

Information implied by agricultural futures option prices

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April 2014

Very preliminary, comments welcomed with open arms. Please do not quote without permission. The paper has benefited from comments received at presentations at Stockholm University and the 2013 Southern Finance Association Meetings. Robert Brooks offered great insights as the SFA discussant. Author information: Pete Locke, M.J. Neeley School of Business, TCU, Fort Worth Texas, 76110. 817-257-5048, plocke@tcu.edu.

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Abstract

I investigate the relationship between futures option prices and futures volatility for corn, wheat and soybean futures and options, using tick data from 1995 through June of 2012. The results reveal a distinct cyclical pattern for corn, wheat and soybean volatility, with this pattern similarly reflected in the respective implied volatilities from options prices. Implied volatility in the option markets is significantly related to future realized volatility, with the strength of this relationship depending on the time to expiration. Forward implied volatilities also are related to the future realized volatility. Implied volatility offers significant value added in the forecast of realized volatility. The well-known Samuelson effect in agricultural futures volatility is also reflected in implied volatilities. I also find a second-order Samuelson effect where the daily range of implied volatilities increases as time to expiration nears. The range of daily implied volatilities is related to the divergence between implied volatility and future realized volatility, or the realized volatility swap rate.

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1. Introduction

Option prices contain information from traders. For example, some researchers are concerned with the extent to which informed traders use option trades to leverage their information about the underlying instrument. Options appear to be responsible for revealing at most a small amount of the fundamental information in equities, with this effect slightly more pronounced around news events. Other studies have investigated the predictive power of implied volatility. In other words, if the option prices and an option model are used to calculate an implied volatility, how is this related to future volatility and/or stock returns? The results in this direction are somewhat mixed. More recent work suggests an interesting relationship between option market liquidity, volatility and returns. Here, using 17 years of agricultural futures options tick data, I examine implied volatility and its relation to future volatility.

I first perform some ground work by describing the history of realized volatility in wheat, corn and soybean futures. I find that over the 17-year sample, these agricultural futures volatilities reveal strong seasonal patterns. Further, this seasonal pattern is predominantly systemic, across expirations, rather than being expiration specific. There are relatively small but significant seasonal swings in the spread between futures volatilities. In addition, I find a strong Samuelson (1965) effect for these commodities, whereby futures volatility increases as time to delivery nears. Next, I calculate daily implied volatilities for different expirations using a standard option pricing model. Implied volatility shows similar seasonality and time-to-expiration effects as realized volatility. Implied volatility for all option expirations is significantly higher for all three commodities in the summer “growing” season. Implied volatility is also significantly related to future realized volatility from the time of observation until the option expiration. I also back out a forward implied volatility measure from pairs of implied

volatilities. This forward implied volatility is significantly related to the realized future volatility for the same time span as that spanned by the forward implied volatility. Finally, I show that implied volatility adds value to an estimate of future realized volatility.

The use of intraday data allow me to investigate any information contained in the dispersion of implied volatilities. Relative illiquidity and unbalanced order flow may cause a widening of the implied volatility range on a day. I calculate the range of daily implied volatilities from the actively traded options. One way to interpret the range of implied volatilities is as an (unsigned) measure of order flow.¹ Alternatively, or perhaps in addition, the implied volatility range could be related to future volatility uncertainty.² I find that the range of implied volatilities is related to the time to expiration, growing as expiration nears. This pattern for the range may be considered a second-order Samuelson effect. In addition, I find that the range is positively related to the “forecast error,” the absolute value of the difference between mean implied volatility and the realized volatility from the time of the observation to expiration. This finding supports models such as Hseih and Jarrow (2013) which are based on option market makers’ inability to completely hedge price risk.

The rest of the paper is organized as follows. In section 2 I discuss some related literature. In section 3 I offer some discussion of the mechanics of futures options, and discuss the general issues related to inferring information from option prices. I use Section 4 to describe the data and offers some sample statistics. I provide results in Section 5 and use section 6 to wrap it up.

2. Related literature

¹ Ni, Pan and Poteshman (2008) find that option order flow is a good predictor of future realized volatility. Similarly, Muravyev (2013) shows that the relationship between option order flow and option returns can be linked to an inventory model.

² Hseih and Jarrow (2013) model volatility uncertainty in an incomplete markets world, where the bid ask spread in the options market reflects the volatility uncertainty due to the inability of market makers to hedge.

Most option information research concentrates on the stock price or stock index value implied by the option price, and the relationship of this implied price to the existing asset price. This line of research takes as given some future stock price distribution (i.e., volatility), sans the current asset price, and proceeds to extract the implied asset or futures price by inverting an option pricing model. Since stock options allow for substantial leverage relative to stocks, it is possible that traders with information about the future stock value would use the vast leverage of option markets to increase their equity exposure, e.g., buying calls when their information is positive or puts when their information is negative. Thus, this line of research seeks to reveal either a lead/lag or some other informational relationship between options and equities, to identify the propensity for informed trading in options prices. Manaster and Rendleman (1982), Stephan and Whaley (1990) and Chan, Chung and Johnson (1993) form an early set of papers, with Chan et al. (1993) tying up this set, building on the prior two papers and finding that there is no evidence of any lead or lag of futures or options transactions prices. Chakravarty, Gulen and Mayhew (2004) find that about 17 percent of fundamental equity information is being discovered in the options market.³ More recently, Broussard, Muravyev and Pearson (2012) find that the primary instigator of a mispricing (i.e., the reason for an potentially arbitrageable overlap of bids and offers) is a change in the stock quote and that subsequent to a mispricing almost always the option quotes respond in kind instead of having the equity quotes reverse.

Other studies have looked at the forecasting power of implied volatility and the existence of an informative variance premium. For example, Canina and Figlewski (1993) find that implied volatility misses the mark in predicting future stock price volatility. Szakmary et al. (2003) offer evidence countering this, showing that implied volatility outperforms historical volatility in predicting future

³ Using technology similar to Chakravarty et al., a recent paper by Boyd and Locke (2013) finds essentially no evidence that natural gas futures options contain information about the natural gas futures price.

realized volatility, over a variety of markets. Egelkraut, Garcia and Sherrick (2007) focus on estimating the forward implied volatility, extracting the forward volatilities from overlapping implied volatilities. Christoffersen and Mazzotta (2005) find that in their proprietary sample of OTC options trades, prices do reveal the future distribution of foreign exchange rates. Carr and Wu (2009) introduce the concept of the variance premium, a measure by which the implied volatility from option prices over-estimates future price volatility. Drechsler and Yaron (2011) find that the variance premium is informative for future stock returns. Johnson and So (2012) also show that when option volume relative to stock volume is high, there is an information signal about future stock prices. Bolen and Whaley (2004), Garleanu, Pedersen and Poteshman (2009) and Muravyev (2013) find that there is a substantial liquidity effect in option prices, with buying or selling pressure having a noticeable effect on implied volatility or the implied volatility “function.”

3. Some background information on futures options trading

For the bulk of my data, futures options trades occurred solely on the floor of a futures exchange, in an arena adjacent to their associated futures market, under the same trading guidelines and restrictions as in the futures market. The value of the futures call option when exercised is the difference between the current futures price and the strike price. The reverse is the value for a put. Futures options are typically American style, with early exercise for in-the-money puts and calls often rational.

When trading physically, the traders are in tiered bowls known as pits, somewhat isolated from trading desks and the outside world. This is a tradeoff for the traders’ unique access to the order flow. The pits are separate for each commodity and also for futures and options. In the physical trading architecture, orders for futures and futures options from outside customers arrive at desks and are hand-flashed to clerks on the top rim of the pit, who relay them down to brokers. With handheld terminals,

orders may be directed to handheld sets, skipping the clerk, but there remains an isolated pit environment. Other traders, executing proprietary trades, are also in the pit. They may trade to supply liquidity to the brokered trades or follow any strategy. There is no obligation in U.S. futures or futures options markets for any trader to maintain a “fair and orderly” market. All in all, trading futures and futures options on the floor was a noisy, seemingly chaotic physical enterprise prior to the late 2000s. Electronic trading originally was enabled by the futures exchange in the 1990s during the hours when pit trading was not occurring. In the 2000s, first futures and later options began trading electronically simultaneous to pit trading. On October 19, 2012, for example, according to the CMEgroup, there were 9,300,000 futures contracts traded on Globex, the CMEgroup’s electronic platform, vs. 74,000 futures contracts traded physically.⁴ On this date options trades were more evenly divided, with a little over 1,000,000 contracts traded on both Globex and in the option pits. Agricultural futures options had slightly more trades in the pit than on Globex. High volume equity futures options (mostly on the S&P Emini contract) were almost all traded electronically, whereas interest rate options were almost all traded in the pit.

From this trading, both pit and later electronic, the tick data I obtain for this study has no information about who is making the trade, only the time of the trade and the price. If one party to a trade is more in a hurry to buy, then the options price will likely be a little higher than if the party in a hurry is selling, mimicking the trading in the futures pit. There is no recorded bid and ask to reference. In the futures markets, there are proprietary members whose trades appear to provide liquidity to the market. However, it is not the case in futures markets that proprietary traders are always less in a hurry, only providing liquidity by buying at the “bid” and selling at the “ask”. Instead, the proprietary traders appear to trade in a more complicated fashion, taking on significant inventory risks and large losses

⁴ I recorded these numbers from the web site of the Cmegroup, where current, but not historical, numbers are readily available.

from time to time. See, for example, Locke and Mann (2005) for some detailed analysis of futures proprietary trading and associated risk and profitability. Extending this to futures options trading, note that the options price will be directly impacted by changes in the futures price and that many different options, i.e., puts and calls as well as various strikes over several expirations will be trading concurrently. There is much more futures trading than options trading, indicating that option values and prices will be constantly impacted by this fundamental factor in addition to any order flow effects or changes in the markets perception of future volatility. An additional complicating factor is that with so many varieties of options trading concurrently, the tick data for any particular option will be sparse relative to trading in the underlying futures.

The futures exchange records into the time and sales system the prices and times of futures and futures options trades which are traded in the pits and for which there is a price change. Also recorded may be bids which are un-hit but exceed the prior traded price or offers which are un-hit but are lower than the prior traded price. In the electronic market, all trades are recorded into time and sales, including repeated trades at the same price, as well as many more bids and offers. The rationale for making available this time and sales, or tick, data is that futures and futures options traders not present on the floor may wish to verify the appropriateness of the price of their trades. And of course such high frequency transparent prices may themselves stimulate trading. This is the most accessible intraday data for futures and futures options research.

Those familiar with equities research would note that an “order flow” is often inferred by seeing the disparity between trades occurring at offers (considered a “buy”) versus bids (considered a “sell”). For example, this is the method used on options data by Muravyev (2013). Even with futures tick data there have been attempts to infer trade direction, using the time series properties of the price sequence. Kurav (2005) investigates some of the issues in futures market microstructure research. Such

procedures are even more problematic for futures options trading, since the sequence of trades is both across strikes and across puts and calls. A better measure of order flow in options would be in terms of the demand and supply of volatility. I.e., is volatility being bought or sold? As rough proxies for volatility order flow, I calculate two measures, the daily range of implied volatilities and the daily trend in implied volatilities for each option expiration. If during the day customers are buying volatility, then the implied volatility may rise, on average, during such a day. If this is a liquidity effect, then there should be no relation between this flow and future realized volatility. However, it may suggest that the mean implied volatility for a day is a noisy measure of future realized volatility.

Extracting information from option prices has involved a variety of methods over time. Using closing prices, Manaster and Rendleman (1982) estimate the implied volatility and the implied stock price simultaneously among a group of options, minimizing the least squared error between model prices and observed prices. Stefan and Whaley (1990) similarly use an implied volatility estimated from the prior day's closing option and stock prices and hold this constant throughout the next trading day to obtain the implied stock price. Other papers such as Chakravarty et al. (2004) similarly rely on a sequential two-step process, although at a higher frequency. Since my focus is on implied volatility I simply use the most recent futures price, combined with option prices, to extract the implied volatility.

4. Data and detailed sample description

My sample is taken from futures and futures options tick data. Tick data are available for futures and options trades from at least the CMEgroup (their "Datamine" facility) and other downstream vendors. Tick data, also called time and sales data, are a history of transaction prices and the time that trades are executed. Repeated trades at the same transactions price from pit trading are not typically recorded. All electronically executed trade prices are recorded. Here I use tick data from 1995 through

May 2012, sometimes shortening the ending to December 2011 for annual statistics. I select three actively traded agricultural commodities, wheat, corn and soybeans. Futures have been traded on exchanges since the mid-19th century, while options on these futures are a more recent innovation, formally allowed by the U.S. Congress in 1982. Currently trading may occur almost around the clock electronically, though the bulk of trading still occurs during regular “pit” hours, when (as of this writing) some exchange members gather on the floor of the exchange to trade. Pit hours for the three commodities examined here are from 9:30 a.m. to 2:00 p.m. Chicago time.⁵ Since 2006 futures and futures options traders have increasingly traded on the electronic Globex market even during regular trading hours. This began with futures and then evolved to options. My prices are taken from a merge of time and sales records from both trading environments.

Figure 1 shows the history of the weekly 2:00 p.m., i.e., closing, futures price series, in dollars per bushel, captured on Wednesdays, for the three commodities. I obtain the price series for these graphs by forming a rolling sequence which is in the spirit of a constant time to maturity. The price series shown are for the nearby, first deferred, and second deferred contracts. For wheat and corn the delivery months are March, May, July, September and December. For soybeans the delivery months are January, March, May, July, August, September and November. My price series rolls forward when the calendar date enters a delivery month. Hence, in January, for soybeans, I use March of that year as the nearby, May of that year as first deferred, and July as second deferred. This expiration order would also be the same for February. However in calendar month March, I make May futures the nearby, and roll the other months up. Looking at all three commodity time series, it should be clear that these commodity prices do not track, for example, the S&P 500 (e.g., there is no evidence of the dotcom bubble), while they do appear to move together, suggesting an agricultural factor for investments

⁵ On occasional scheduled major United States Department of Agriculture crop announcement days the opening is moved up to 7:20 a.m. Chicago time, 10 minutes prior to an announcement.

purposes (not on the agenda for this paper). Some suggest this lack of correlation with the equities market as a reason to include commodities or commodity funds in a diversified portfolio.

Figure 2 presents the historical volatility of the futures prices of the three commodities over the sample period. I calculate a daily volatility measure by taking the absolute value of daily logarithmic price change and scaling this up to a normally distributed annualized standard deviation.⁶ The figure presents the history of overlapping 100 trading day moving averages of the transformed volatility, with the starting date of the sample on the horizontal axis. Again for presentation purposes I present weekly (Wednesday) observations. The data reveal the distinct seasonality of these agricultural futures volatilities. The seasonality in volatility affects all three of the presented rolling maturities. For example, in June, the delivery months represented are July (old crop), September and December (new crops) for wheat and corn. Thus, the variability in the futures price volatility appears systemic, moving with the agricultural seasons and affecting all futures prices, across agricultural years, rather than being expiration specific. While the seasonality appears to be predominantly systemic, I also investigate the spread between nearby, first deferred and second deferred volatilities.⁷ For each day, I calculate the difference between the 100 day mean standard deviations. The results are presented in figure 3. The graphs again present the Wednesday observations. The spreads also reveal a seasonal pattern, albeit on a much smaller magnitude. The differences in volatilities are of a relatively small magnitude, never more than 5%.

To test the significance of these seasonal patterns, I regress the daily volatility measure (the daily scaled absolute price change) against that observation's calendar month, the futures delivery month and

⁶ That transformation, based on the expected value of the log of the absolute price change, is $\hat{\sigma}_t = \left| \ln \left(\frac{P_t}{P_{t-1}} \right) \right| * \sqrt{252 * \frac{\pi}{2}}$.

⁷ Much thanks to Robert Brooks for the suggestion to look at these spreads, related to his 2012 *Journal of Derivatives* paper.

the time-to-delivery (in years). The results for the three commodities are in table 1. The intercept is the December calendar month and the December delivery month for wheat and corn, and December calendar month and November delivery month for soybeans. I calculate the time to delivery from the observation date to the 15th calendar day of the delivery month and then transform this into an annualized measure by dividing by 365.⁸ Thus a time to delivery of .5 is one half of a year. The results in table 1 show that for wheat, the last four calendar months of the year prior to December have significantly lower volatility than December. For corn and soybeans, the calendar months from March through July have substantially and significantly higher volatility than December. For soybeans, all the expirations are slightly more volatile than November (the intercept). For wheat and corn, these data reveal no relationship between the delivery month per se and volatility. However, for all three commodities, the time to delivery is significant, with wheat volatility rising at a rate of 9.4 percent per year as the time to delivery falls, corn volatility rising at 7.0 percent per year as the time to delivery falls, and soybean volatility rising at 2.6 percent per year as the time to delivery falls. This increasing volatility as delivery nears is consistent with what is commonly referred to as the Samuelson effect (Samuelson 1965). Brooks (2012) relates the Samuelson effect to arbitrage costs. If arbitrage is costly, as it may be in these agricultural commodities, especially short arbitrage, then there is theoretical support for a Samuelson effect. Otherwise arbitrage would keep cash and futures prices linked by the cost of carry, with equivalent volatilities. Brooks (2012) finds that the Samuelson effect is most noticeable in futures which are difficult to arbitrage against cash. Karali, Dorfman and Thurman (2010) and Karali and Thurman (2010) also find evidence of the Samuelson effect in agricultural markets using a different technology.

⁸ The last day to trade futures is before the 15th calendar day of the month. Delivery occurs throughout the month. There is no exact delivery date, which remains an option within the delivery window for the short position.

5. Implied volatility and results

In this section I investigate implied volatility. I match each selected option observation with the most recent futures observation prior to that option observation for that expiration.⁹ I use only the major option expirations, that is, expirations which coincide with a futures delivery. These form the bulk of futures options trading. The moneyness of each option is determined for each observation by its strike relative to this recent (contemporaneous) futures price. I limit the sample to the more actively traded at- or out-of-the-money options. For calls, I select options where the ratio of the strike K to the futures F , is constrained by $K/F > .95$, and for puts where $K/F < 1.05$. To eliminate noisy observations, for each observation of each option for each $\frac{1}{2}$ hour bracket I required more than three trades within the bracket to select the option. I obtain daily interest rates from the St. Louis Federal Reserve (FRED).¹⁰ I calculate American futures option prices using Cox, Ross and Rubenstein (1979) (CRR) adapted for futures options. The implied volatility for the observation, using the contemporaneous futures, the observed option premium, risk free interest rate, and time to expiration, is the volatility for which the CRR value is equal to the observed traded premium.

⁹ I focus on the options expirations which are aligned with futures delivery months. Later in the sample there is some slight trading in other expiration months with the same futures, but to date the vast majority of option trading occurs in what I will categorize as the major expiration months. For other expiration months, the reference futures contract is the one with the nearest delivery months. For example, for corn options with an expiration month of February, the relevant futures month is March. These intermediate expirations are not widely used in my sample.

¹⁰ I use the available four-week, three-month, six-month and one-year treasury rates. On FRED, the four-week treasury rate only begins in 2001. Prior to 2001, I impute a four-week treasury rate as 90 percent of the one-month LIBOR rate, which is available for a longer period. A regression of daily treasury four-week rates on one-month LIBOR gives a coefficient of .92 for 2001 to 2006. Including post 2006 data, i.e., the financial crisis, drops this coefficient down to .85 (even though from press reports LIBOR was apparently manipulated *down* during this period). Thus, I settle on 90 percent as a reasonable compromise. A higher interest rate will be consistent with higher call values and lower put values, all other things equal, so there is no reason to expect any particular bias from this. I linearly interpolate between the implied continuously compounded fixed rates to find a rate for each particular time to expiration under one year.

In table 2 I present some information on the distribution of the selected daily observations for each option expiration. The table presents the mean and median number of observations for each expiration each day, across the year. The observations per expiration per day grow over time. In 1995 there was an average of three observations per expiration per day for wheat. A blip up in 2007 in observations is associated with the rise in electronic futures trading during the day. By 2011 there was an average of around eight observations per expiration per day.¹¹ The volume at a lot of these strike prices for these observations will be small, but this is information not provided in the data set. The restriction of three observations per half hour will mitigate highly illiquid observations. There was similar growth in the use of more strikes by options traders for corn and soybean options.

5.a. *Implied volatility*

I calculate the mean daily implied volatility for each option expiration, using all the active ½ hour selections across puts/calls/strikes (out-of-the-money) as the unit of observation each day. In table 3, I present the results of a regression of the daily mean implied volatility against calendar months, expiration months, and time to expiration. This analysis parallels that performed to generate the results in table 1. Only the major expirations are used, that is those expiration names which are the same as the normal futures delivery months. The results on time to expiration are in the range of the results for the realized volatilities, about a 12 percent per year increase in implied volatility for wheat, a 10 percent increase in volatility for corn, and about a three percent increase in volatility for soybeans as time to expiration nears. For wheat and soybeans, implied volatility is significantly higher in the summer months, holding expiration month and time to expiration constant. For all commodities, all expiration months have a significantly lower implied volatility than the prime new crop delivery month, November

¹¹ From 1995 till 2005 there was steady growth in pit tick observations, but nothing compared to the dramatic change associated with the introduction of electronic trading during pit trading hours around 2007/2008. It appears that Globex began seriously cannibalizing futures trading from the pit in 2008, a move anticipated by the exchange as they had demutualized prior to this.

(corn and wheat) or December (soybeans), holding time to expiration and calendar month constant. These expiration month results are somewhat different from the realized volatility results. Recall that table 1 employs the daily volatility estimate, whereas table 3 is presenting results using implied volatility, which in the CRR is assumed to be the volatility from the observation date until the option expiration. Thus, for example, in July, the daily volatility could be high, but the September implied volatility need not be high.

I next relate the implied volatility at a point in time to the realized volatility from that point in time to the option expiration. On each day which is one, two, three, four, five, or six months from an option expiration, I select the mean implied volatility for that expiration.¹² Next, from this day forward until the expiration of those options, I calculate the future volatility as the mean absolute logarithmic futures price change, annualized and adjusted for normality. My analysis differs substantially from Szakmary et al. (2003). In particular, because I am able to use multiple delivery months over the 17 years, I can hold the time to expiration constant (at from 1 to 6 months) and mitigate overlapping observations, especially in the shorter terms of 1 to 3 months. I next regress this realized volatility against the implied volatility, for each of the six time frames, with fixed effects for expiration months. Since the time to expiration is fixed, the expiration month dummies offer double duty as (a few) calendar month dummies. Recall that as the time to expiration nears, the implied volatility rises (see above), as does the realized volatility. This analysis brings these two results together.

The results are presented in table 4. The expiration month variables are rarely significant, and I save space by not reporting these. For all commodities and time frames, the slope coefficient is always significant. The parameter estimates are all greater than .5, and up to .86. My measure of mean daily implied volatility seems to fit well with future realized volatility. The unreported adjusted R-squares are

¹² Actually, the time to expiration is in terms of twelfths of years, but I used the short cut term “month” rather than one-twelfth of a year, two twelfths, etc. I use all days less than 1/12, 1/6 etc. to expiration.

almost all between 30 percent and 50 percent. Similar to Szakmary et al. (2003) I find that implied volatility is significantly associated with future realized volatility.

While implied volatility is clearly related to future realized volatility, does the options market per se offer us information about future volatility which is not otherwise directly available? To this end I employ a simple measure, the fit of a model predicting future volatility, with three nested models. This is not an exhaustive set of possible market information beyond the implied volatility, but considering the strength of the following results, I feel this finding will stand up to alternative specifications. I use the same monthly windows as above. Future realized volatility is the measured volatility from the observation date to the expiration of the option, as above. For historical volatility, I use the realized volatility over the last 30 trading days up to the observation date. The first regression is future realized volatility (from the date to expiration) against historic volatility (30 days prior to the observation date). The second model includes expiration month specific dummy variables (which also may be interpreted as seasonal dummies, since the days-to-expiration are fixed in each model). The third model has all the above variables plus the implied volatility on that day. This final model has the previous two models sequentially nested. The results from these three regressions, over the six different future volatility estimation windows, are presented in tables 5 and 6. In table 5 I present the adjusted R-squares from these regressions. If implied volatility is informative regarding future volatility, then its presence in the regression model should add value in terms of increased adjusted R-square, or predictive ability. Indeed this is always the case, for all three commodities for all six estimation windows. The results indicate that implied volatility increases the predictability of future volatility by about 20 percent over historical volatility, after controlling for seasonality. The addition of seasonal dummies alone, which should be helpful since the annual volatility shows such a sharp pattern, do not improve on the historical volatility measure much.

I present the coefficients for these regressions in table 6. The coefficient on historical volatility falls dramatically, with a couple of exceptions, when implied volatility is added to the regression. The addition of seasonal dummies does not affect the coefficient on historical volatility much. Considering both the dramatic R-square results and the clear coefficient changes, the results suggest that implied volatility is incrementally significantly informative about future volatility. The options market offers some significant new information about future volatility.

I next analyze forward volatilities. On any day there are several expirations of options trading. Each of these, viewed independently, is related to the volatility from the observation time to the expiration of that option. However, these timeframes overlap. Thus, on a date in January, the implied volatility for March is for the period from that date in January until near the end of February, and the implied volatility from the May options is for the period from that date in January to near the end of April. Recall that options expire near the end of the month prior to the option's month name. In this next analysis I calculate implied forward volatilities and the realized volatility between the two expirations. The implied forward volatility is calculated similar to continuously compounded forward interest rates, using the variance (squared implied standard deviation) and weighting by time. I do this for 3, 4, 5 and 6 twelfths of years prior to the expiration of the longer dated option. Thus, the end of January is about 3 twelfths of a year prior to the expiration of May, and the implied for the March to May period is backed out of the implied volatilities for the May and March expirations. The future realized volatility is calculated from the end of February (March expiration) to the end of April (May expiration). Similarly, the end of December is around four-twelfths prior to the May option expiration. The regressions are run separately for the various forward ranges. The results are presented in table 7.

All coefficients are highly significant. The adjusted R-squares hover around 50%. The results are strongest for wheat, where the coefficients are nearest to 1. Indeed for the 3 month window, the

result is 1.04. Three months out with two expirations is, for example, the January to late April example stated above, backing out the implied forward volatility from the March and May implied volatilities, and forecasting the late February to late April volatility (the time between the March and May expirations). Corn point estimates are in the .6 to .8 range. Soybeans, somewhat lower. Nonetheless, the results indicate that forward volatilities in these agricultural commodities are at least partially predictable by backing out the forward implied volatility from pairs of options. This indicates that there is value added in the long term option prices over the short term option prices.

5.b. Daily range of implied volatility

I also calculate each day the range of implied volatility estimates for each expiration and the intraday trend in implied volatility. One way to view the range of implied volatilities is as a rough measure of illiquidity and/or volatility uncertainty. These are factors which would be reflected in a volatility bid-ask spread. The range is the breadth of implied volatilities that traders have agreed to during a day. Similarly, the range could be interpreted as an indirect measure of (unsigned) order flow, with the intraday trend perhaps more reflective of signed order flow. Order flow (the difference between the volume of trades at the “offer” and the volume of trades at the “bid”) has been shown to be important in conditioning inferences made from option prices. Bid and offer prices prior to a futures option transaction are not recorded in the time and sales data, and volume is only available for Globex trades. Thus my use of the implied volatility range as a substitute for a measure of liquidity. Table 8 presents the analysis similar to table 3, with the range of implied volatilities substituted for the implied volatility as the endogenous variable. Similar to implied volatility, the range of implied volatilities increases as the time to expiration draws near. The range rises at about 10 percent per year for wheat and corn, and 30 percent per year for soybeans. For wheat, the fall months have a slightly lower volatility range than for December. For corn, many months have a slightly higher volatility range than

December. For soybeans, October has a slightly higher range, and the spring months a slightly lower range than December. Wheat and corn exhibit some expiration specific effects. Soybeans show a strong expiration effect. The November expiration has a significantly higher implied volatility range than the other expiration months. These findings offer support for the Hsieh and Jarrow (2014), incomplete markets view of options market making. Similar to Brooks' (2012) argument for the Samuelson effect in some futures prices, if option traders cannot hedge sufficiently, or, similarly, the implied volatility cannot be arbitrated, there is room for a Samuelson effect in futures' volatility uncertainty, and for which the daily range of implied volatilities may be seen as a proxy.

From table 8, the range of implied volatilities from intraday option prices is clearly related on time to maturity. This range may be interpreted as market uncertainty regarding the forthcoming volatility. Similarly, it could represent a liquidity effect independent of uncertainty. I relate this daily range to the "forecast error" that is the error between the implied volatility and the realized volatility, again using fixed windows of one to six months to mitigate overlapping observations. If the implied volatility range is an indicator of uncertainty regarding future volatility, then it is possible that the forecast error could be related to the range. For each day, as in table 8, I calculate the absolute value of the difference between the realized volatility up to expiration and the mean implied volatility for that expiration. This forecast error is regressed against the range of implied volatilities on that day. The results are reported in table 9. For all commodities, the first two months of forecast errors are significantly related to the range of implied volatilities. In other words, with only one or two months to expiration, a wider range of implied volatilities on a day indicates that the mean implied volatility is less informative about the future realized volatility. There are spotty significant results for the longer time frames. These results suggest that there appears to be some information in the range of implied

volatilities on a day, with a wider range meaning that traders are less certain about forthcoming volatility.

Some research, e.g. Muravyev (2013), has looked at the information in option order flow. For example, an increase in the purchase of options, puts or calls, during a day may result in an increase in implied volatility over that day. Whether or not this increase is a liquidity effect due to “noise” traders or a permanent effect from “informed” traders is an interesting question. My data do not allow a direct calculation of order flow. As an admittedly rough proxy, I calculate the trend in implied volatility throughout the day. Each day which is 1, 2, 3, 4, 5 or 6 months to expiration of an option, I regress the implied volatility for all options sampled that day against the time of day of the sampling. I use this intraday trend to predict the signed forecast error, the realized volatility minus the implied volatility. The results are presented in table 10 and are decidedly unhelpful, with sign switching depending on the time to expiration, and statistical significance scarce.

6. Conclusion

I use 17 years of tick data for wheat, corn and soybeans futures and futures options. I find a significant seasonal pattern in realized volatility, which is reflected in the volatility implied by options prices. In addition, volatility, both implied and realized, rises as expiration nears, confirming a Samuelson effect. Implied volatility in these three agricultural commodity options is significantly related to the resulting futures volatility. Implied forward volatility is also significantly related to future realized volatility. I back this forward implied volatility out from the implied volatilities of two option expirations.

While the results are pretty clear that implied volatility is associated with future realized volatility, an interesting question is the value added of implied volatility. In other words, does the implied volatility provide information about future volatility which is not available elsewhere? As a

first approximation, I use a measure of historical volatility as other available public information. If implied volatility is helpful, then, after controlling for historical volatility, and seasonality, the predictability of future realized volatility ought to increase. I find strong evidence that this is the case. Using three nested models, I find that adding implied volatility to a regression of future volatility on historical volatility is highly significant, adding about 20 percent to the adjusted R-square. There appears to be significant information in futures options prices which is not readily available in other public information.

I also study the intraday variation in implied volatility, as measured by the range of implied volatilities. These are the different implied volatilities that traders have agreed to during a day. This measure could be a proxy for order flow, or simply market uncertainty regarding the forthcoming realized volatility. I find that the range follows a pattern similar to implied volatility, rising as expiration nears. Also the daily range of implied volatilities is related in the short run to the “forecast error,” the absolute value of the difference between daily implied volatility and future realized volatility. The intraday trend in implied volatility, which I offer as a proxy for order flow, is not helpful in predicting the signed forecast error.

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Table 1. Futures volatility by calendar month, expiration month, time to delivery

Variable	Wheat			Corn			Soybeans		
	Estimate	StdErr	Probt	Estimate	StdErr	Probt	Estimate	StdErr	Probt
Intercept	30.94%	0.23%	<.0001	24.99%	0.23%	<.0001	20.18%	0.00196	<.0001
Time to delivery	-9.43%	0.18%	<.0001	-7.01%	0.18%	<.0001	-2.64%	0.00179	<.0001
Calendar months									
January	-0.57%	0.25%	0.0217	-0.27%	0.25%	0.2849	-0.04%	0.21%	0.8280
February	-0.62%	0.25%	0.0143	1.43%	0.26%	<.0001	1.30%	0.21%	<.0001
March	0.52%	0.24%	0.0348	4.32%	0.25%	<.0001	3.05%	0.21%	<.0001
April	-0.70%	0.25%	0.0048	4.26%	0.25%	<.0001	3.40%	0.21%	<.0001
May	0.26%	0.25%	0.2941	5.08%	0.25%	<.0001	3.81%	0.21%	<.0001
June	-0.39%	0.25%	0.1157	3.94%	0.25%	<.0001	3.81%	0.21%	<.0001
July	0.09%	0.25%	0.7089	2.51%	0.25%	<.0001	3.02%	0.21%	<.0001
August	-1.70%	0.24%	<.0001	-0.21%	0.25%	0.3903	0.91%	0.21%	<.0001
September	-1.13%	0.25%	<.0001	-0.28%	0.25%	0.262	0.51%	0.21%	0.0166
October	-2.05%	0.24%	<.0001	-1.60%	0.25%	<.0001	-0.14%	0.20%	0.4972
November	-2.23%	0.25%	<.0001	-2.04%	0.25%	<.0001	-0.09%	0.21%	0.6504
Delivery months									
January	NA	NA	NA	NA	NA	NA	0.69%	0.17%	<.0001
March	0.19%	0.16%	0.2345	0.09%	0.16%	0.5954	0.59%	0.17%	0.0005
May	0.05%	0.16%	0.7307	-0.04%	0.16%	0.8267	0.50%	0.16%	0.0023
July	0.13%	0.16%	0.4092	-0.06%	0.16%	0.7269	0.54%	0.16%	0.0010
August	NA	NA	NA	NA	NA	NA	0.41%	0.18%	0.0208
September	0.10%	0.16%	0.5420	-0.23%	0.16%	0.1482	0.52%	0.17%	0.0023

Each day the absolute close to close return on the first 5 futures contracts for each of the 3 commodities is calculated and scaled to the expected absolute value from the normal distribution, annualized. This value is regressed against the time to delivery and two sets of qualitative variables, the calendar month in which the observation is made, and the particular delivery month. For corn and wheat the December delivery month and December calendar month are in the intercept. For soy the November delivery month and December calendar month are in the intercept.

Table 2 Distribution of daily observations per expiration

	Wheat		Corn		Soybeans	
	Mean	Median	Mean	Median	Mean	Median
1995	2.80	2.00	4.34	2.00	11.57	7.00
1996	3.33	2.00	8.30	4.00	15.98	12.00
1997	6.07	4.00	9.92	7.00	22.53	17.00
1998	5.46	4.00	9.38	6.00	14.36	11.00
1999	5.64	4.00	9.25	7.00	16.38	12.00
2000	4.67	4.00	10.22	7.00	16.69	12.00
2001	3.45	3.00	7.44	5.00	16.04	12.00
2002	4.44	3.00	7.86	4.00	21.64	15.00
2003	4.48	3.00	7.03	5.00	27.72	20.00
2004	3.53	3.00	12.46	7.00	27.36	20.00
2005	3.29	2.00	9.62	6.00	26.60	16.00
2006	4.04	3.00	13.10	9.00	19.19	13.00
2007	14.64	9.00	30.86	19.00	34.47	25.00
2008	5.23	3.00	16.15	12.00	16.83	12.00
2009	2.46	2.00	11.55	7.00	12.60	7.00
2010	5.21	3.00	12.08	7.00	13.27	8.00
2011	7.57	5.00	21.69	12.00	20.98	11.00

Note: Option prices are sampled each half hour each day, taking the last trade for all at or out of the money options matched with the last traded futures price each half hour, provided there were 3 or more trades within that half hour in that option. Only options with expirations less than one year are sampled. For each expiration X day, the total number of observations that day is calculated. Then the mean and median of this number is calculated across each year.

Table 3 Implied volatility by calendar month, expiration month, time to expiration

Variable	Wheat			Corn			Soybeans		
	Estimate	StdErr	Probt	Estimate	StdErr	Probt	Estimate	StdErr	Probt
Intercept	35.51%	0.39%	<.0001	34.20%	0.24%	<.0001	27.11%	0.25%	<.0001
timetoexpiration	-12.06%	0.45%	<.0001	-10.15%	0.24%	<.0001	-3.05%	0.25%	<.0001
Calendar months									
January	-0.68%	0.44%	0.1218	-0.46%	0.28%	0.1012	-0.26%	0.25%	0.3096
February	1.27%	0.45%	0.0043	-0.16%	0.29%	0.5906	-0.72%	0.25%	0.0044
March	0.66%	0.45%	0.1405	1.29%	0.29%	<.0001	1.44%	0.25%	<.0001
April	0.38%	0.46%	0.4054	1.72%	0.29%	<.0001	1.30%	0.26%	<.0001
May	-1.58%	0.46%	0.0006	1.92%	0.30%	<.0001	1.97%	0.27%	<.0001
June	-0.80%	0.46%	0.0786	3.73%	0.30%	<.0001	3.26%	0.26%	<.0001
July	-1.79%	0.47%	0.0001	1.35%	0.30%	<.0001	2.37%	0.26%	<.0001
August	-0.41%	0.46%	0.3708	-0.06%	0.29%	0.8258	0.08%	0.26%	0.7568
September	-0.67%	0.47%	0.1522	-1.36%	0.30%	<.0001	-0.48%	0.26%	0.0665
October	0.47%	0.45%	0.2954	-0.31%	0.29%	0.2787	-0.01%	0.25%	0.9645
November	-0.07%	0.46%	0.8810	-0.42%	0.29%	0.1564	-0.12%	0.26%	0.6281
Delivery months									
January	NA	NA	NA	NA	NA	NA	-3.85%	0.20%	<.0001
March	-3.74%	0.27%	<.0001	-4.68%	0.18%	<.0001	-3.55%	0.19%	<.0001
May	-2.84%	0.31%	<.0001	-5.19%	0.19%	<.0001	-3.90%	0.18%	<.0001
July	-0.86%	0.26%	0.0010	-2.21%	0.18%	<.0001	-2.70%	0.17%	<.0001
August	NA	NA	NA	NA	NA	NA	0.10%	0.20%	0.6380
September	-1.19%	0.29%	<.0001	0.67%	0.19%	0.0005	1.16%	0.20%	<.0001

Options prices are sampled at half hour intervals and matched with the most recent futures price to calculate an implied volatility for that observation. Each day the mean implied volatility is calculated for each expiration across these half hour observations. All observations are combined and the implied volatility is regressed against the time to expiration, the calendar month in which the observation is made, and the particular delivery month. For corn and wheat the December delivery and December calendar are the intercept. For soybeans the November Delivery and December calendar are in the intercept.

Table 4 Implied volatility forecasting realized volatility

	Wheat		Corn		Soybeans	
	intercept	volatility	intercept	volatility	intercept	volatility
1 month	0.06057	0.69916	0.03511	0.72057	0.07393	0.64223
	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>
2 months	0.10193	0.66261	0.04951	0.72777	0.06999	0.64579
	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>
3 months	0.0937	0.66767	0.04293	0.73389	0.08801	0.54391
	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>
4 months	0.08711	0.68128	0.04938	0.70465	0.07218	0.54734
	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>
5 months	0.04635	0.85817	0.03157	0.71178	0.06841	0.57809
	<i>0.0062</i>	<i><.0001</i>	<i>0.0131</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>
6 months	0.03257	0.84688	0.01898	0.74779	0.04269	0.6654
	<i>0.1618</i>	<i><.0001</i>	<i>0.2865</i>	<i><.0001</i>	<i>0.0029</i>	<i><.0001</i>

Note: The realized volatility 1, 2, 3, 4, 5, and 6 months following an observation of implied volatility is regressed against that implied volatility. Not reported are expiration specific dummies, which are generally insignificant. The two columns for each commodity are the intercept and the slope coefficient for the implied volatility, the mean implied volatility for the day. For each time to expiration, 1 through 6 months, the table presents the estimated intercept and slope coefficient, above italicized probability values.

Table 5. Historical, implied volatility and future realized volatility, r-squares

	Model	Estimation window					
		1 month	2 month	3 month	4 month	5 month	6 month
Wheat	Historical	41.43%	37.80%	38.15%	42.21%	47.64%	48.64%
	Add seasonal	42.56%	39.23%	39.95%	45.73%	49.61%	54.23%
	Add implied	64.44%	58.78%	53.28%	56.29%	61.47%	66.48%
Corn	Historical	43.31%	42.06%	40.55%	41.27%	41.88%	38.71%
	Add seasonal	50.62%	49.97%	48.80%	49.29%	49.32%	48.49%
	Add implied	70.97%	62.66%	60.35%	55.58%	55.10%	51.42%
Soy	Historical	34.43%	34.08%	32.12%	29.45%	27.48%	31.30%
	Add seasonal	40.20%	40.36%	38.44%	37.10%	38.10%	39.20%
	Add implied	64.10%	56.18%	45.44%	42.11%	43.89%	47.75%

Note: Each day which is 1 month, 2 months, 3 months, 4 months, 5 months or 6 months from the expiration of a commodity option, three measures are calculated. One is the average implied volatility from the options market. The second is the future volatility, going forward from the current date to the expiration of the option. The third is the historical volatility, looking back 30 days from the current date. Three regressions are run with the future volatility as the dependent variable, cumulatively adding independent variables. The first regression uses only the historical volatility on the right side. The second adds expiration specific dummies. The third adds in the implied volatility. The table presents adjusted Rsquares from the regressions.

Table 6. Historical, implied and future realized volatility, parameters

		Future volatility estimation window											
		1 month		2 month		3 month		4 month		5 month		6 month	
		Historical	Implied	Historical	Implied	Historical	Implied	Historical	Implied	Historical	Implied	Historical	Implied
Wheat	Historical	0.611	-----	0.578	-----	0.582	-----	0.594	-----	0.708	-----	0.712	-----
	Add seasonal	0.627	-----	0.581	-----	0.588	-----	0.594	-----	0.696	-----	0.619	-----
	Add implied	0.251	0.547	0.223	0.522	0.277	0.482	0.332	0.436	0.446	0.535	0.364	0.593
Corn	Historical	0.570	-----	0.565	-----	0.554	-----	0.546	-----	0.548	-----	0.554	-----
	Add seasonal	0.593	-----	0.588	-----	0.583	-----	0.572	-----	0.573	-----	0.568	-----
	Add implied	0.232	0.557	0.259	0.516	0.275	0.504	0.354	0.389	0.363	0.381	0.428	0.319
Soy	Historical	0.520	-----	0.516	-----	0.497	-----	0.495	-----	0.490	-----	0.511	-----
	Add seasonal	0.543	-----	0.546	-----	0.535	-----	0.530	-----	0.519	-----	0.508	-----
	Add implied	0.234	0.502	0.236	0.480	0.345	0.310	0.397	0.292	0.392	0.331	0.338	0.424

Note: Each day which is 1 month, 2 months, 3 months, 4 months, 5 months or 6 months from the expiration of a commodity option, three measures are calculated. One is the average implied volatility from the options market. The second is the future volatility, going forward from the current date to the expiration of the option. The third is the historical volatility, looking back 30 days from the current date. Three regressions are run with the future volatility as the dependent variable, cumulatively adding independent variables. The first regression uses only the historical volatility on the right side. The second adds expiration specific dummies. The third adds in the implied volatility. The table presents the coefficient on historical volatility, and the coefficient on implied volatility when it is added to the independent variables. The seasonal dummies are unreported, and of varying sign and significance. All coefficients are significant with a probability value less than .001.

Table 7 Forward volatility regression

Bracket	Wheat	Corn	Soybeans
2			0.5214 <i>0.0057</i>
3	1.04335 <i>0.0003</i>	0.60285 <i>0.0032</i>	0.6952 <i><.0001</i>
4	0.74627 <i><.0001</i>	0.78414 <i><.0001</i>	0.27463 <i>0.0072</i>
5	0.76348 <i>0.0088</i>	0.70508 <i><.0001</i>	0.26904 <i>0.009</i>
6	1.29077 <i>0.0002</i>	0.78652 <i><.0001</i>	0.35573 <i>0.0007</i>

Note: The forward volatility is the volatility between two option expirations. The implied forward volatility is backed out of those two option expirations implied volatilities back in time. The bracket 2, 3, 5 and 6 are twelfths of a year back from the expiration of the longest duration option of the pair. The regression, run by bracket, has the forward volatility as the dependent, and the forward implied volatility as the explanatory variable.

Table 8 Implied volatility range by calendar month, expiration month, time to expiration

Variable	Wheat			Corn			Soybeans		
	Estimate	StdErr	Probt	Estimate	StdErr	Probt	Estimate	StdErr	Probt
Intercept	7.22%	0.39%	<.0001	11.42%	0.21%	<.0001	26.82%	0.26%	<.0001
timetoexpiration	-9.19%	0.45%	<.0001	-9.63%	0.20%	<.0001	-30.25%	0.27%	<.0001
Calendar months									
January	0.23%	0.31%	0.4542	1.38%	0.24%	<.0001	-0.91%	0.27%	0.0006
February	1.27%	0.45%	0.0039	1.38%	0.25%	<.0001	-0.44%	0.27%	0.1028
March	0.66%	0.45%	0.1742	1.14%	0.25%	<.0001	-1.34%	0.27%	<.0001
April	0.38%	0.46%	0.5426	1.20%	0.25%	<.0001	-0.91%	0.27%	0.0008
May	-1.58%	0.46%	0.9955	0.90%	0.26%	0.0005	-2.61%	0.28%	<.0001
June	-0.80%	0.46%	0.0002	2.18%	0.26%	<.0001	0.47%	0.27%	0.0860
July	-1.79%	0.47%	0.0255	2.25%	0.26%	<.0001	2.90%	0.28%	<.0001
August	-0.41%	0.46%	<.0001	1.18%	0.25%	<.0001	1.05%	0.27%	0.0001
September	-0.67%	0.47%	<.0001	0.33%	0.26%	0.1983	-0.48%	0.28%	0.0832
October	0.47%	0.45%	<.0001	1.28%	0.25%	<.0001	2.21%	0.26%	<.0001
November	-0.07%	0.46%	0.0016	0.89%	0.25%	0.0004	0.66%	0.27%	0.0140
Delivery months									
January	NA	NA	NA	NA	NA	NA	-8.80%	0.21%	<.0001
March	-0.57%	0.19%	0.0026	-1.78%	0.16%	<.0001	-7.40%	0.20%	<.0001
May	-0.73%	0.22%	0.0010	-3.54%	0.16%	<.0001	-6.74%	0.19%	<.0001
July	1.13%	0.19%	<.0001	-1.37%	0.15%	<.0001	-3.97%	0.18%	<.0001
August	NA	NA	NA	NA	NA	NA	-7.09%	0.21%	<.0001
September	-0.86%	0.21%	<.0001	-1.31%	0.16%	<.0001	-7.23%	0.21%	<.0001

Options prices are sampled at half hour intervals and matched with the most recent futures price to calculate an implied volatility for that observation. Each day the mean implied volatility is calculated for each expiration across these half hour observations. All observations are combined and the implied volatility is regressed against the time to expiration, the calendar month in which the observation is made, and the particular delivery month. For corn and wheat the December delivery and December calendar are the intercept. For soybeans the November Delivery and December calendar are in the intercept.

Table 9 Volatility forecasting error and implied volatility range

	Wheat		Corn		Soybeans	
	intercept	range	intercept	range	intercept	range
1 month	0.03178 <i><.0001</i>	0.14061 <i><.0001</i>	0.03484 <i><.0001</i>	0.14756 <i><.0001</i>	-0.01272 <i>0.0396</i>	0.21516 <i><.0001</i>
2 months	0.03096 <i><.0001</i>	0.087 <i>0.0219</i>	0.02302 <i><.0001</i>	0.2808 <i><.0001</i>	0.00737 <i>0.2271</i>	0.19259 <i><.0001</i>
3 months	0.02499 <i><.0001</i>	0.17829 <i>0.0106</i>	0.01303 <i>0.0135</i>	0.33052 <i>0.0066</i>	0.02394 <i>0.0086</i>	0.1538 <i>0.0009</i>
4 months	0.04146 <i><.0001</i>	0.00875 <i>0.8519</i>	0.04165 <i><.0001</i>	0.16185 <i>0.0007</i>	0.05598 <i><.0001</i>	0.0921 <i>0.0351</i>
5 months	0.03734 <i><.0001</i>	0.18597 <i>0.0102</i>	0.04775 <i><.0001</i>	0.29639 <i><.0001</i>	0.03705 <i><.0001</i>	0.1834 <i><.0001</i>
6 months	0.03817 <i><.0001</i>	0.1887 <i>0.0479</i>	0.06445 <i><.0001</i>	0.20062 <i>0.0021</i>	0.0617 <i><.0001</i>	-0.00469 <i>0.9173</i>

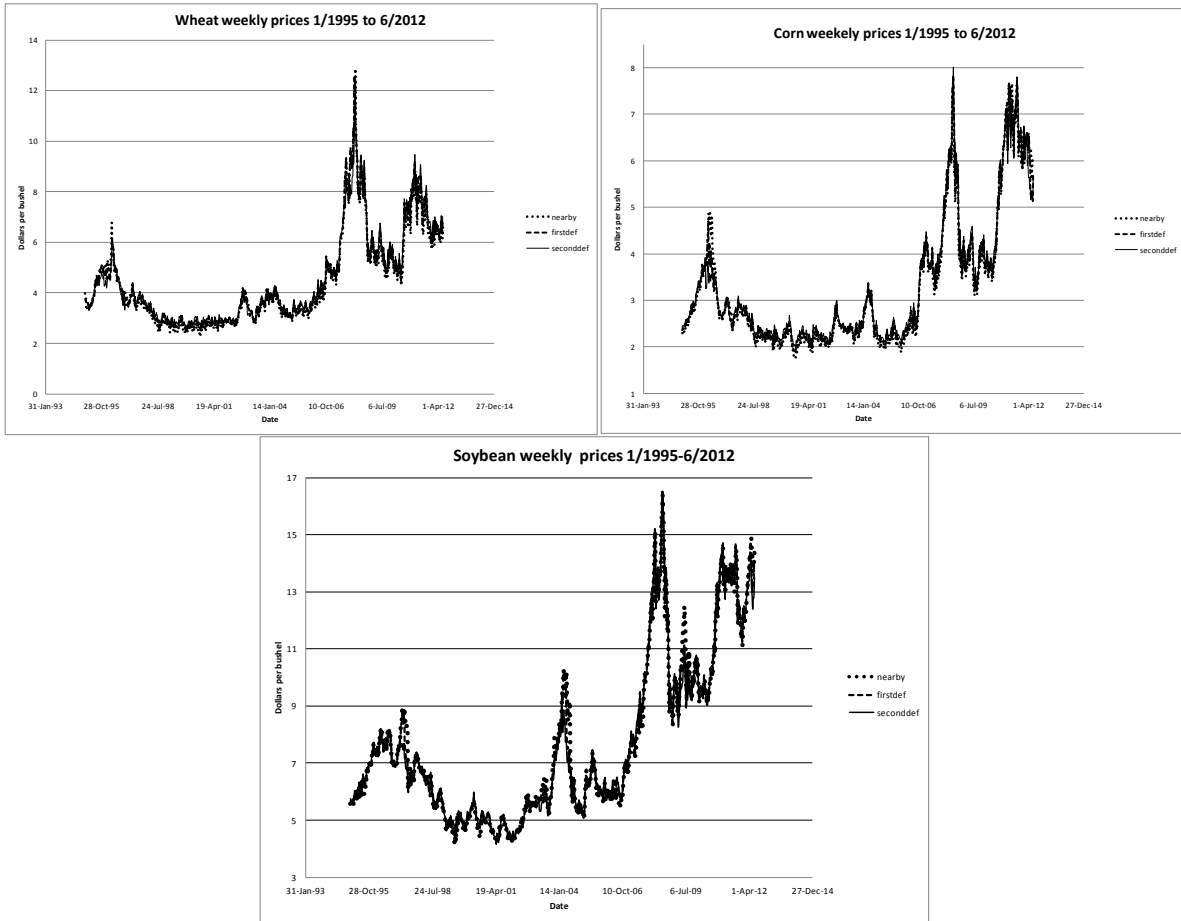
Note: In panel B, the absolute value of the difference between the implied volatility and the realized volatility is regressed against the range of implied volatilities on a given day, again, the realized volatilities look forward 1, 2, 3, 4, 5 and 6 months from the observation day. The two columns for each commodity are the intercept and the slope coefficient for the implied volatility range, the range of implied volatilities for the day.

Table 10 Intraday change in volatility and signed volatility forecast error

	Wheat		Corn		Soybeans	
	intercept	volslope	intercept	volslope	intercept	volslope
1 month	-0.04269	5.35218	-0.05085	-1.09046	-0.01453	4.30981
	<i><.0001</i>	<i>0.0078</i>	<i><.0001</i>	<i>0.4432</i>	<i>0.0062</i>	<i>0.0448</i>
2 months	0.000104	-12.23583	-0.02395	4.25676	-0.02072	-2.16295
	<i>0.9851</i>	<i><.0001</i>	<i><.0001</i>	<i>0.1777</i>	<i><.0001</i>	<i>0.4295</i>
3 months	-0.00034	2.64681	-0.03143	-7.47921	-0.03429	-2.97389
	<i>0.9514</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i><.0001</i>	<i>0.1522</i>
4 months	0.0053	-2.88781	-0.03444	-4.0026	-0.06119	-11.51648
	<i>0.4232</i>	<i>0.0572</i>	<i><.0001</i>	<i>0.0502</i>	<i><.0001</i>	<i><.0001</i>
5 months	0.000882	-2.41861	-0.05509	1.31861	-0.05008	-4.68202
	<i>0.8913</i>	<i>0.6176</i>	<i><.0001</i>	<i>0.6775</i>	<i><.0001</i>	<i>0.0004</i>
6 months	0.02009	8.20491	-0.05833	-0.44776	-0.04845	2.19773
	<i>0.0343</i>	<i>0.0612</i>	<i><.0001</i>	<i>0.7822</i>	<i><.0001</i>	<i>0.0298</i>

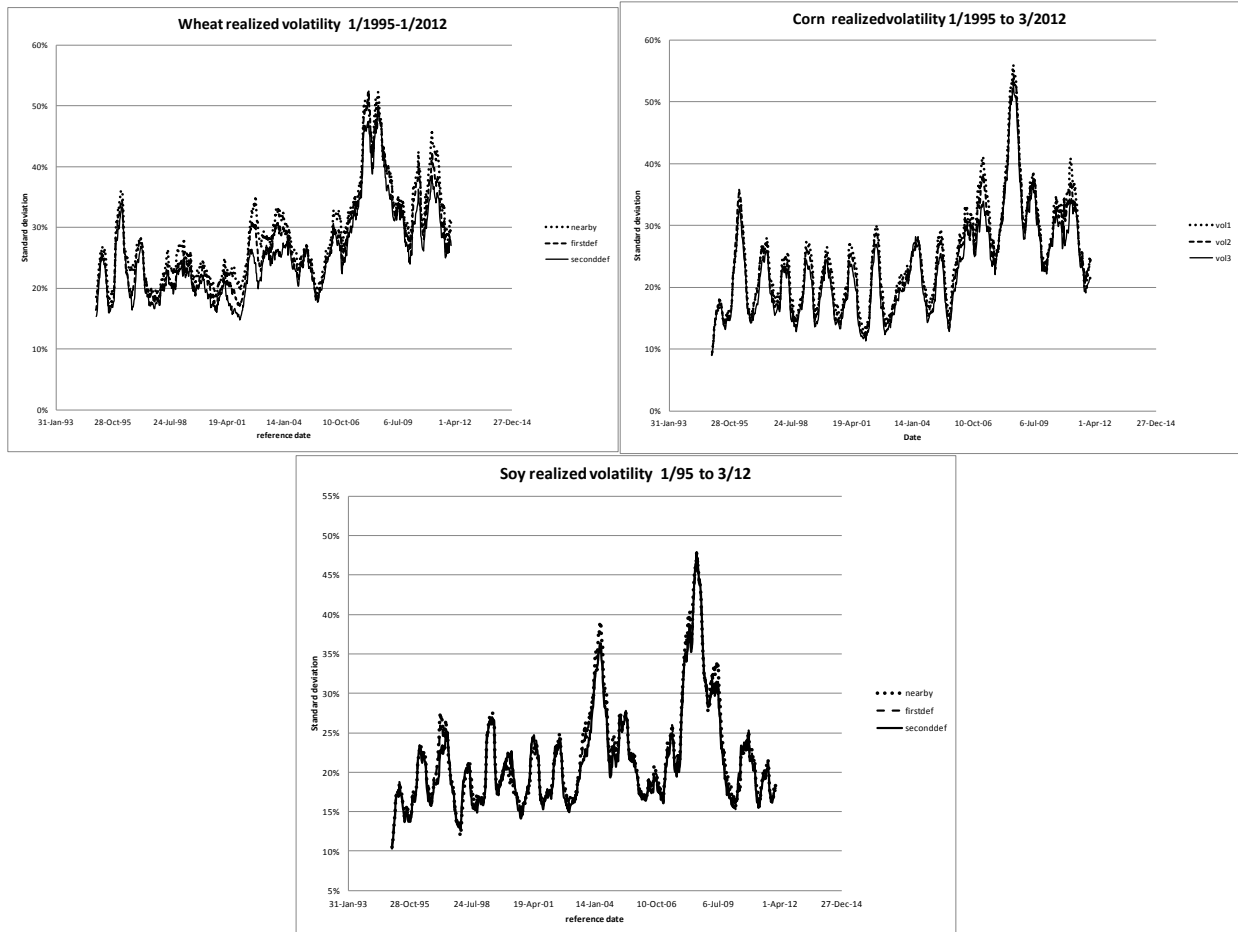
Note: The signed forecast volatility error (realized minus implied) 1, 2, 3, 4, 5, and 6 months following an observation of implied volatility is regressed against the intraday change (slope of a regression of volatility against time-of-day) in implied volatility on that day. Not reported are expiration specific dummies, which are generally insignificant. The two columns for each commodity are the intercept and the slope (volslope) coefficient for the implied volatility, the mean implied volatility for the day. For each time to expiration, 1 through 6 months, the table presents the estimated intercept and slope coefficient, above italicized probability values.

Figure 1. Rolling weekly futures prices of three agricultural commodities



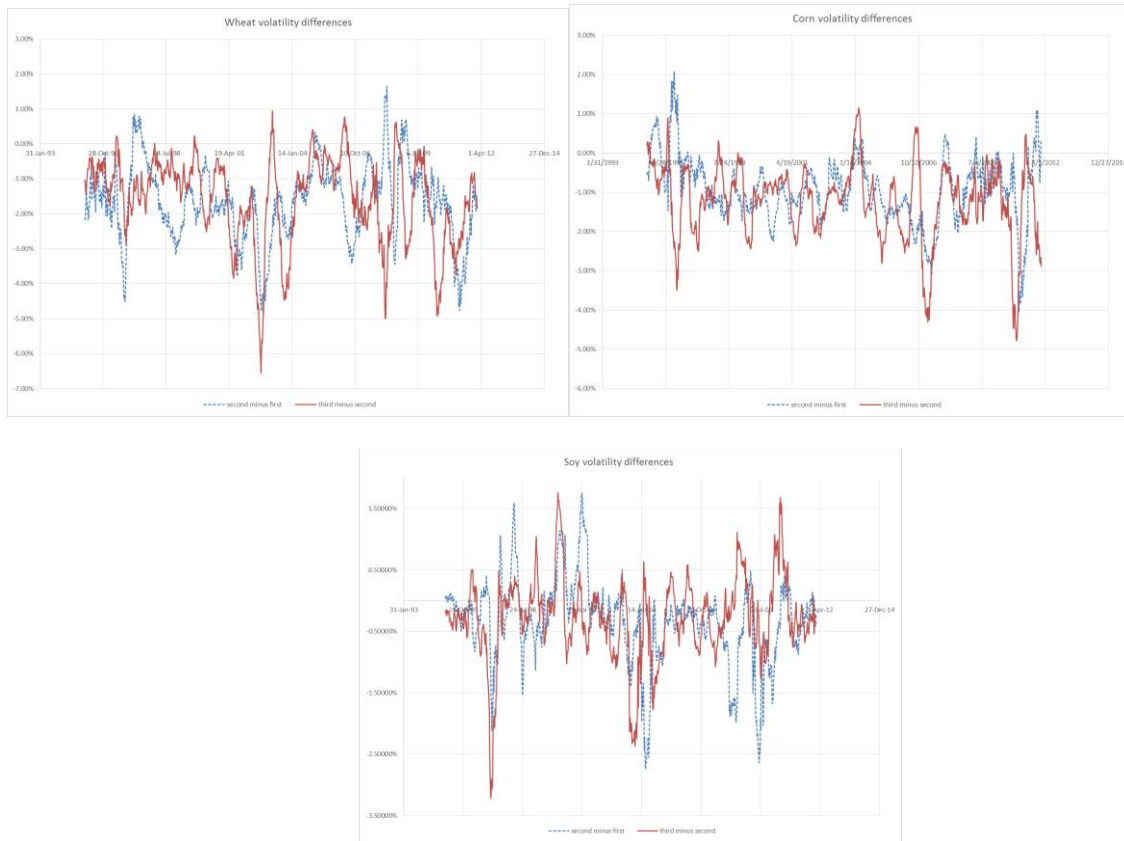
Note: Each day 3 futures prices are captured, the nearby, first deferred, and second deferred. Generally these are the nearest to delivery, next, etc. However, in the delivery month, the nearby is switched to the second nearest to delivery. Prices are captured on Wednesday for expository purposes.

Figure 2. Rolling weekly futures price volatility, 100 day forward average



Note: Each day the absolute price change is calculated and scaled to the expected value of the absolute value of a normal variable. Next, a forward looking 100 day mean is captured. This is done for the nearby, first deferred, and second deferred. Generally these are the nearest to delivery, next, etc. However, in the delivery month, the nearby is switched to the second nearest to delivery. Volatilities are captured on Wednesday for expository purposes.

Figure 3. Differences between volatilities, second deferred minus first, third deferred minus second



Note: Each day the absolute price change is calculated and scaled to the expected value of the absolute value of a normal variable. Next, a forward looking 100 trading day mean of these is captured. This is done for the nearby, first deferred, and second deferred, rolling forward as contracts mature. Generally these are the nearest to delivery, next, etc. However, in the delivery month, the nearby is switched to the second nearest to delivery. Next the difference between first and second deferred contracts, and third and second contracts are taken. These differences are captured on Wednesday for expository purpose.