects. Figure 1 provides a conceptual illustration of the mediation model we use.

[Insert Figure 1]

The mediation regression framework to test the magnitude and statistical significance of each effect involves three regressions. We include in our regressions dummy variables for each month of the year ($MONTH$) to address seasonality effects, and include the logarithm of the number of trades that occur during the day (LN_NT) to account for liquidity (see Bessembinder et al., 1996; Duong and Kalev, 2008):

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

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

$$RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t \quad (6)$$

The regression using Equation (4) establishes the time-to-maturity pattern of information asymmetry (coefficient β). The regression using Equation (5) separates the impact information asymmetry has on return volatility (coefficient δ) from that of time-to-maturity (the price elasticity effect, coefficient ψ). The regression using Equation (6) allows us to determine the total effect of time-to-maturity on return volatility (Ψ). The indirect effect (the speculative effect) can be calculated as either $(\Psi - \psi)$ or $(\beta * \delta)$, as 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 using Equations (4), (5) and (6) following Sobel (1982) 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 total 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, obtained from the regressions using Equations (4), (5) and (6).

3. Empirical results

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

We start our analysis by examining Hong's (2000) prediction that information asymmetry rises as futures roll toward maturity. Whilst Hong (2000) highlights that this pattern is conditioned on shocks to the fundamental value of the underlying asset being more persistent than noise shocks, we expect, under normal market conditions, this should generally be the case. In Figure 2 we plot average daily information asymmetry on the number of days to maturity for each futures contract. The plots lend support to Hong's (2000) assertion as it shows that for all futures, average daily information asymmetry trends upwards as the futures approach maturity. To investigate this further, in Table 2 we divide each futures contract into two, based on the number of days there are to maturity. The results reveal that the average level of information asymmetry is always 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 difference is statistically significant at the one percent level for all futures. Taking Gold as an example, the average information asymmetry in the period far from maturity is 0.084 and in the period close to maturity it is 0.064. The difference, 0.020, represents a 31.25% rise.

[Insert Figure 2]

[Insert Table 2]

To further test this relationship, Table 3 presents the regression results from Equation (4) of regressing our information asymmetry measure, θ_{MRR}, on the number of days to maturity (TTM), without (Panel A) and with (Panel B) controlling for seasonality (month dummies) and liquidity (LN_NT).[5] We expect a negative coefficient for TTM if information asymmetry is to rise when maturity nears (i.e. information asymmetry is negatively related to the number of days to maturity). As expected, in both Panels, the coefficients for TTM are negative and are statistically significant at the one percent level for eleven of the futures, and at the five percent level for Gold. The proportional increase in information asymmetry over a futures life indicates that the trend is economically significant. Using Corn as an illustration, the average level of information asymmetry is 0.051 (see Table 1). The coefficient of -0.681x10^{-3} for TTM in Panel B implies that when a Corn futures contract rolls another 10 days towards maturity, information asymmetry will rise by 6.81 cents ($(-10) \times (-0.681 \times 10^{-3})$), or 13.35% ($0.00681/0.051$). Corn futures average daily trading volume is 135,954 (Table 1), implying that a 6.81 cent

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

increase in information asymmetry is associated with a $925.8 higher daily trading cost ($0.00681 \times 135{,}954$). Similar analysis for the futures in our sample shows that the average 10-day increase in information asymmetry is 8.25% (7.63 cents), which is equivalent to a rise of $440 in average daily trading costs.

[Insert Table 3]

3.2. The speculative effect and the price elasticity effect

Having established the presence of a time-to-maturity pattern of information asymmetry within all our futures, we proceed to examine whether this has a bearing on the time-to-maturity pattern of futures return volatility (the speculative effect). However, based on how we observe information asymmetry rising as futures roll to maturity, Hong (2000) predicts that the speculative effect will reduce return volatility over a contract's life. In contrast, we suggest that the speculative effect will increase return volatility.

The logic behind Hong's (2000) argument is that when uninformed hedgers know they are facing a higher information disadvantage, they trade less and return volatility declines. We suggest otherwise. If we instead assume that uninformed hedgers are, namely, focused on hedging, then their incentive to discover the level of information asymmetry within the futures will not naturally be present. Their trading will therefore not be related to the information asymmetry within the market and rather be related to other factors. Trading behavior of liquidity traders, for example, is mainly driven by liquidity concerns. In addition, if we also introduce overconfident, small speculators into the market, we postulate that this will further increase return volatility as information asymmetry rises. The reason being small speculators will miscalibrate the private signals they receive, which leads them to trade more aggressively.

The impact of this will be more noticeable as futures near maturity as the implicit value of receiving private signals grow closer to maturity.

To illustrate this, we present in Appendix A a simplified model of trading and returns that incorporates these features and shows, under these conditions, (i) the speculative effect will have a positive effect on return volatility; (ii) the presence of overconfident, small speculators will strengthen this relationship; and (iii) due to their overconfidence, the relative activity of small speculators to large speculators will grow as futures near maturity.

We test our hypothesis of the impact that the speculative effect will have against Hong's (2000) prediction by regressing Equation (5). To identify the impact that information asymmetry and time-to-maturity have on return volatility, return volatility (RV) is regressed on both information asymmetry (θ_{MRR}) and time-to-maturity (TTM), whilst controlling for seasonality ($MONTH$) and liquidity (LN_NT). Table 4 shows that, consistent with our expectation, the coefficients for θ_{MRR} are positive and significant at the one percent level across all futures, suggesting that information asymmetry positively impacts return volatility. If we look at Soybean meal for an example, the coefficient for θ_{MRR} is 22.611. When information asymmetry increases by one standard deviation (0.015, see Table 1), return volatility rises by 0.339 (0.015x22.611), which is approximately half of its standard deviation (0.672, see Table 1). The coefficients for TTM, which are the coefficients for the price elasticity effect, are mixed. The coefficients for LN_NT are positive and highly significant at the one percent level for all futures except Soybean oil. This is consistent with the notion that return volatility is positively related to liquidity.

[Insert Table 4]

Having substantiated the directions of the two relationships that information asymmetry has with time-to-maturity (upward trending) and with return volatility (positive), we expect the speculative effect to have a positive impact on the time-to-maturity pattern of return volatility. To confirm this, we regress Equation (6) to get the total effect of time-to-maturity on return volatility. We then proceed to use these results, along with the results from the regressions of Equations (4) and (5), to calculate the coefficients and statistical significance of the speculative and the price elasticity effects.

We report the effects in Table 5. As expected, the coefficients for the speculative effect are consistently negative and significant at the one percent level for all futures. On the other hand, the results for the price elasticity effect are mixed. The coefficients are positive and significant at the one percent level for Soybean and Feeder cattle, and at the ten percent level for Corn. It is insignificant for Wheat, and is negative and significant, to at least the five percent level, for the remaining futures.

[Insert Table 5]

The economic impact the speculative effect has on return volatility is significant. Taking Live cattle as an example, the coefficient of -14.426x10^{-3} for the speculative effect indicates an increase of 0.144 $((-10) \times (-14.42 \times 10^{-3}))$ in return volatility when the futures contract rolls ten days toward to maturity. Since return volatility is measured as a natural logarithm, this means the speculative effect is responsible for an increase of 15.48% ($e^{0.144} - 100\%$) in daily realized volatility. Similar analysis for other futures in our sample shows that, on average, the speculative effect raises daily realized volatility by 6.87% for every ten days.

To provide a visual illustration of these effects, Figure 3 shows the impact of the speculative effect on the time-to-maturity pattern of return volatility. We can see that the speculative effect consistently supports the upward pattern of return volatility over a futures life. In some cases the price elasticity effect strengthens the speculative effect (such as for Soybean and Soybean meal) while in other cases it works against the speculative effect (Corn and Feeder cattle). However, for most futures, the speculative effect is strong enough to increase return volatility as maturity nears. The coefficients for the total effect are negative and significant at the one percent level for eleven futures and insignificant for Feeder cattle.

[Insert Figure 3]

There are several points worth discussing from the above results. First, the mixed results for the price elasticity effect may be explained by the state variable hypothesis (Anderson and Danthine, 1983). The reason is that 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 to maturity, we can see a positive price elasticity effect on the slope of return volatility. Otherwise, if information flows are clustered far from maturity, the effect will be negative.

Second, our results imply that the time-to-maturity pattern of return volatility observed in previous studies are not only caused by the Samuelson (price elasticity) effect, but rather the interplay between this effect and the speculative effect. 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. This could be the reason behind the mixed empirical results found in other studies.

3.3. Small speculators in the market

Our model suggests that the positive impact of the speculative effect on return volatility will be further moderated when small speculators are present. Specifically, we expect small speculators to be more active, relative to large speculators, as futures roll toward their maturity. To find evidence of this, we test the relationship between the relative level of trading by small speculators and time-to-maturity. Since detailed data for intraday trading by each group is not available, we rely on two indirect proxies to measure the relative trading level of small speculators: average trade size and gross open interest.

We posit that smaller average trade sizes throughout the day indicate that small speculators are more active, as they usually trade in more modest volumes. Although it is possible to argue that with the growth of algorithmic trading it is easy for larger investors to split large orders into smaller parcels, we would then expect this order splitting to happen throughout the life of the futures contract. So, as long as we compare daily trade sizes relative to trade sizes throughout the life of a futures contract, we will be able to control for this. In addition, we account for order splitting in our calculations by aggregating trades within five seconds where there are no quote updates. Thus, we expect that a lower relative daily trade size indicates more trading by small speculators. Daily average trade size is calculated as:

$$Tradesize_t = \frac{Volume_t}{NT_t} \tag{7}$$

where $Volume$ and NT are the trading volume and the number of trades occurring during the day, respectively.

Our second proxy for capturing small speculator activity is gross open interest. The weekly Commitments of Traders (COT) report available from the Commodity Futures Trading Mission (CFTC) includes the open interest positions for different categories based on the type of market participant. These categories are Producer/Merchant/Processor/User, Swap Dealers, Money Managers, Other Reportables, and Non-Reportable Positions. We associate the Producer/Merchant/Processor/User category as hedgers who trade to hedge their supply/demand of the commodity. Traders under the Swap Dealers (SD), Money Managers (MM), and Other Reportables (OR) categories will predominantly be large, institutional speculators. The Non-Reportable Positions (NR) category reflect small positions, likely from the small speculators we are interested in capturing. Based on this, we can estimate the weekly proportion of small speculators gross (long plus short) open interest position relative to that of large speculators:

$$SmallOI_w = \frac{NR_w}{SD_w + MM_w + OR_w} \tag{8}$$

One issue with the $SmallOI$ measure is that our time series for each futures is based on examining contracts closest to maturity, while the open interest data from the COT report is aggregated from all the contracts that are trading at the time. We therefore use the $SmallOI$ measure for only six selected futures that the COT data are broken down by "old" and "other" crop years. According to the CFTC, data for the "old" crop year is the aggregated data for the few contracts that are close to maturity (these contracts are maturing within the current crop year, or "old" crop year, in contrast to the contracts that will mature in the subsequent years, or "other" crop years). As the contracts used to construct our time series are those with the highest volume at the time, we can assume that their open interest position make up a high proportion of the "old" crop year open interest data. The six futures with the "old" open interest data are Corn, Wheat, Soybean, Soybean meal, Soybean oil, and Lean hogs. For other futures, aggregated data of all contracts presents too much noise.

To estimate the relative trading activity of small speculators over the life of a futures contract, we regress $Tradesize$ and $SmallOI$ on time-to-maturity (TTM), whilst controlling for seasonality and liquidity:

$$Tradesize_t = \alpha + \zeta TTM_t + MONTH + \varepsilon_t \tag{9}$$

$$SmallOI_w = \alpha + \zeta TTM_w + LN\_NT_w + MONTH + \varepsilon_w \tag{10}$$

Note that in Equation (9) we do not include our control for liquidity (LN_NT) since LN_NT and $Tradesize$ will be interdependent. $SmallOI$ is measured on a weekly basis so for the regression using Equation (10) the independent variables are collapsed into average weekly measures, and $MONTH$ is the month when the week starts.

The results for Equation (9) are shown in Table 6 and the results for Equation (10) are shown in Table 7. Consistent with our expectation, Table 6 shows that the coefficients for TTM are positive for all futures, indicating that the average daily trade size is smaller when the futures contract is closer to maturity. The coefficients are significant at the one percent level for Corn, Soybean, Soybean meal, Live cattle and Silver; at the five percent level for Feeder cattle and Soybean oil; and at the ten percent level for Wheat, Gold, Copper and Crude oil. Also, by splitting a contract's life we find that trade size is, on average, 2.89% smaller in the fourth, relative to the first, quartile.

Table 7 provides evidence that the proportional open interest position of small speculators increases nearer to maturity for four of the six futures we have data for. The coefficients for TTM are negative and significant at the five percent level for Corn, Soybean and Wheat and at the ten percent level for Lean hogs. On average, the proportion of small speculator open interest increases 18.19% over the contract life for those four futures. The coefficients are insignificant for Soybean meal and Soybean oil. Overall, the results suggest that small speculators are relatively more active when futures approach maturity and information asymmetry arises based on their open interest positions.

[Insert Table 6 and Table 7]

Finally, in Table 8 we run panel regressions across all our futures to see the impact that trade size has on return volatility. Regression 1 shows the significant, positive impact that the presence of more small speculators (lower trade size) has on return volatility. Regression 2 tests our model's second prediction that a rise in small speculators will positively moderate the impact that information asymmetry has on return volatility. We create a dummy variable that is equal to one if the trade size is below the median level for the futures contract on any given day, and zero otherwise. The interaction coefficient of this dummy variable with our information asymmetry variable is negative and significant at the one percent level, indicative of the speculative effect being stronger in the presence of more small speculators.

[Insert Table 8]

4. Robustness tests

We conduct some additional tests for robustness. First, to account for potential autocorrelation in return volatility, we include the previous day's return volatility as a control variable when we run the regressions for return volatility in Equations (5) and (6). Table 9 shows that the results remain robust. The coefficients for the speculative effect are negative and significant at the one percent level for eleven futures and at the five percent level for Copper.

[Insert Table 9]

Second, we 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 similar to the MRR method, although less utilized in the literature. The daily adverse selection component is computed by estimating the two following equations simultaneously using GMM [Equation (25), page 1015 and Equation (21), page 2014]:

$$\Delta P_t = \frac{S}{2} Q_t + (\alpha_{HS} + \beta_{HS} - 1) \frac{S}{2} Q_{t-1} - \alpha_{HS} \frac{S}{2} (1 - 2\pi) Q_{t-2} + e_t \qquad (11)$$

$$\mathrm{E}(Q_{t-1} | Q_{t-2}) = (1 - 2\pi) Q_{t-2} \qquad (12)$$

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). 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. Since α_{HS} reflects the adverse selection cost relative to other components of the spread, while we are interested in the absolute measure of information asymmetry, we multiple α_{HS} by the half-spread to get the absolute value.

$$HS = \alpha_{HS} \times \frac{\bar{S}}{2} \tag{13}$$

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

Table 10 shows the results for the time-to-maturity pattern of information asymmetry and Table 11 shows the results for the effects when we use HS as our information asymmetry variable in the mediation regressions. In general, our results hold for ten of the twelve futures in our sample.

[Insert Table 10 and Table 11]

5. Conclusion

This paper 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, we show that an economically significant speculative effect drives the positive relationship that the literature (Rutledge, 1976; Anderson, 1985; Milonas, 1986; Khoury and Yourougou, 1993; Bessembinder et al., 1996; and Duong and Kalev, 2008.) generally finds between time-to-maturity and return volatility. We provide evidence supporting Hong's (2000) assertion that information asymmetry is negatively related to the life of a futures contract. However, our empirical results also show this leads to a positive, as opposed to his prediction of a negative relationship, with return volatility. We argue this is due to uninformed hedgers not learning about the information asymmetry structure of the futures market and that overconfident, small speculators are active within the market.

Taken together, our results provide a new perspective on the time-to-maturity pattern of return volatility and the role that small speculators may play in this relationship. This raises interesting directions for future research. This would include how information flows affect the observable speculative effect, as this will have a direct bearing on information asymmetry within the market.

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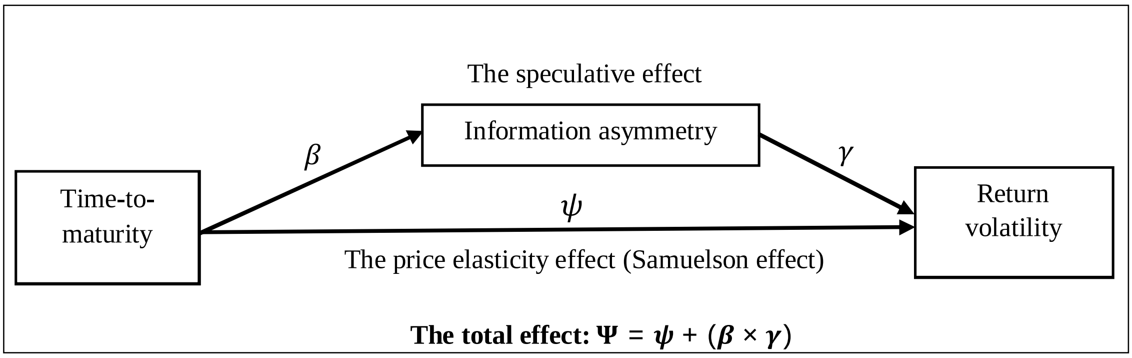
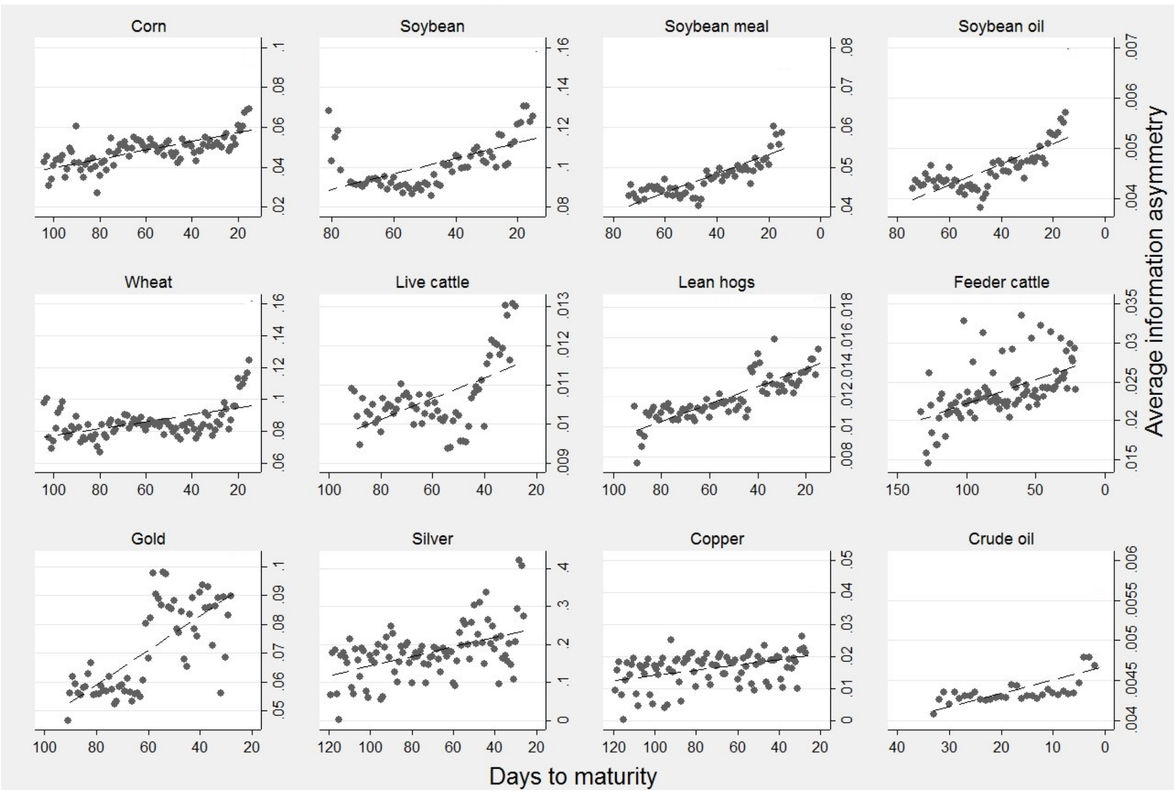
Figure 1. The speculative effect versus the price elasticity effect.



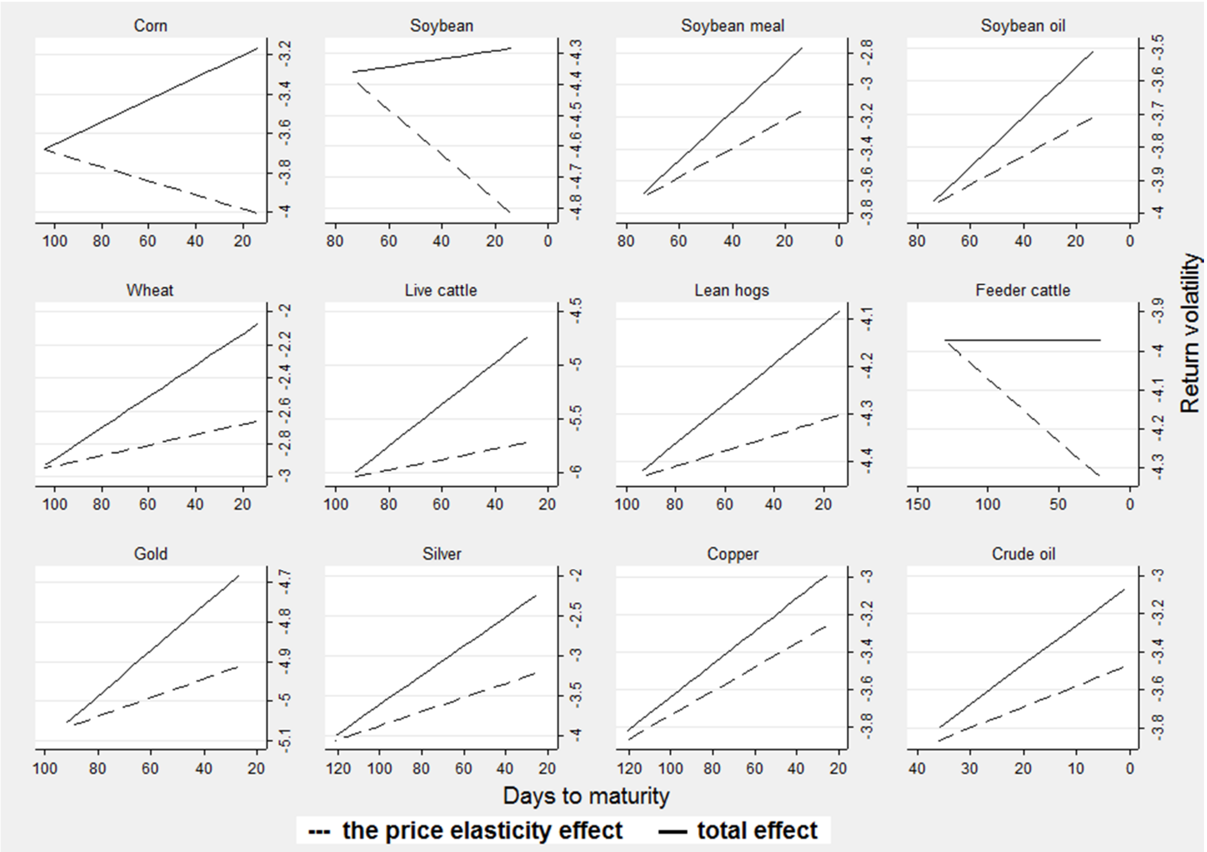
This figure illustrates the mediation framework we use. The time-to-maturity/ return volatility relationship materializes from two channels; with one being classified as the direct channel (the price elasticity effect), and the second being an indirect channel (the speculative effect) through a mediating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

Figure 2. The time-to-maturity pattern of information asymmetry



This figure illustrates the time-to-maturity pattern of information asymmetry, measured by the information asymmetry component of the bid-ask spread estimated from Madhavan, Richardson and Rooman's (1997) model. The scatter points represent the average information asymmetry for each day to maturity. The dotted line is the fitted trend line.

Figure 3. The impact of the speculative effect on the time-to-maturity pattern of return volatility



This graph illustrates the impact of the speculative effect on the time-to-maturity pattern of return volatility. 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 total effect.

Table 1: Futures contract details and descriptive statistics.

Futures	Futures exchange	Expiration month	Mean (std.) daily return volatility	Mean (std.) daily information asymmetry		Mean (std.) daily trading volume
				Absolute value	Percentage of the spread	
Corn	CBOT	3,5,7,9,12	-3.682 (0.838)	0.051 (0.029)	37.05% (17.09%)	135,953 (54,119)
Soybean	CBOT	1,3,5,7,8,9,11	-4.097 (0.652)	0.104 (0.036)	64.61% (12.01%)	83,896 (42,433)
Soybean meal	CBOT	1,3,5,7,8,9,10,12	-3.603 (0.672)	0.049 (0.015)	74.85% (11.34%)	31,228 (14,562)
Soybean oil	CBOT	1,3,5,7,8,9,10,12	-3.828 (0.719)	0.005 (0.001)	71.82% (11.47%)	41,198 (20,042)
Wheat	CBOT	3,5,7,9,12	-3.280 (0.779)	0.088 (0.034)	58.90% (11.47%)	52,887 (22,096)
Live cattle	CME	2,4,6,8,10,12	-5.074 (0.801)	0.011 (0.003)	64.13% (11.33%)	21,632 (8,052)
Lean hogs	CME	2,4,5,6,7,8,10,12	-4.135 (0.859)	0.012 (0.006)	67.88% (11.57%)	17,006 (6,765)
Feeder cattle	CME	1,3,4,5,8,9,10,11	-5.042 (0.800)	0.024 (0.007)	77.91% (12.56%)	3,059 (1,363)
Gold	COMEX	2,4,6,8,10,12	-4.710 (0.701)	0.075 (0.055)	77.63% (10.16%)	112,106 (74,312)
Silver	COMEX	1,3,5,7,9,12	-3.467 (0.849)	0.197 (0.170)	78.53% (9.22%)	43,882 (21,472)
Copper	COMEX	3,5,7,9,12	-4.064 (0.828)	0.018 (0.016)	91.83% (9.23%)	42,747 (17,301)
Crude oil	NYMEX	Every month	-3.682 (0.838)	0.005 (0.001)	65.58% (9.50%)	285,108 (114,547)

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 dollar value (θ_{MRR}) and as the percentage of the spread ($\theta_{MRR} / (\phi + \theta_{MRR})$). Trading volume is the daily number of contracts being traded.

Table 2: Univariate tests of the relationship between information asymmetry and time-to-maturity.

Futures	Information asymmetry		
	Close to maturity	Far from maturity	Difference (t-statistic)
Corn	0.054	0.047	0.007*** (7.15)
Soybean	0.113	0.093	0.020*** (11.16)
Soybean meal	0.053	0.045	0.008*** (10.73)
Soybean oil	0.005	0.004	0.001*** (10.94)
Wheat	0.093	0.083	0.010*** (5.57)
Live cattle	0.011	0.010	0.001*** (3.05)
Lean hogs	0.013	0.011	0.002*** (6.69)
Feeder cattle	0.024	0.022	0.002*** (4.46)
Gold	0.084	0.064	0.020*** (7.19)
Silver	0.225	0.166	0.059*** (4.57)
Copper	0.019	0.016	0.003*** (2.52)
Crude oil	0.005	0.004	0.001*** (8.93)

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.

Table 3: Testing the time-to-maturity pattern of information asymmetry.

	Panel A: Results without controls $\theta_{MRR_t} = \alpha + \beta TTM_t + \varepsilon_t$					
	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
TTM (x10^{-3})	-0.248***	-0.677***	-0.289***	-0.024***	-0.341***	-0.026***
	(-7.52)	(-12.00)	(-13.23)	(-11.10)	(-7.47)	(-5.44)
Intercept	0.064***	0.131***	0.060***	0.006***	0.105***	0.012***
	(31.71)	(44.87)	(56.31)	(55.68)	(37.07)	(38.11)
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.039	0.106	0.106	0.094	0.054	0.020
	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
TTM (x10^{-3})	-0.058***	-0.045***	-0.653**	-1.284***	-0.086***	-0.056***
	(-8.36)	(-6.85)	(-8.27)	(-4.76)	(-3.10)	(-10.20)
Intercept	0.015***	0.026***	0.112***	0.272***	0.021***	0.005***
	(31.71)	(59.09)	(20.33)	(13.68)	(16.43)	(49.93)
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.029	0.025	0.039	0.013	0.010	0.129
	Panel B: Results when controlling for seasonality and liquidity $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$					
	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
TTM (x10^{-3})	-0.681***	-0.552***	-0.269***	-0.018***	-0.473***	-0.099***
	(-8.97)	(-6.26)	(-6.74)	(-7.79)	(-5.02)	(-10.36)
LN_NT	0.027***	-0.006**	-0.003***	-0.001***	-0.004	0.003***
	(10.85)	(-2.25)	(-3.20)	(-4.55)	(-1.14)	(7.38)
Intercept	-0.163***	0.179***	0.083***	0.010***	0.140***	-0.007***
	(-7.11)	(7.34)	(11.56)	(10.08)	(4.74)	(-2.62)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.268	0.391	0.269	0.292	0.126	0.174
	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
TTM (x10^{-3})	-0.033***	-0.047***	-0.599**	-6.215***	-0.149***	-0.022***
	(-6.26)	(-4.06)	(-5.44)	(-7.63)	(-2.61)	(-7.63)
LN_NT	-0.004***	0.005***	-0.024***	-0.019	-0.005**	-0.001***
	(-9.49)	(15.55)	(-16.28)	(-1.30)	(-2.17)	(-9.59)
Intercept	0.047***	-0.009***	0.325***	0.794***	0.076***	0.015***
	(12.62)	(-4.24)	(21.32)	(5.06)	(3.39)	(14.27)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.453	0.213	0.546	0.124	0.081	0.348

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 (θ_{MRR}) calculated using Madhavan, Richardson and Rooman's (1997) model. Time to maturity (TTM) is the number of days until expiration. LN_NT is the logarithm of the number of trades during the day. $MONTH$ represents a vector of dummy variables for each month. 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 4: Testing the impact of information asymmetry and time-to-maturity on return volatility.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
θ_{MRR}	13.599***	10.452***	22.611***	176.423***	13.383***	145.905***
	(18.60)	(19.92)	(14.52)	(8.91)	(24.15)	(23.11)
TTM (x10^{-3})	3.573*	-7.319***	-9.037***	-4.423***	-3.181	-4.913**
	(1.76)	(-4.17)	(-4.35)	(-2.89)	(-1.55)	(-2.10)
LN_NT	0.503***	0.490**	0.334***	0.029	0.510***	0.555***
	(7.93)	(14.79)	(8.65)	(0.49)	(9.00)	(12.51)
Intercept	-9.005***	-9.131***	-6.995***	-4.706***	-8.646***	-10.873***
	(-17.55)	(-31.77)	(-20.42)	(-8.85)	(-19.48)	(-39.22)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.397	0.336	0.252	0.178	0.430	0.541
	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
θ_{MRR}	77.651***	67.594***	11.225***	1.523***	15.800***	447.654***
	(6.43)	(24.23)	(16.03)	(17.88)	(6.61)	(13.73)
TTM (x10^{-3})	-1.615	3.181**	-5.066***	-8.826***	-6.418***	-11.044***
	(-1.37)	(2.08)	(-3.90)	(-3.71)	(-2.68)	(-5.79)
LN_NT	0.682***	0.319***	0.343***	0.285***	0.304***	0.820***
	(11.18)	(10.57)	(13.85)	(7.92)	(6.73)	(20.44)
Intercept	-10.459***	-9.010***	-8.606***	-5.756***	-6.766***	-14.221***
	(-17.64)	(-41.96)	(-28.49)	(-15.32)	(-15.68)	(-28.27)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.229	0.212	0.399	0.254	0.169	0.482

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 is the natural logarithm of the daily five-minute realized volatility (RV) . Information asymmetry is measured by the daily information asymmetry component of the bid-ask spread (θ_{MRR}) calculated following Madhavan, Richardson and Rooman's (1997) model. Time to maturity (TTM) is the number of days until expiration. LN_NT is the logarithm of the number of trades during the day. $MONTH$ represents a vector of dummy variables for each month. 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 5: The speculative effect and the price elasticity effect.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
The speculative effect (x10^{-3})	-9.257***	-5.771***	-6.091***	-3.163***	-6.336***	-14.426***
	(-7.99)	(-5.86)	(-6.23)	(-5.59)	(-4.36)	(-10.35)
The price elasticity effect (x10^{-3})	3.573*	-7.319***	-9.037***	-4.423***	-3.181	-4.913***
	(1.76)	(-4.17)	(-4.35)	(-2.89)	(-1.55)	(-2.10)
Total effect (x10^{-3})	-5.684**	-13.090***	-15.128***	-7.585***	-9.517***	-19.339***
	(-2.49)	(-6.70)	(-5.12)	(-4.53)	(-3.89)	(-9.13)
Observations	1512	1512	1512	1512	1512	1512
	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
The speculative effect (x10^{-3})	-2.569***	-3.191***	-6.722***	-9.468***	-2.349***	-9.691***
	(-4.18)	(-4.62)	(-7.18)	(-8.46)	(-2.78)	(-5.93)
The price elasticity effect (x10^{-3})	-1.615	3.181**	-5.066***	-8.826***	-6.418***	-11.044***
	(-1.37)	(2.08)	(-3.90)	(-4.19)	(-2.68)	(-5.79)
Total effect (x10^{-3})	-4.184***	-0.010	-11.788***	-18.294***	-8.767***	-20.735***
	(-2.94)	(-0.01)	(-7.88)	(-8.04)	(-3.54)	(-8.25)
Observations	1512	1512	1512	1512	1512	1512

This table measures the speculative effect and the price elasticity effect. 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) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$. 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 logarithm of the number of trades during the day. $MONTH$ represents a vector of dummy variables for every month of the year. The coefficient for the total 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 $(\Psi - \psi)$. 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 6: Trade size and time-to-maturity.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
TTM	0.062***	0.024***	0.013***	0.011**	0.015*	0.021***
	(3.32)	(3.56)	(3.43)	(2.45)	(1.74)	(6.65)
Intercept	14.198***	6.665***	5.404***	10.907***	7.213***	4.340***
	(11.93)	(15.91)	(21.06)	(6.76)	(12.93)	(26.63)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.083	0.337	0.151	0.063	0.025	0.032

	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
TTM	0.004**	0.001**	0.003*	0.016***	0.001*	0.005*
	(-2.39)	(2.27)	(1.87)	(6.84)	(1.58)	(1.80)
Intercept	1.539***	4.245***	2.148***	1.844***	4.171***	10.863***
	(5.36)	(32.34)	(7.49)	(10.99)	(5.36)	(11.38)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.121	0.058	0.075	0.056	0.023	0.030

This table examines the relationship between daily trade sizes and futures time-to-maturity using the following regression: $Tradesize_t = \alpha + \zeta TTM_t + MONTH + \varepsilon_t$, where $Tradesize$ is the daily average trade size. Time to maturity (TTM) is the number of days until expiration. $MONTH$ represents a vector of dummy variables for each month. 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 7: Relative open interest of small speculators and time-to-maturity.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Lean hogs
TTM (10^{-3})	-1.839**	-2.375**	-1.596	0.322	-0.790**	-0.018*
	(-2.44)	(-2.18)	(-0.95)	(0.50)	(-2.15)	(-1.73)
LN_NT	0.028**	-0.014	-0.190***	-0.017	-0.018	-0.032***
	(2.00)	(-0.042)	(-3.83)	(-1.12)	(-1.34)	(-5.74)
Intercept	0.164	0.391***	2.036***	0.371***	0.352***	0.499***
	(1.33)	(8.96)	(4.46)	(3.46)	(2.78)	(11.96)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	312	312	312	312	312	312
Adjusted R^2	0.235	0.277	0.279	0.351	0.214	0.551

This table examines the relative level of open interest from small speculators over the futures contract life using the following regression: $SmallOI_w = \alpha + \zeta TTM_w + LN\_NT_w + MONTH + \varepsilon_w$, where $SmallOI$ is the proportion of small speculators gross open interest position relative to that of large speculators. Time to maturity (TTM) is the number of days until expiration. $MONTH$ represents a vector of dummy variables for each month. 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 8: The moderating role of small speculators on the speculative effect.

	Model (1)	Model (2)
$Tradesize$	-0.0719***	
	(-3.21)	
$D_{Tradesize}$		-0.412***
		(-8.99)
θ_{MRR} (10^{-3})		0.006***
		(20.17)
$D_{Tradesize} \times \theta_{MRR}$ (10^{-3})		-0.003***
		(-8.02)
TTM (10^{-3})	-2.081**	-1.388
	(-2.60)	(-1.63)
Intercept	-3.576***	-3.820***
	(-25.26)	(-74.30)
$MONTH$ dummies and futures fixed effects	YES	YES
Observations	18,144	18,144
Adjusted R^2	0.113	0.150

Model (1) examines the relationship between $Tradesize$ and return volatility using the panel regression: $RV_{it} = \alpha + \beta Tradesize_{it} + \gamma TTM_{it} + MONTH + \varepsilon_{it}$. Model (2) tests the moderating effect using the panel regression: $RV_{it} = \alpha + \delta {\theta_{MRR}}_{it} + \mu {D_{Tradesize}}_{it} + \upsilon {D_{Tradesize}}_{it} \times {\theta_{MRR}}_{it} + \psi TTM_{it} + MONTH + \varepsilon_{it}$, where $D_{Tradesize}$ is a dummy variable that takes the value of one if $Tradesize$ is above the median size within each futures, and zero otherwise. All t-statistics reported in parentheses are based on standard errors clustered by each futures. Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively.

Table 9: The speculative effect and the price elasticity effect when controlling for autocorrelation in return volatility.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
The speculative effect (x10^{-3})	-7.326***	-4.717***	-5.012***	-2.537***	-4.840***	-12.947***
	(-7.65)	(-5.77)	(-6.10)	(-5.39)	(-4.35)	(-9.97)
The price elasticity effect (x10^{-3})	0.574	-8.121***	-8.620***	-4.182***	-4.566**	-6.741***
	(0.29)	(-4.99)	(-4.75)	(-2.77)	(-2.42)	(-3.86)
Total effect (x10^{-3})	-6.751***	-12.838***	-13.632***	-6.719***	-9.406***	-19.688***
	(-3.21)	(-7.12)	(-7.00)	(-4.35)	(-4.35)	(-9.75)
Observations	1511	1511	1511	1511	1511	1511
	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
The speculative effect (x10^{-3})	-2.045***	-2.588***	-4.934***	-5.382***	-0.933**	-7.314***
	(-4.14)	(-4.57)	(-7.03)	(-7.34)	(-2.39)	(-5.74)
The price elasticity effect (x10^{-3})	-1.479	2.397**	-3.702***	-6.025***	-2.413	-3.727***
	(-1.20)	(2.49)	(-3.38)	(-3.89)	(-1.36)	(-5.66)
Total effect (x10^{-3})	-3.523***	-0.191	-8.636***	-11.407***	-3.345*	-11.041***
	(-2.69)	(-0.17)	(-6.77)	(-6.13)	(-1.84)	(-7.80)
Observations	1511	1511	1511	1511	1511	1511

This table examines the speculative effect and the price elasticity effect. We regress (i) $\theta_{MRR_t} = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, (ii) $RV_t = \alpha + \delta\theta_{MRR_t} + \psi TTM_t + RV_{t-1} + LN\_NT_t + MONTH + \varepsilon_t$, and (iii) $RV_t = \alpha + \Psi TTM_t + RV_{t-1} + LN\_NT_t + MONTH + \varepsilon_t$.. 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 logarithm of the number of trades during the day. $MONTH$ represents a vector of dummy variables for every month of the year. The coefficient for the total 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 $(\Psi - \psi)$. 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 10: Testing the time-to-maturity pattern of information asymmetry using Huang and Stoll's (1997) adverse selection component of the bid-ask spread.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
TTM (x10^{-3})	-0.303***	-0.158*	-0.098**	-0.004*	-0.260***	-0.017
	(-5.17)	(-1.87)	(-2.16)	(-1.74)	(-2.63)	(-0.98)
LN_NT	0.004**	-0.002	-0.003***	-0.002	0.001	-0.001***
	(2.33)	(-1.04)	(-3.54)	(-1.44)	(0.06)	(-4.52)
Intercept	-0.013	0.043**	0.037***	0.002**	0.022	0.014***
	(-0.85)	(2.09)	(4.67)	(2.53)	(0.72)	(6.06)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.065	0.040	0.098	0.030	0.044	0.017

	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
TTM (x10^{-3})	-0.020**	0.010	-0.486***	-2.147***	-0.065**	-0.011***
	(-2.02)	(1.07)	(-4.47)	(-3.51)	(-1.99)	(-3.01)
LN_NT	-0.001**	-0.001***	-0.011***	-0.015*	-0.001	-0.001***
	(-2.51)	(-5.08)	(-6.49)	(-1.67)	(-1.02)	(-2.92)
Intercept	0.013***	0.012***	0.127***	0.334***	0.021**	0.004***
	(4.44)	(6.66)	(7.57)	(3.14)	(1.99)	(3.56)
$MONTH$	YES	YES	YES	YES	YES	YES
Observations	1512	1512	1512	1512	1512	1512
Adjusted R^2	0.012	0.017	0.095	0.066	0.016	0.045

This table presents the results for testing the time-to-maturity pattern of information asymmetry using the following regression: $HS_t = \alpha + \beta TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, where 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. $MONTH$ represents a vector of dummy variables for each month. 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 11: The speculative effect and the price elasticity effect when using Huang and Stoll (1997) adverse selection component of the spread.

	Corn	Soybean	Soybean meal	Soybean oil	Wheat	Live cattle
The speculative effect ($x10^{-3}$)	-4.023***	-0.635*	-0.235*	-0.154*	-1.983**	-0.059
	(-5.07)	(-1.93)	(-1.94)	(-1.88)	(-2.31)	(-0.52)
The price elasticity effect ($x10^{-3}$)	-1.661	-12.455***	-14.893***	-7.431***	-7.533***	-19.280***
	(-7.59)	(-6.48)	(-7.12)	(-6.83)	(-3.27)	(-7.33)
Total effect ($x10^{-3}$)	-5.684**	-13.090***	-15.128***	-7.585***	-9.517***	-19.339***
	(-2.49)	(-6.70)	(-5.12)	(-4.53)	(-3.89)	(-9.13)
Observations	1512	1512	1512	1512	1512	1512

	Lean hogs	Feeder cattle	Gold	Silver	Copper	Crude oil
The speculative effect ($x10^{-3}$)	-0.282*	0.112	-1.903***	-2.800***	-1.068*	-1.553***
	(-1.75)	(0.98)	(-5.01)	(-4.83)	(-1.86)	(-2.60)
The price elasticity effect ($x10^{-3}$)	-3.902***	-0.122	-9.885***	-15.494***	-7.699***	-19.183***
	(-2.76)	(-0.10)	(-7.90)	(-6.86)	(-3.19)	(-7.81)
Total effect ($x10^{-3}$)	-4.184***	-0.010	-11.788***	-18.294***	-8.767***	-20.735***
	(-2.94)	(-0.01)	(-7.88)	(-8.04)	(-3.54)	(-8.25)
Observations	1512	1512	1512	1512	1512	1512

This table examines the speculative effect and the price elasticity effect. We regress (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) $RV_t = \alpha + \Psi TTM_t + LN\_NT_t + MONTH + \varepsilon_t$, HS is the daily absolute value of the adverse selection component of the bid-ask spread calculated following Huang and Stoll (1997) model. TTM is the number of days until expiration. LN_NT is the logarithm of the number of trades during the day. $MONTH$ represents a vector of dummy variables for every month of the year. The coefficient for the total 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 $(\Psi - \psi)$. 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.

Appendix A: A simple model of trading and returns with the presence of liquidity hedgers and small speculators that are overconfident.

Here we provide an illustration that is based on a simplification of Hong's (2000) dynamic model. It has the advantage of providing us with a closed-form solution and a basic point of reference for why the speculative effect may be positively related to time-to-maturity when we model uninformed hedgers as not learning about their relative informational disadvantage. In addition, we allow for the presence of overconfident, small speculators that moderate this relationship.

Hong (2000) considers two classes of investors, informed speculators and uninformed hedgers. Under the condition that fundamental shocks are more persistent than nonmarketed income shocks, he argues that futures return volatility is lower when closer to maturity because uninformed hedgers rationally learn that they are more informationally disadvantaged and hence less incentivized to trade. We re-examine this by removing the assumption of learning and instead introduce traders who do not learn about their informational disadvantage, as well as traders who learn with miscalibration. Specifically, we consider three types of traders: a mass $(1-\lambda)$ of large speculators (denoted by traders L), a mass λ of small speculators (denoted by traders S), and hedgers (denoted by traders H) and three periods, indexed as $t = 0$ (far away from maturity), $t = 1$ (close to maturity), and $t = 2$ (maturity).

We use a similar information structure as Benos (1998). 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 $d \sim N(\bar{d}, \sigma_d^2)$. Following Hong (2000), we assume that when the futures contract is far away from maturity, information asymmetry is minimal. Specifically, at $t = 0$, all traders have identical prior beliefs that $d \sim N(\bar{d}, \sigma_d^2)$. When it is close to maturity (i.e., $t = 1$), information asymmetry arises due to traders L and 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. All uncertainty is resolved at $t = 2$.

Unlike Hong (2000), we assume that traders H do not learn about their informational disadvantage. There can be a multiple number of reasons for this, including that H are liquidity traders in the sense of Grossman and Stiglitz (1980). In other words, their aggregate demand for futures is represented by $h_t \sim N(0, \sigma_h^2)$, $t = 0, 1$. It means that the trading behaviour of traders H is motivated by liquidity reasons, not information reasons. 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 contrast with Hong (2000). Another key departure from Hong (2000) is that, in the same vein as Delong *et al.* (1990), we introduce traders S who learn with overconfidence. We will further show the moderating role that these traders play. There are two key differences between traders L and trader S. First, while traders L hold a rational belief regarding the precision of the private signal they receive, traders S overestimate it. In particular, while traders L believe that $\epsilon \sim N(0, \sigma_\epsilon^2)$, traders S miscalibrate that $\epsilon \sim N(0, \sigma_c^2)$, where $\sigma_c^2 (< \sigma_\epsilon^2)$ indicates the overconfidence level of traders S. Second, in following Hong (2000), we assume that traders L 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.

For simplicity, we follow Kelsey *et al.* (2011) and restrict our attention to linear trading strategies of speculators.[6] Specifically, at *t* = 0, the trading strategy of traders i, $i = L, S$ is as follows, respectively:

[6] 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.

$$D_0^L = \alpha^L[E^L(d) - p_0 + z_0], \tag{1}$$

$$D_0^S = \alpha^S[E^S(d) - p_0], \tag{2}$$

where $\alpha^i > 0$ reflects the risk tolerance of traders i, E^i represents the expectation operator of traders i, and p_0 is the futures price at $t = 0$. Equations (1) and (2) state 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 for traders L.

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

$$(1-\lambda)D_0^L + \lambda D_0^S + h_0 = 0. \tag{3}$$

Solving for the equilibrium price p_0^* yields:

$$p_0^* = \bar{d} + \frac{h_0}{(1-\lambda)\alpha^L + \lambda\alpha^S} + \frac{(1-\lambda)\alpha^L Z_0}{(1-\lambda)\alpha^L + \lambda\alpha^S}. \tag{4}$$

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

$$D_1^L = \alpha^L[E^L(d|s) - p_1 + z_1], \tag{5}$$

$$D_1^S = \alpha^S[E^S(d|s) - p_1], \tag{6}$$

where p_1 is the futures price at $t = 1$. Note that, at $t = 1$, traders L 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. Traders S also receive the private signal s, but overestimate its precision.

By the Bayesian updating rule, we obtain:

$$E^L(d|s) = \bar{d} + \frac{\sigma_d^2}{\sigma_d^2 + \sigma_\epsilon^2}(s - \bar{d}), \tag{7}$$

$$E^S(d|s) = \bar{d} + \frac{\sigma_d^2}{\sigma_d^2 + \sigma_c^2}(s - \bar{d}). \tag{8}$$

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

$$(1 - \lambda)D_1^L + \lambda D_1^S + h_1 = 0. \tag{9}$$

Solving for the equilibrium price p_1^* yields:

$$p_1^* = \bar{d} + \left[\frac{(1-\lambda)\alpha^L}{(1-\lambda)\alpha^L + \lambda\alpha^S}\frac{\sigma_d^2}{\sigma_d^2 + \sigma_\epsilon^2} + \frac{\lambda\alpha^S}{(1-\lambda)\alpha^L + \lambda\alpha^S}\frac{\sigma_d^2}{\sigma_d^2 + \sigma_c^2}\right](s - \bar{d})$$
$$+ \frac{h_1}{(1-\lambda)\alpha^L + \lambda\alpha^S} + \frac{(1-\lambda)\alpha^L z_1}{(1-\lambda)\alpha^L + \lambda\alpha^S}. \tag{10}$$

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 (4) and (10), the difference in futures return volatility between $t = 1$ and $t = 0$ (DiV) is given by:

$$DiV = \left[\frac{(1-\lambda)\alpha^L}{(1-\lambda)\alpha^L + \lambda\alpha^S}\frac{\sigma_d^2}{\sigma_d^2 + \sigma_\epsilon^2} + \frac{\lambda\alpha^S}{(1-\lambda)\alpha^L + \lambda\alpha^S}\frac{\sigma_d^2}{\sigma_d^2 + \sigma_c^2}\right]^2 (\sigma_d^2 + \sigma_\epsilon^2), \tag{11}$$

which is positive, indicating that futures return volatility is higher the closer the contract is to maturity. This is in sharp 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 overturned if the trading behaviour of uninformed hedgers is driven by hedging concerns and not based on learning about their informational disadvantage.[7] We thus obtain our first result:

Result 1*: If uninformed hedgers are liquidity traders (or there is no learning by uninformed hedgers about their informational disadvantage), then as information asymmetry arises, futures return volatility is higher the closer the contract is to maturity.*

Next, we examine how the presence of small speculators that are overconfident moderates Result 1. Note that $\lambda = 0$ means that there is no trader S. Also, $\partial DiV / \partial \lambda > 0$, i.e., DiV is strictly increasing in λ. Thus, DiV is lowest when $\lambda = 0$, implying that DiV is higher in the presence of traders S than in the absence of traders S, and DiV is higher when there are more traders S. Furthermore, $\partial DiV / \partial \sigma_c^2 < 0$, i.e., DiV becomes greater when σ_c^2 is smaller, which states that DiV is higher when small speculators are more overconfident. These findings are summarized in our second result:

Result 2: *Ceteris paribus, the effect of information asymmetry on the relationship between time to maturity and futures return volatility is more pronounced in the presence of small speculators, if there are more small speculators, or if small speculators are more overconfident.*

Finally, we examine how trading volume changes when moving from $t = 0$ (far away from maturity) to $t = 1$ (close to maturity). To isolate our main concern, we focus on the situation where the private signal is positive and the nonmarketed income shocks are normalized to their mean ($s > \bar{d}$ and $z_t = 0$).[8] From Equations (1), (2), (5), and (6), it follows that:

[7] It is evident from the analysis that our results do not require traders H to be liquidity traders. The key requirement is that traders H do not learn about their informational disadvantage.
[8] Focusing on positive values of $D$is innocuous as our empirical analysis considers trade sizes.

$$\frac{D_0^S}{D_0^L} = \frac{\alpha^S}{\alpha^L}, \tag{12}$$

$$\frac{D_1^S}{D_1^L} = \frac{\alpha^S}{\alpha^L}\left(\frac{\bar{d} + \frac{\sigma_d^2}{\sigma_d^2 + \sigma_c^2}\left(s - \bar{d}\right) - p_1^*}{\bar{d} + \frac{\sigma_d^2}{\sigma_d^2 + \sigma_\epsilon^2}\left(s - \bar{d}\right) - p_1^*}\right). \tag{13}$$

Because $\sigma_c^2 < \sigma_\epsilon^2$, we obtain that $D_1^S/D_1^L > D_0^S/D_0^L$. This says that, driven by the miscalibration of traders S, the ratio of trading volume of traders S to that of traders L is higher when closer to maturity. We thus obtain our third result:

Result 3: *Driven by small speculators' miscalibration, the ratio of small speculators' trading volume relative to large speculators' is higher when closer to maturity.*