Are Hedgers Informed? An Examination of the Price Impact of Large Trades in Agricultural Futures Markets

Alex Frino, Vito Mollica and Shunquan Zhang

Macquarie University Graduate School of Management

Current Draft: 15 May 2015

Abstract

The ‘received’ view in the finance literature is that hedgers are uninformed traders who use futures to fix future price movements in order to prevent losses from unexpected and unknown fluctuations in the purchase or sale price of a commodity. In this paper, we examine transactions executed by large traders in relatively illiquid deliverable futures market where most transactions go to expiration and are therefore executed by hedgers. We provide evidence that the price impact of large buyer-initiated transactions is permanent, consistent with the proposition that they are executed by traders perceived to be informed. We also provide evidence that the permanent price impact of buyer-initiated transactions increases with the size of the trade. This evidence is contrary to the “received” view in the literature, and implies that transactions long hedgers, particularly large long hedgers in agricultural futures markets are informed.

Are Hedgers Informed? An Examination of the Price Impact of Large Trades in Agricultural Futures Markets

1. Introduction

The ‘received’ view in the finance literature is that hedgers are agents who do not know the future price movements of an underlying commodity, and therefore seek to fix the purchase or sale price of that commodity to insure their business from unexpected or unpredictable price fluctuations. Hull (2006) asserts this view by stating that companies using futures to hedge “have no particular skills or expertise in predicting variables such as interest rate, exchange rate and commodity prices … by hedging, they avoid unpleasant surprises such as sharp rises in the price of a commodity that is being purchased” (p.49-50). This view pervades theoretical literature which typically assumes or implies that hedgers are uninformed (eg. Chakravarty and Sarkar, 1997, Spiegel and Subrhmanyam, 1992). This view also underlies the set of literature which examines the traditional risk premium (or normal backwardation) view of futures prices and implies that hedgers place excessive price pressure on futures prices which are exploited by speculators, and therefore hedgers lose on average. This theory has been tested by examining the hypothetical ex-post trading profits/losses of “commercial traders” in CFTC commitment of traders report whom they assume are hedgers, and document that “commercial traders” typically lose (see Dewally, Ederington and Dewally 2013).

There are many a-priori reasons to believe that hedgers, particularly large ones, that use futures contracts to fix purchase or sales prices of underlying commodities are informed. For example, long hedgers sell their finished products into markets which drive demand for underlying assets and can have insights into the existence of changes in broad macroeconomic conditions well before they are announced by any government-related statistical body. Furthermore, they will have specific insights into the effect of changes in broad macroeconomic conditions on demand for their products and hence demand for the underlying inputs required to produce them. Consequently, in contrast to the received view, it is highly likely that hedgers have private information which may drive their decision to hedge (or not hedge) and therefore their trades may be (perceived as) informed.

In this paper, we use a methodology originally developed by Kraus and Stoll (1972) to test whether large transactions in securities markets are informed. The methodology involves decomposing the initial price impact of a trade into 'temporary' and 'permanent' components. The temporary component is the price paid for liquidity by a transaction while the permanent component represents the information imparted by the transaction. This methodology has been used to examine heavily-traded cash-settled financial futures contracts in the past, where hedgers are likely to be a relatively smaller component of the market. These studies include Berkman et.al. (2005), Brailsford and Frino (2005), Frino and Oetomo (2005), Frino, Bjursell, Wang, and Lepone (2008), and Ahn, Kang and Ryu (2010) who examine large trades in heavily-traded cash-settled *financial* futures markets where speculators and arbitrageurs are likely to make up the majority of futures traders. This paper extends this previous literature by examining a futures market which is likely to be dominated by hedgers.

We examine wheat futures traded on the Australian Securities Exchange (ASX). These futures contracts are (1) deliverable, (2) typically delivered,[1] and (3) relatively illiquid. Since the futures contracts are deliverable and typically delivered, then the traders in these futures contracts are interested in transacting the underlying commodity and hence are hedgers. The fact that the securities are quite illiquid, implies that the costs of a round-trip trade are likely to keep out speculators. Hence, the commodity futures contracts traded on the ASX are likely to be dominated by hedgers.

The remainder of this paper is structured as follows. In the next section the data and methodology are described. Section 3 reports results and robustness tests. Section 4 concludes.

2. Data and Methodology

[1] Our discussions with Exchange personnel revealed that 80 percent of grain futures on the exchange go to delivery.

Data

The data used in this study are sourced from Thomson Reuters Tick History (*TRTH*), managed and distributed by *SIRCA*. The data records all transactions, daily settlement and updates of the best level bid/ask. Each row documents date, time, record type, price, volume and associated contract. Our study focuses on the New South Wales Wheat futures contracts listed on the ASX, the most actively traded agriculture commodity futures contract on ASX. NSW Wheat contracts were first listed for trading on May 20, 2003 with the following contract specifications: quoted in price per tonne, 20 tonnes per contract; each contract has a quotation tick size of 10 cents; unlike equity and bond futures contracts which expire on a quarterly cycle, agriculture futures expiry months are January, March, May, July and September. All contracts can be traded in day and night sessions, however the daily settlement price is determined at the close of day trading session. Trades occur either on market (via the centralized limit order book), or off market (trades above a certain trade volume are only permitted to be traded off market). Prior to 2011 the minimum lot size for an off market trade was 200, this subsequently was increased to 500 following the launch of the ASX new futures trading platform ASX Trade 24. All contracts were initially listed on Sydney Future Exchange (SFE). Our sample period extends from the date of listing to March 2015.

Empirical Method

In order to measure price impacts, it is necessary to account for whether traders are buyer or seller initiated. Following Ellis, Michaely and O'Hara (2000), we classify trades as buyer or seller-initiated by comparing trade prices to prevailing bid-and ask quotes. If the trade price is above the midpoint of the prevailing best bid and ask, the trade is classified as buyer-initiated; conversely if the trade is executed below the prevailing best bid and ask, the trade is classified as seller imitated.

In order to measure the price impact of large trades in Australian agriculture futures contracts we adopt measures developed by Holthausen, Leftwich and Myers (1987,1990), specifically the temporary, permanent and total price impacts of trades. Temporary price effects reflect the revision in prices following a large transaction, while permanent price effects denote the change in prices conditioned on information inferred from block trades. The temporary effect is measured by comparing the block trade price to an equilibrium price following the block trade, while differences between pre and post-equilibrium prices derive the permanent price effect of a block trade. The temporary and permanent price effect of a block trade jointly estimates the total price effect of a block trade. Chan and Lakonishok (1993) and Keim and Madhavan (1998) advocate temporary and total price impacts as measures of execution costs, where pre- and post-equilibrium prices act as benchmark prices.

Given the objective of this study is to determine if hedgers are informed about future prices by examining price impacts around large trade, one needs a definition of what is considered a large trade. One definition that may be utilized is that imposed by the exchange permitting traders to execute orders off-market. There are two problems with such an approach, first the minimum trade size has changed during the sample period examined. Prior to 2011, trades of 200 lots were permitted to be traded away from the limit order book. Post 2011, the requirement increased to order of 500 lots. Secondly, the liquidity of the futures fluctuates greatly among contracts. This means that an exchange defined block trade in a more liquid contract would naturally have lower impacts on the prices than the same futures with less liquidity. To overcome these issues, we rank trades based on traded volumes, scaled by the total volume of each individual contract. Using this scaled trade volume measure, we divide the top half of the trades for each futures into four groups: Group 1 contains trades with scaled volume in the 95th percentile and above; Group 2 includes trades from 90th to 95th percentile; Group 3 includes trades from 75th to 95th percentile and Group 4 includes trades from 50th to 75th percentile. For each trade within each group we measure the associated price impacts as follows:

$$TotalImpact_i = \ln(Price_i / PreTradePrice_i),$$

$$TemporaryImpact_i = \ln(Price_i / PostTradePrice_i),$$

$$PermanentImpact_i = \ln(PostTradePrice_i / PreTradePrice_i),$$

where $Price_i$ is transaction price for each trade, the equilibrium market price prior to the block transaction, $PreTradePrice_i$ is the settlement price of the previous day, and

PostTradePrice$_i$ is the closing settlement price of the block transaction day to reflect the equilibrium market price post block transaction.[2]

As reported earlier, the contracts have different level of liquidity given expiry months. Price impacts can behave differently in trading days with high turnover, volatility in comparison with much quieter days (Chan and Lakonishok, 1993; Keim and Madhavan, 1998). Other factors such as time to maturity of the contract can also influence trading impacts. We thus control these factors in a regression analysis. The following regression models is estimated in our analysis:

$$s_i = \alpha + \sum_{j=1}^{3} \beta_{j,i} \cdot VolumeDummy_{j,i} + \sum_{k} \gamma_{k,i} \cdot Control_{k,i} \qquad Eq. 1$$

where s_i is one of the three variables: total, permanent and temporary impacts for trade i; $VolumeDummy_{j,i}$ represent the volume dummy variable for the j_{th} group ($j=1,2,3$); the intercept α thus measures the price impacts of the base group, group 4, which contains trades ranked from 50$^{\text{th}}$ to 75$^{\text{th}}$ percentile by scaled volume. $Control_{k,i}$ here contain three control variables: $ln(DayExpiry)$ measures the natural log of the number of days left for the contract to expiry, when the i_{th} trade occurs; $ln(max/min)$ shows the log of daily maximum and minimum prices for the contract, our proxy for daily volatility; $ln(TradeNo)$, the log of number of trades occurred in the contract, captures the general level of trading activities.

3. Results

Daily summary statistics for buyer and seller initiated large trades for NSW Wheat futures contracts are reported in Table I.

[INSERT TABLE I]

Table I highlights the illiquidity of agriculture futures in the Australian market, across all contract expiry dates, on average approximately four large trades per day are executed in NSW Wheat futures; this pales in comparison to trading in the ASX200 Share Price Index futures contracts, which trades on average 13,000 times per day or treasury bonds which trade

[2] To avoid outlier values that could bias our result, we windsorize price impacts at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.

over 2,000 per day (Frino, Mollica and Webb, 2014). Across the sample of large trades identified, the average trade volume for buyer initiated trades are 59 lots, representing approximately $337,000; sales are slightly larger at $347,000. Total day trading volume is slightly larger for sales, 271 vis-à-vis 253 for purchases across the sample period. Table I reports summary statistics for each of the four categories of large or block trades. Group 1 which contains the largest 5 percent of trades, in terms of lots per trade are 64 percent larger than respective trades in Group 4 for purchases, and 45 percent larger for sales, respectively. In terms of average trade value, Group 1 blocks purchases are $706,198, and very similar to Group 2 at $686,910, while Group 3 and 4 sales are very similar at $525,730 and $504,540 respectively.

Table II reports three measures of average total, temporary and permanent price effects for agriculture futures contract traded on the ASX. Consistent with research examining the price impact of block trades in equities markets, the total price impact of buyer initiated trades is positive and significant, while the total price impact of seller-initiated trades is negative and significant. Consistent with the literature examining equities markets block trades, an asymmetry in the size of impacts exists between buyer and seller initiated trades, with buyer initiated trades larger than sales. The average price impact across all block trades in wheat futures is 0.63 percent for purchases and -0.30 percent for sales. Unlike in equities markets where typically price reversals are observed following block sales and continuations following block purchases, in the case of agriculture futures block traders pay a liquidity premium for purchases and sales. The reversal, however is not sufficient to fully explain the price impact of block trades, as prices remain permanently higher level following block purchases and lower following block sales, consistent with the information hypothesis associated with large trades.

[INSERT TABLE II]

Panel B of Table II, reports average price impacts for each group of trade size. The liquidity effects for the largest trades in NSW Wheat futures are 0.27 percent for buy trades, and -0.32 percent for sell trades respectively. For the smallest trades, the temporary price effects are 0.23 percent and -0.15 percent. We observe such price reversals following large buys and sells of similarly magnitude for Groups 2 and 3 large trades. Table II, reports the total price impacts range from 0.57 percent to 0.83 percent for the largest purchases. While for sales the total price impact ranges -0.21 percent to -0.43 percent. In terms of permanent price effects

Table II reports across the four trade size classification for purchases, the price impacts are significant and suggestive of increasing in trade size. The average permanent price impact of the smallest blocks is 0.38 percent as compared to 0.56 percent for the largest. Conversely, results for sales permanent price effects are insignificantly different from zero across groups 1 through 3, however statistically significant and negative for all but the smallest category of block trades, with an information effect of -0.12 percent.

Turning to tests of the relation between price impact and trade size, Table III reports coefficient estimates of Equation 1. We observe that the coefficients on the trade size dummy variables increase monotonically from the smallest to largest block trades for buys for permanent price effects. The coefficient estimate on Group 1 trades is 0.22, statistically significant at the 10% level of significance, suggesting that buy trades in the largest trade group result in a much larger permanent price impact than the base group, which contains 50^{th} to 75^{th} percentile trades. Group 2 (90^{th} to 95^{th} percentile) and group 3 (75^{th} to 90^{th}) both reports insignificant estimates, indicating that both groups do not behave differently from the base. This suggests that after controlling for other market factors, the largest group of buy trades leave a much higher price permanent impact than other large trades. In contrast results reported for sales suggest the permanent price impact is not a function of trade size.

[INSERT TABLE III]

In terms of total price effects, similar conclusions can be drawn for buyer and seller initiated trades. Table III reports after controlling for volatility, days to expiry and general market liquidity, the largest group of block purchases on average costs 21 basis points more than the smallest group of blocks trades (statistically significant at the 5 percent level). In terms of sales, no discernable pattern in depicted. Explaining to some an extent why the total price impacts are insignificant for sales, results reported in Table III for the temporary price impacts demonstrate that liquidity costs are greater as trade size category increases, the same cannot be said of block buys.

Given the extant literature synthesizes that trades move due to either information or market frictions, in order to control for information flows, we undertake a robustness test to control for the release of crop reports by the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), World Agricultural Supply and Demand Estimates

(WASDE), and the United States Department of Agriculture (USDA). [3] Sourcing announcement date for each of these reports from Bloomberg, we re-estimate Equation 1 with a dummy variable for days on which wheat crop reports are released.

[INSERT TABLE IV]

Results reported in Table IV confirm aforementioned results. Even after controlling for news days, permanent price effects are positively correlated with trade size for the largest block trades. These results are consistent with the view that the information content of a trade is related to trade size (Easley and O'Hara, 1987). In relation to sales, we do not observe a significant relationship between trade size and price impacts. Interestingly, Table IV reports the coefficient estimates on the announcement dummy is statistically significant for buys, and insignificant for sales in terms of permanent and temporary price effects. In relation to

4. Conclusions

The behaviour of block traders has received considerable attention, especially in the context of the measurement of best execution and market transparency. This is due the measurement of the price effects associated with block trades is of substantial importance to regulators and policy makers concerned with promoting market liquidity, and investors who seek superior investment returns with minimal implementation costs. However, this literature has predominately focused on highly liquid equities and associated derivative securities. In this study we examine the price impact of block trades in an agricultural commodity which is highly illiquid.

We provide evidence that the price impact of large buyer-initiated transactions is permanent, consistent with the proposition that they are executed by traders perceived to be informed. We also provide evidence that the permanent price impact of buyer-initiated transactions increases with the size of the trade. This evidence is contrary to the "received" view in the literature, and implies that transactions long hedgers, particularly large long hedgers in agricultural futures markets are informed.

[3] Discussions with wheat traders highlighted the importance of US data.

References

Ahn, H. J., Kang, J., & Ryu, D. (2010). Information Effects of Trade Size and Trade Direction: Evidence from the KOSPI 200 Index Options Market*. *Asia‐Pacific Journal of Financial Studies*, *39*(3), 301-339.

Berkman, H., Brailsford, T., & Frino, A. (2005). A note on execution costs for stock index futures: Information versus liquidity effects. *Journal of Banking & Finance*, *29*(3), 565-577.

Chakravarty, S., & Sarkar, A. (1997). Traders' broker choice, market liquidity and market structure. *FRB of New York Staff Report*, (28).

Chan, L. K., & Lakonishok, J. (1993). Institutional trades and intraday stock price behavior. *Journal of Financial Economics*, *33*(2), 173-199.

Dewally, M., Ederington, L. H., & Fernando, C. S. (2013). Determinants of Trader Profits in Futures Markets. *Available at SSRN 1781975*.

Easley, D.N. & O'Hara, M. (1987). Price, trade size, and information in securities markets. Journal of Financial Economics, 19, pp. 69-90.

Ellis, K., Michaely, R., & O'Hara, M. (2000). The accuracy of trade classification rules: Evidence from Nasdaq. *Journal of Financial and Quantitative Analysis*,*35*(04), 529-551.

Frijns, B. M. Scholtus and D. van Dijk. (2014) Speed, Algorithmic Trading and Market Quality around Macroeconomic News Announcements, Journal of Banking and Finance 38, 89-105.

Frino, A., Bjursell, J., Wang, G. H., & Lepone, A. (2008). Large trades and intraday futures price behavior. *Journal of Futures Markets*, *28*(12), 1147-1181.

Frino, A., & Oetomo, T. (2005). Slippage in futures markets: Evidence from the Sydney Futures Exchange. *Journal of Futures Markets*, *25*(12), 1129-1146.

Holthausen, R. W., Leftwich, R. W., & Mayers, D. (1987). The effect of large block transactions on security prices: A cross-sectional analysis. *Journal of Financial Economics*, *19*(2), 237-267.

Holthausen, R. W., Leftwich, R. W., & Mayers, D. (1990). Large-block transactions, the speed of response, and temporary and permanent stock-price effects. *Journal of Financial Economics*, *26*(1), 71-95.

Hull, J. C. (2006). *Options, futures, and other derivatives*. Pearson Education India.

Keim, D. B., & Madhavan, A. (1998). The cost of institutional equity trades.*Financial Analysts Journal*, *54*(4), 50-69.

Kraus, A., & Stoll, H. R. (1972). Price impacts of block trading on the New York Stock Exchange. *The Journal of Finance*, *27*(3), 569-588.

Spiegel, M., & Subrahmanyam, A. (1992). Informed speculation and hedging in a noncompetitive securities market. *Review of Financial Studies*, *5*(2), 307-329.

Table I

Descriptive Statistics by Trade Size Categories

		NSW WHEAT		*Group 1*		*Group 2*		*Group 3*		*Group 4*	
		Buy	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*
Volume per Trade (contract)	Mean	59.06	61.39	134.93	128.61	125.2	125.59	105.69	95.869	81.851	88.651
	Median	46	50	100	100	87.5	100	80	70	100	100
Volume per Trade ($1000)	Mean	336.99	347.17	706.198	684.795	686.91	667.29	593.9	525.73	475.07	504.54
	Median	222	239	512.98	562	361.82	374.4	424.9	405.6	467	488
Daily Volume (contract)	Mean	253.20	271.06	203.579	187.275	168.99	186.23	178.46	173.56	162.21	190.59
	Median	140	150	100	104	100	100	100	100	100	120
Daily Volume ($)	Mean	1444.66	1532.83	1065.49	997.157	927.16	989.44	1002.8	951.78	941.51	1084.7
	Median	771.78	811.50	605	660	396	501.6	582.99	580	625.8	754.5
Daily Trades No.	Mean	4.29	4.42	1.50877	1.45614	1.3498	1.4828	1.6886	1.8104	1.9818	2.1499
	Median	3	3	1	1	1	1	1	1	1	2

This table describes the summary statistics of all trades for each futures. *Volume per trade* and *Daily Volume* are recorded in both number of contracts and its corresponding dollar value respectively. *Daily Trades No.* reports the number of trades occurred on a daily basis. Results reported in the first two columns summaries across trade size groups 1 through 4, while the remaining columns report results for each of the four categories.

Table II

Price Impacts using Daily Settlement Prices as Pre and Post Block Trade Equilibrium Prices

	N		*Volume*		*Total (%)*		*Temporary (%)*		*Permanent (%)*	
Size	*Buy*	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*
Panel A: All Trades										
	2746	2982	98.1	97.8	0.63	-0.3	0.22	-0.2	0.4	-0.1
					(22.65)	(-10.30)	(11.54)	(-11.35)	(12.47)	(-2.29)
Panel B: Price Impacts by Groups										
1	258	249	135	96	0.830	-0.430	0.270	-0.320	0.560	-0.110
					(8.55)	(-4.62)	(3.08)	(-3.86)	(4.92)	(-0.90)
2	274	301	129	82	0.670	-0.260	0.300	-0.250	0.370	0.000
					(7.94)	(-3.37)	(5.25)	(-4.7)	(3.8)	(-0.04)
3	797	869	125	89	0.570	-0.210	0.170	-0.220	0.400	0.010
					(11.47)	(-4.6)	(5.11)	(-7.77)	(7.07)	(0.15)
4	1417	1563	126	27	0.610	-0.270	0.230	-0.150	0.380	-0.120
					(15.77)	(-7.43)	(8.83)	(-6.47)	(8.29)	(-2.84)

Panels A and B, report average total, temporary and permanent price impact of NSW Wheat futures contract from March 2003 to March 2015. Panel A reports results across trade size groups 1 through 4, while Panel B reports results for each of the four categories. *N* reports the number observations in each group, representing buyer and seller initiated trades. *t*-statistics are reported in parentheses.

Table III

Regression Analysis of Total, Temporary and Permanent Price Impacts on Trade Size

	Total (%)		*Temporary (%)*		*Permanent (%)*	
	Buy	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*
Group 1	0.21	-0.07	-0.01	-0.13	0.22	0.06
	(2.0)	(-0.7)	(-0.1)	(-1.8)	(1.8)	(0.5)
Group 2	0.09	0.06	0.02	-0.09	0.07	0.16
	(0.9)	(0.7)	(0.3)	(-1.5)	(0.6)	(1.5)
Group 3	-0.04	0.08	-0.09	-0.07	0.05	0.15
	(-0.6)	(1.4)	(-1.9)	(-1.7)	(0.7)	(2.2)
Intercept	0.88	-0.24	0.58	-0.15	0.30	-0.09
	(5.2)	(-1.5)	(4.8)	(-1.4)	(1.5)	(-0.5)
Days to Expiry	-0.08	-0.05	-0.06	-0.01	-0.02	-0.04
	(-2.5)	(-1.8)	(-2.9)	(-0.5)	(-0.4)	(-1.2)
Volatility	-0.06	0.00	0.53	-1.62	-0.59	1.62
	(-0.3)	(0)	(3.6)	(-4.2)	(-2.4)	(2.5)
# Transactions	0.05	0.10	-0.02	0.03	0.08	0.07
	(1.7)	(3.3)	(-1.1)	(1.6)	(2.1)	(1.9)

Table III reports the results from the following regression

$$s_i = \alpha + \sum_{j=1}^{3} \beta_{j,i} \cdot VolumeDummy_{j,i} + \sum_{k} \gamma_{k,i} \cdot Control_{k,i}$$

where s_i is one of the three variables: total, permanent and temporary impacts for trade i; $VolumeDummy_{j,i}$ represent the volume dummy variable for the j_{th} group (j=1,2,3); the intercept α thus measures the price impacts of the base group, group 4. $Control_{k,i}$ here contain three control variables: $ln(DayExpiry)$ measures the natural log of the number of days left for the contract to expiry; $ln(max/min)$ shows the log of daily maximum and minimum prices for the contract; $ln(TradeNo)$, the log of number of trades occurred in the contract. All coefficients are tested against 0 and resulted *t*-statistics are reported in parentheses.

Table IV

Robustness Test Controlling for release of Australian and US Government Wheat Outlook Reports

	Total (%)		*Temporary (%)*		*Permanent (%)*	
	Buy	*Sell*	*Buy*	*Sell*	*Buy*	*Sell*
Group 1	0.22	-0.06	-0.02	-0.12	0.24	0.06
	(2.09)	(-0.58)	(-0.26)	(-1.72)	(1.95)	(0.51)
Group 2	0.09	0.07	0.02	-0.09	0.07	0.16
	(0.93)	(0.75)	(0.27)	(-1.43)	(0.64)	(1.49)
Group 3	-0.04	0.09	-0.09	-0.07	0.05	0.15
	(-0.6)	(1.44)	(-1.9)	(-1.61)	(0.63)	(2.21)
Intercept	0.90	-0.27	0.55	-0.17	0.35	-0.10
	(5.27)	(-1.71)	(4.6)	(-1.59)	(1.74)	(-0.56)
Announcement Dummy	-0.06	0.07	0.07	0.04	-0.13	0.03
	(-1.05)	(1.38)	(1.79)	(1.13)	(-1.98)	(0.53)
Days to Expiry	-0.08	-0.05	-0.06	-0.01	-0.01	-0.04
	(-2.5)	(-1.7)	(-2.9)	(-0.5)	(-0.4)	(-1.2)
Volatility	-0.05	0.00	0.52	-1.62	-0.58	1.61
	(-0.3)	(-0.1)	(3.6)	(-4.2)	(-2.4)	(2.5)
# Transactions	0.06	0.10	-0.03	0.03	0.08	0.06
	(1.8)	(3.2)	(-1.2)	(1.6)	(2.3)	(1.8)

Table IV reports the results from the following regression

$$s_i = \alpha + \sum_{j=1}^{3} \beta_{j,i} \cdot VolumeDummy_{j,i} + \sum_{k} \gamma_{k,i} \cdot Control_{k,i}$$

where s_i is one of the three variables: total, permanent and temporary impacts for trade i; $VolumeDummy_{j,i}$ represent the volume dummy variable for the j_{th} group (j=1,2,3); the intercept α thus measures the price impacts of the base group, group 4. $Control_{k,i}$ here contain four control variables: *Announcement* a dummy variable set equal to one on days ABARE or USDA wheat reports are published and zero otherwise; $ln(DayExpiry)$ measures the natural log of the number of days left for the contract to expiry; $ln(max/min)$ shows the log of daily maximum and minimum prices for the contract; $ln(TradeNo)$, the log of number of trades occurred in the contract. All coefficients are tested against 0 and resulted *t*-statistics are reported in parentheses.