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Abstract

This paper investigates the information role of algorithmic traders (AT) in the Nifty index option market. I analyse a unique dataset to test for information-based trading by looking at the effect of net buying pressure of options on implied volatilities. According to the direction-learning hypothesis, (directional) informed investors' net buying pressure of calls (puts) raises the implied volatilities of calls (puts) and lowers the implied volatilities of puts (calls). In addition, their net buying pressure can also predict future index returns. According to the volatility-learning hypothesis, (volatility) informed investors' net buying pressure is always positively related to implied volatilities. I find that these relations do not hold for AT and, therefore, infer absence of information-based trading by AT. On the contrary, I find the direction-learning hypothesis to hold for non-AT who, in this market, are primarily individual investors.

Keywords: Implied Volatility; Net buying pressure; Index option market

JEL Code: G13, G14

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Contents

1 Introduction

Technological advances in financial markets have led to an influx of algorithmic traders (AT): traders who use computer algorithms to place orders. Brogaard (2010) documents more than 50% of the trades in the US equity markets having come from AT. Since algorithms can process information much faster than human traders, their speed enables them to become informed by analysing the trading activity of other informed investors (Harris, 2003; Frino *et al.*, 2012). Various questions on their role in financial markets hence relate to whether they generate "informed" trading in markets.

Algorithmic traders may become informed by either trading based on information on the future prices (directional trading) or the future volatility (volatility trading) of the underlying asset.[1] To exploit their private information, the directional AT may choose to trade in the spot or the option market, while volatility AT only trade in the option market. Theoretically, directional AT would also prefer to trade in the option market due to higher leverage of options.[2] Option prices may move due to either of the two types of informed trading. I examine if AT engage in informed trading by testing the impact of the net buying pressure of algorithmic traders on the prices, and therefore, the implied volatilities of the Nifty index options at the National Stock Exchange, India.

There are three potential explanations that can describe the relationship between net buying pressure and implied volatility: limits to arbitrage, volatility-learning, and direction-learning. The first is based on the view that option markets exhibit limits to arbitrage — liquidity suppliers in option markets absorb large positions in particular option series and face increased hedging cost and demand higher compensation for the increased risk. As a result, increases in net buying pressure increase option prices and implied volatilities.

The second view is that option prices move when investors' expectation about future volatility of the underlying asset changes. The occurrence of a volatility shock is signalled to investors through order imbalances which changes the investors' expectation about future volatility. Therefore, the implied volatil-

[1] Capelle-Blancard (2001) notes the distinction between the two types of informed traders: directional and volatility traders.

[2] Researchers, therefore, have argued that information flows from the option market to the spot market (Black, 1975; Easley *et al.*, 1998). The empirical research has been ambiguous with some supporting (Amin and Lee, 1997; Easley *et al.*, 1998; Pan and Poteshman, 2006) this direction of the flow of information and others contradicting it (Stephan and Whaley, 1990; Chiang and Fong, 2001; Chan *et al.*, 2002; Choy and Wei, 2012).

ities change accordingly and a positive relation emerges between net demand for options and their corresponding implied volatilities. Such option investors are volatility traders.

In the third view, movement in option prices results from changes in investors' expectation about the direction of the future price of the underlying asset. Order imbalances change investors' expectation about future price movements of the underlying asset and change option prices and implied volatilities accordingly. Specifically, implied volatilities of calls (puts) are positively related to the net demand for calls (puts) and negatively related to the net demand for puts (calls). These option investors are directional traders. However, the same relation between implied volatility and net buying pressure can also emerge if investors anticipate future price movements based on intuition rather than superior information. In this case, the investors are noise traders.

I use a unique dataset that identifies both the initiator of an option trade — as a buyer or seller — and the class of the trader(s) — AT or non-AT to investigate the information content of the net buying pressure of AT. The data provides two advantages over other studies involving AT or that rely on order imbalances. First, the initiator of a trade is clearly identified and does not rely on algorithms designed to infer trades as buy/sell trades (Lee and Ready, 1991). Second, it does not rely on proxies for AT which lead to weak identification (Hendershott *et al.*, 2011). Apart from identifying AT/non-AT trades, the dataset also identifies traders as one of custodians, proprietary traders, or non-custodian non proprietary traders.

I find that the Indian index option market has experienced a shift in investor profile from individual investors (who are mostly non-AT) to proprietary investors (who are mostly AT). This increasingly dominant role of AT provides a significant opportunity to examine the information role of AT in an electronic limit order book market without designated market markers. I also document both the aggregate behaviour of AT vs non-AT as well as their behaviour within the observed categories. This helps contrast the impact of an investor group within AT/non-AT. For instance, custodians' demand for out-of-the-money (OTM) put options to hedge their portfolios may affect implied volatilities differently.

Using intra-day observations, I estimate regression models developed by Bollen and Whaley (2004) to test the three hypotheses in the index option market. I find that the direction-learning and the volatility-learning hypotheses do not hold for AT: neither in aggregate, nor for any specific investor subgroup within AT. This suggests that AT do not engage in direction or volatility based informed trading in the Nifty index option market. Interestingly, the net demand for options by AT and the corresponding implied volatilities also do not follow predictions from the limits to arbitrage hypothesis. To contrast with the non-AT, I find that the direction-learning hypothesis holds for non-AT in aggregate as well as for each investor subgroup. This implies that non-AT engage in informed trading based on information about the direction of the future movements in the underlying asset prices.

Kang and Park (2008) also find evidence in favour of the direction-learning hypothesis for the KOSPI 200 index option market. While their results hold across all investors, I find supporting evidence only for a subset of investors (non-AT) in the Nifty index option market. On the contrary, Bollen and Whaley (2004) find evidence in favour of the limits to arbitrage hypothesis for the S&P 500 index option market.

Since the results supporting the direction-learning hypothesis for non-AT may be due to noise trading in the index option market (Kang and Park, 2008), I perform an additional test to distinguish directional trading from noise trading. Under this test, I examine the ability of net buying pressure to predict future index returns. I find that the net buying pressure from non-AT has predictive power for future index returns. Within the non-AT category, I find that the net buying pressure of the custodian group has the lowest degree of predictability for future index returns (smallest coefficient). In some cases such as at-the-money (ATM) calls, ATM puts, and OTM puts, it has no predictability. This is in contrast to other emerging derivatives markets where foreign institutional investors play a strong informational role (Ahn *et al.*, 2008; Chou and Wang, 2009; Chang *et al.*, 2009; Wen-liang and He, 2014). I also test whether the net buying pressure of AT or any investor group within AT has any predictive power for future index returns. Consistent with earlier results that AT are not directional traders, I find that the net buying pressure has no predictability.

In the literature that examines the link between informed trading and AT, Hendershott and Riordan (2009) find that the AT monitor markets for information and contribute more to the discovery of efficient prices than human traders. Viljoen *et al.* (2014) document that *increase in AT is followed by an increase in market information and support that algorithmic traders are informed*. Unlike previous studies, Frino *et al.* (2012) investigate how AT may become informed by analysing their trading activities around earnings announcement. They provide evidence for the Australian market that AT benefit from the faster speed of trade execution during periods of release of information. I look at these linkages from the perspective of whether AT engage in direction or volatility based informed trading in the index option market and find results that contradict this emerging consensus.

The remainder of the article is organized as follows: Section 2 introduces the hypotheses that explain the linkages between net buying pressure and movements in implied volatilities. Section 3 presents the data and describes the trading and net buying pressure pattern across different investor categories. Section 4 presents the empirical methodology and results. Section 5 concludes.

2 Net buying pressure and implied volatility

The option pricing theory developed by Black and Scholes assumes a frictionless market where suppliers of option market liquidity can perfectly and costlessly hedge their inventories resulting in flat supply curves. Changes in demand to buy or sell options have no impact on option prices and hence implied volatilities. There is no relation between net buying pressure of options and implied volatilities.

Assumptions of the standard option pricing model are unrealistic and options cannot be hedged perfectly since markets are incomplete because of transaction costs, stochastic volatility, and jumps in underlying prices (Figlewski, 1989). Therefore, demand for a particular option may affect its price and implied volatility.

There are three potential explanations for changes in demand for options to affect prices and hence implied volatilities. First, net buying pressure of options drives the shape of implied volatilities due to limits of arbitrage. Second, the information embedded in the net buying pressure relates to investors' expectation of future underlying asset volatility. Third, the information relates to investors' expectation about future movements in underlying asset's price. They can be explained further by the three differentiating hypotheses.

Limits to arbitrage: Theoretically, financial arbitrage requires no capital and entails no risk; in reality, both exist and limit effectiveness of arbitrage (Shleifer and Vishny, 1997; Liu and Longstaff, 2004). Bollen and Whaley (2004) argue that the supply curve of an option is upward sloping resulting from these limits to arbitrage. Liquidity suppliers in the market absorb large positions in particular option series and face increased hedging cost and demand higher compensation for the increased risk. As a result, option prices increase and subsequently implied volatilities. Given a supply curve with a positive slope, excess buyer initiated trades cause option price and implied volatility to rise, and excess seller motivated trades cause implied volatility to fall. Hence, a positive relation emerges between net buying pressure and implied volatility.

Volatility-learning: This hypothesis assumes that the slope of the supply curve of each option is flat. Option prices move when investors' expectation about future volatility of the underlying asset changes. Consequently, the supply curve shifts. If a volatility shock occurs and is signalled to investors through order imbalances, then this order imbalance will change the investors' expectations about future volatility. Therefore, the implied volatilities will change accordingly and a positive relation will emerge between demand for options and their corresponding implied volatilities. According to Bollen and Whaley (2004), such option investors are volatility traders.

Bollen and Whaley (2004) introduce two empirical tests to distinguish between the these two alternative hypotheses. The first test involves the lagged changes in implied volatility in a regression that investigates the relation between changes in implied volatility and net demand. According to the limits to arbitrage hypothesis, changes in implied volatilities would reverse as risk holding liquidity suppliers would want to re-balance their portfolio. This would result in a negative serial correlation between changes in implied volatility and hence a negative coefficient on the lagged variable. In contrast, under the volatility-learning hypothesis, the changes in implied volatilities would show no serial correlation since information would already be reflected in the prices and implied volatilities through trading activities of investors.

The second test uses the demand for ATM options on changes in implied volatilities of other options to distinguish the first two hypotheses. Under the limits to arbitrage hypothesis, it is not necessary that implied volatilities of different options move together since implied volatility of an option series is affected by its own net demand. Therefore, the net demand for ATM options may not affect the implied volatilities of other option series. However, under the volatility-learning hypothesis, the demand for ATM options plays an important role in determining the implied volatility of all options. Since ATM options are most informative regarding future volatility of the market, their net buying pressure drives changes in implied volatility of all options in the same direction.

Bollen and Whaley (2004) concentrate on volatility shocks and assume that option traders are volatility traders. Kang and Park (2008) argue that option traders may also be directional traders and introduce a third hypothesis that distinguishes volatility traders from directional traders. They refer to it as the direction-learning hypothesis.

Direction-learning: This hypothesis also assumes that the slope of each option is flat. However, movement in option prices result from changes in expectation about the direction of future underlying asset price movements. Order imbalances will change investors' expectations about the direction of future price movements of the underlying asset. Therefore, option prices and hence implied volatilities will change accordingly. Investors in this market are directional traders. A directional trader unlike a volatility trader bases her trading decisions based on future price movements instead of future volatility.

Using Bollen and Whaley's tests, Kang and Park (2008) differentiate the direction-learning hypothesis from the other hypotheses. First, they predict a negative coefficient on lagged changes in implied volatility same as the limits to arbitrage hypothesis but in contrast to the volatility-learning hypothesis. They argue that when a positive (negative) shock is known to informed investors at time t, they place buy orders in calls (puts) and sell orders in puts (calls). There is a positive (negative) net buying pressure on calls and negative net buying pressure on puts. As a result, prices and implied volatilities increase (decrease) for calls and decrease (increase) for puts at time t. At $t + 1$, when the information arrives in the underlying market, the index price rises and implied volatilities of calls falls (rises) and puts rises (falls). This implies a negative serial correlation between changes in implied volatilities.

Second, under the direction-learning hypothesis, there is information about future movements in prices embedded in the net buying pressure variable. As a result, the implied volatility of a call (put) option exhibits a positive (negative) relation to net buying pressure of call option, and a negative (positive) relation to net buying pressure of put option. This in contrast to the first two hypotheses that always predict a positive coefficient on the net buying pressure variable.

3 Data

The analysis in this paper uses data on the NSE-50 (Nifty) index and index options at the National Stock Exchange (NSE) of India Ltd. The index options have a three month expiry cycle; near (one) month, next month (two), and far month (three). The long term Nifty index options have three quarterly expiries (March, June, Sept & Dec cycle) and next 8 half yearly expiries (Jun, Dec cycle). The options expire on last Thursday of the month. Since long term contracts are extremely illiquid, only the first three expiries are used for this paper which contribute nearly 99% of the volume to this market.

NSE is the fourth largest derivative exchange in the world in terms of number of contracts traded (Table 1) and the second largest in number of contracts traded in equity index (Table 2). NSE is thus a source of high quality data about exchange-traded derivatives.

Table 1 Global exchanges: number of contracts traded and/or cleared

Rank	Exchanges	Jan-Dec 2012	Annual % change
1	CME Group	2,890,036,506	-14.7
2	Eurex	2,291,465,606	-18.8
3	National Stock Exchange of India	2,010,493,487	-8.6
4	NYSE Euronext	1,951,376,420	-14.5
5	Korea Exchange	1,835,617,727	-53.3

Source: FIA, http://www.futuresindustry.org/volume-.asp

Table 2 Ranked by the number of contracts traded in equity index

Rank	Contracts	Jan-Dec 2011	Jan-Dec 2012	Annual % Change
1	Kospi 200 Opt, KRX	3,671,662,258	1,575,394,249	-51.7
2	S&P CNX Nifty Opt, NSE India	868,684,582	803,086,926	-7.6
3	SPDR S&P 500 ETF Opt, CME	729,478,419	585,945,819	-19.7
4	E-mini S&P 500 Fut, CME	620,368,790	474,278,939	-23.5
5	RTS Fut, Moscow Exchange	377,845,640	321,031,540	-15.0

Source: FIA, http://www.futuresindustry.org/volume-.asp

The options data is available at the tick-by-tick frequency and includes all trades and orders, with prices and quantities time-stamped to jiffies, from the NSE for the period January 2009 - August 2013. In this dataset, each trade and order is tagged with an investor type flag and an AT flag. This allows to identify if an order/trade originated from a custodian (C)/proprietary (P)/ non-custodian non-proprietary (NCNP) and AT/non-AT trader.[3] The custodians represent the institutional investors while the NCNP would primarily be the retail investors but would also include hedge funds and brokerages trading on behalf of their clients.

[3]The identification is done at the level of the I.P. address of the computer from where the order is generated.

The option deltas and implied volatilities are computed using the Black-Scholes formula. In the delta computation, the standard deviation is proxied by historical volatility of return of the Nifty index over the most recent sixty trading days. The interest rates used in the implied volatility estimation are the one and three month MIBOR rates obtained from the NSE website[4] along with the dividend yields.

Table 3 Moneyness category definitions (Bollen and Whaley, 2004)

Call	Delta range	Put	Delta range
1 DITM	$0.875 < \Delta_c \leq 0.98$	1 DOTM	$-0.125 < \Delta_p \leq -0.02$
2 ITM	$0.625 < \Delta_c \leq 0.875$	2 OTM	$-0.375 < \Delta_p \leq -0.125$
3 ATM	$0.375 < \Delta_c \leq 0.625$	3 ATM	$-0.625 < \Delta_p \leq -0.375$
4 OTM	$0.125 < \Delta_c \leq 0.375$	4 ITM	$-0.875 < \Delta_p \leq -0.625$
5 DOTM	$0.020 < \Delta_c \leq 0.125$	5 DITM	$-0.980 < \Delta_p \leq -0.875$

Table 4 Implied vs realised volatility

The table presents the year-wise median and overall average implied volatility estimates for calls and puts under each option delta category in Panel A. Panel B presents the year-wise median of daily differences between implied and realised volatility and the overall average difference for calls and puts. The delta values and the implied volatilities are computed using the closing prices of the Nifty index. The sample period is January 2009 - August 2013.

	Panel A: Median implied volatility					Panel B: Median differences between implied and realised volatility				
Year	1	2	3	4	5	1	2	3	4	5
	Call									
2009	33.76	34.21	33.99	32.80	34.21	1.69	-0.36	-2.34	-4.24	-2.76
2010	19.66	19.58	18.24	17.15	17.13	2.00	2.30	1.61	0.49	0.35
2011	16.75	20.66	19.76	18.49	19.45	-1.27	0.42	-0.42	-1.25	-0.50
2012	17.13	16.92	16.59	15.95	15.75	2.38	1.79	0.74	0.12	0.49
2013	10.53	14.34	14.23	14.25	14.54	-1.21	0.35	0.07	-0.01	1.01
Avg	19.57	21.14	20.56	19.73	20.21	0.72	0.90	-0.07	-0.98	-0.28
	Put									
2009	45.13	40.53	36.94	32.80	37.15	9.08	5.14	1.37	-1.57	3.97
2010	24.61	22.57	20.45	18.26	19.23	8.52	6.24	4.03	2.29	3.50
2011	28.60	25.51	22.93	22.06	23.70	7.54	5.08	3.20	2.64	5.13
2012	22.61	19.98	18.67	16.62	16.27	5.55	3.35	1.86	0.50	0.69
2013	19.41	17.88	16.94	16.56	16.90	5.19	3.75	2.93	2.44	3.95
Avg	28.07	25.29	23.18	21.26	22.65	7.18	4.71	2.68	1.26	3.45

Each option is classified into one of the five moneyness categories based on

[4] http://www.nseindia.com/

their deltas as shown in (Table 3). The year-wise median and the overall average implied volatility estimates for calls and puts under each category are reported in Table 4. The year-wise median and the overall average implied volatility of puts are higher than calls for all moneyness categories. The overall average implied volatility estimates for calls and puts monotonically decrease to the 4th category, and then increase marginally in the 5th category. For puts, the DOTM options have a significantly higher average implied volatility than DITM options, while for calls DOTM is only marginally higher than DITM. The table also reports the year-wise median of daily differences between implied and realised volatility and the overall average under each option category. The overall average of the median differences indicate that the historical volatilities of the Nifty index are much lower than the implied volatilities of the Nifty index options for puts, regardless of the moneyness. However, for calls, this holds only for DITM and ITM options.

3.1 Type of investors in the index option market

Time-series trends of proportion of trades initiated indicate a declining pattern for the non-custodian non-proprietary (NCNP) group, an increasing pattern for the proprietary (P) group, and no consistent pattern for the custodian (C) group. An increasing trend for AT is also observed. This rise in AT activity may also be related with the introduction of co-location services by the NSE (Figures 1 and 2).

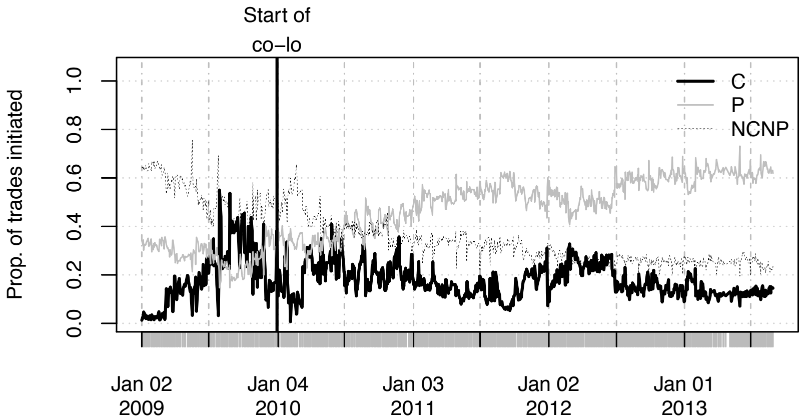
Table 5 reports the traded volume for each investor group and AT/non-AT. The custodians initiated 17.4% of the trades, of which 10.3% were initiated by the AT and 7.1% by the non-AT. The proprietary traders initiated 50.3% of the trades of which 33.2% were initiated by the AT and 17.1% by the non-AT. Lastly, the NCNP initiated 32.3% of the trades, of which 6.1% were initiated by the AT and 26.2% by the non-AT. Overall, the AT initiated 49.6% trades while the non-AT initiated 50.4% trades.

The numbers indicate that the Indian option market is increasingly dominated by proprietary traders who are essentially AT. This is unique to the Indian market as other emerging markets such as the KOSPI 200 index option market is dominated by individual investors (Kang and Park, 2008). It is also in contrast to developed markets such as the S&P 500 index option market which is dominated by institutional investors (Bates, 2003; Lakonishok *et al.*, 2007).

The number of calls traded in the Nifty index option market at 51% calls is

Figure 1 Proportion of trades initiated across investor categories

The graphs below is the time-series of the proportion of Nifty option trades initiated across investor types for the period January 2009 - January 2013. The vertical line in each graph indicates introduction of co-location services by NSE in January 2010.
The top graph shows the proportion of trades initiated by custodians (C), proprietary (P), and non-custodian non-proprietary (NCNP) respectively. In recent years, proportion of trades initiated by proprietary has increased substantially. It has decreased for NCNP and has not changed much for custodian.
The bottom graph shows the proportion of trades initiated by AT and non-AT respectively. It clearly indicates that AT have become dominant players in the Nifty index option market.



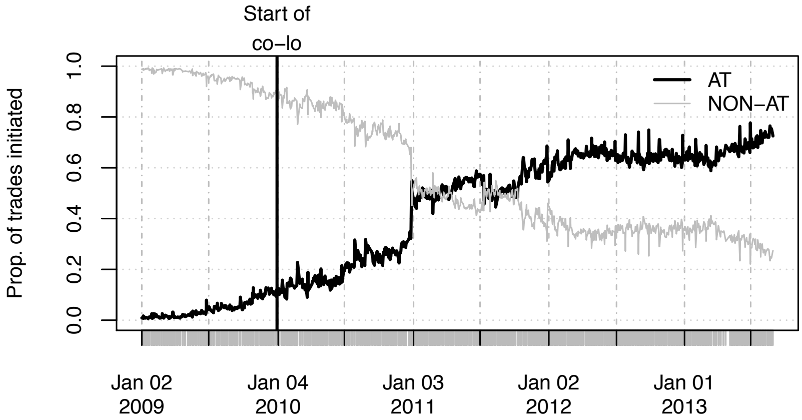
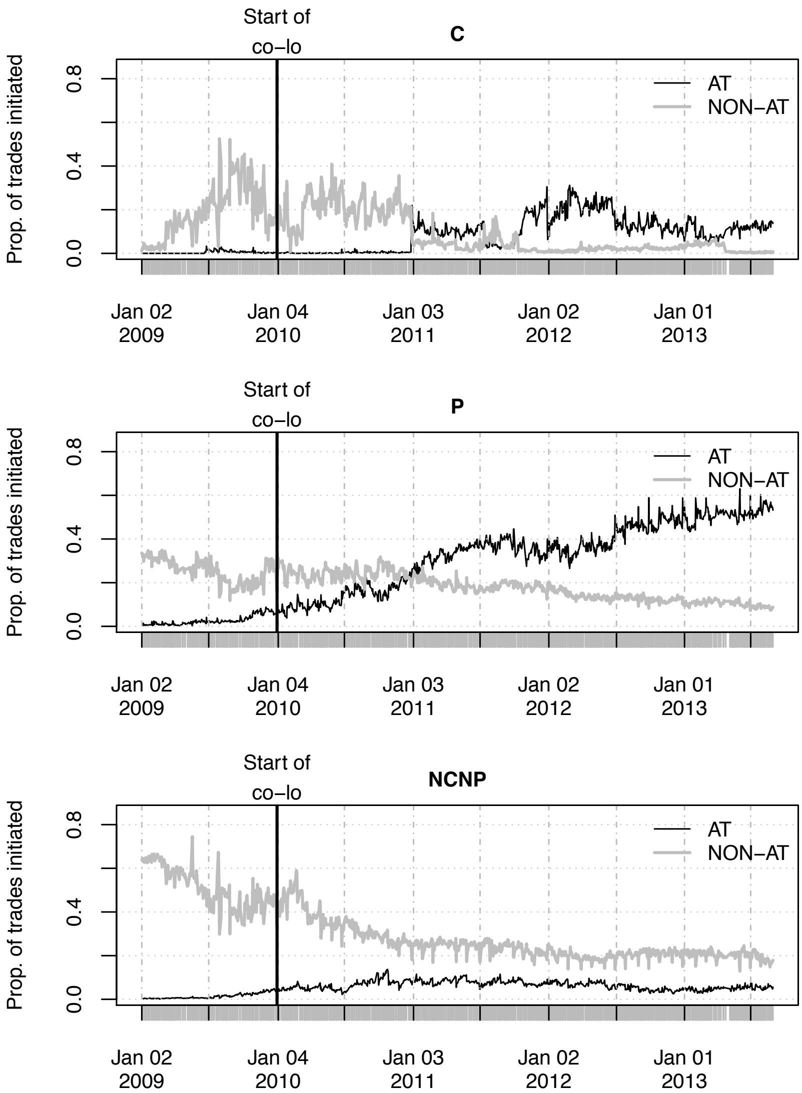


Figure 2 Proportion of trades initiated, AT vs non-AT

The figure plots the proportion of Nifty option trades initiated by AT and non-AT for each investor category: custodians (C), proprietary (P), non-custodian non-proprietary (NCNP) for the period January 2009 - August 2013. The vertical lines indicate the introduction of co-location by NSE in January 2010. The proportion of trades initiated are increasing for AT and decreasing for non-AT under each category. Both proprietary and custodian group show higher AT participation while NCNP are essentially non-AT.



marginally higher than the puts traded at 49%. In contrast, Kang and Park (2008) find significantly higher calls at 56% than puts at 44% in the KOSPI 200 index option market. While in the S&P 500 index option market, 45% were calls and 55% were puts (Bollen and Whaley, 2004). For index calls, the ATM and OTM options (category 3 & 4) are the most active. For index puts, OTM puts are the most active. Followed by ATM puts and DOTM puts.

Table 6 reports the net buying pressure[5] in calls and puts across investor types and AT/non-AT. Overall, the custodians are net buyers of calls and puts, the proprietary traders net sellers of calls and puts, and the NCNP net buyers of calls and net sellers for puts. For AT in each investor category, the custodians are net buyers of calls and puts, the proprietary traders are net buyers of calls and net sellers for puts, and the NCNP net sellers of calls and puts. For non-AT in each category, the custodians continue to be net buyers of calls and puts but the proprietary traders are net sellers of calls and puts and the NCNP net buyers of calls and net sellers for puts.

Overall, there is net selling of calls and puts in the Nifty index option market. This is in contradiction to the results in the literature for the SPX and the KOSPI index options. Bollen and Whaley (2004) find net selling of calls and net buying of puts in the SPX options market, while Kang and Park (2008) find the reverse in the KOSPI options market. Among AT, there is net buying of calls and net selling of puts. The reverse holds for non-AT. Among custodians, both for AT and non-AT, large net buying pressure of OTM index puts suggests their preference for OTM puts for portfolio insurance.

Figures 3 and 4 show scatter plots of the pairs of net buying pressure of calls and puts for AT and non-AT respectively. Also, each figure shows scatter plots for each investor type under AT/non-AT. Each point in these scatter plots denotes a pair of the magnitudes of the net buying pressures of calls and puts over a five-minute interval. Prima facie, the relationship appears to be negative for AT and non-AT. For each investor type within AT/non-AT, it appears to be negative for the proprietary and the NCNP investor categories but marginally positive for the custodians.

[5]Since the dataset consists of all trades and orders for the Nifty index options, they are matched to identify whether a particular trade is buyer initiated or seller initiated. The initiating order is the one which enters the market and gets matched with an already existing order in the limit order book. Every trade is thus identified as a buyer or a seller initiated trade. The net buying pressure is computed as the difference between the number of buyer initiated contracts and the number of seller initiated contracts multiplied by the absolute value of the option's delta.

Table 5 Number of Nifty index options traded

The table presents the number of contracts traded in the Nifty index options market across investor types. The delta values are computed using the closing prices of the Nifty index, the MIBOR rates as risk-free rates, and the historical volatility over the most recent sixty trading rates. The period of analysis is January 2009 - August 2013. All trades are allocated into three investor types: custodians (C), proprietary (P), and non-custodian non-proprietary (NCNP). They are further classified into AT/non-AT.

	AT				NON-AT			
	Calls		Puts		Calls		Puts	
Delta Class	No. of Contracts	Prop. of Total	No. of Contracts	Prop. of Total	No. of Contracts	Prop. of Total	No. of Contracts	Prop. of Total
C								
1	1,852,299	0.001	31,776,160	0.011	797,118	0.001	15,756,919	0.009
2	11,000,099	0.005	44,986,156	0.019	4,448,935	0.004	22,115,253	0.014
3	37,315,032	0.018	30,784,031	0.014	14,908,034	0.010	12,946,719	0.009
4	48,151,541	0.021	8,643,202	0.004	20,992,805	0.014	3,257,601	0.003
5	21,824,391	0.009	1,665,367	0.001	11,094,985	0.007	572,982	0.000
Totals	120,143,362	0.054	117,854,916	0.049	52,241,877	0.036	54,649,474	0.035
P								
1	6,949,912	0.004	64,246,322	0.030	3,695,969	0.001	56,955,240	0.017
2	37,694,144	0.024	112,542,870	0.062	25,942,681	0.010	101,178,387	0.034
3	93,625,260	0.056	81,463,716	0.050	84,126,078	0.030	72,127,324	0.026
4	112,639,329	0.060	30,205,956	0.020	91,360,386	0.032	18,462,453	0.007
5	47,653,748	0.021	6,715,935	0.004	49,685,357	0.013	3,150,811	0.001
Totals	298,562,393	0.166	295,174,799	0.166	254,810,471	0.086	251,874,215	0.085
NCNP								
1	1,573,962	0.001	8,394,542	0.004	5,792,129	0.003	55,292,434	0.018
2	7,875,887	0.005	17,306,224	0.010	40,083,963	0.017	124,528,061	0.051
3	18,343,956	0.012	17,119,880	0.011	131,447,172	0.055	100,937,908	0.042
4	16,276,916	0.009	5,850,556	0.004	121,022,369	0.048	26,338,246	0.012
5	6,278,375	0.003	1,413,992	0.001	42,846,785	0.012	4,463,344	0.002
Totals	50,349,096	0.031	50,085,194	0.031	341,192,418	0.135	311,559,993	0.126

Table 6 Net buying of Nifty index option contracts

The table presents the net buying pressure across investor types in the Nifty index options market. The delta values are computed using the closing prices of the Nifty index, the MIBOR rates as risk-free rates, and the historical volatility over the most recent sixty trading rates. The period of analysis is January 2009 - August 2013. All trades are allocated into three investor types: custodians (C), proprietary (P), and non-custodian non-proprietary (NCNP). They are further classified as AT/NON-AT.

	AT		NON-AT	
	Calls	Puts	Calls	Puts
Delta Class	No. of Contracts	No. of Contracts	No. of Contracts	No. of Contracts
		C		
1	-241,069.056	25,581.11	-26,474.40	54,961.97
2	288,820.441	137,827.00	114,904.31	448,781.99
3	191,752.010	105,943.09	298,833.27	127,213.27
4	-116,565.935	23,688.40	113,002.21	-81,220.27
5	14,074.032	-138,886.43	19,015.65	-91,789.37
Totals	137,011.492	154,153.18	519,281.04	457,947.58
		P		
1	-187,185.717	42,179.57	-227,306.05	-66,187.69
2	1,028,865.238	-1,280,340.82	208,264.17	-925,377.55
3	924.557	457,909.10	-409,379.07	-42,941.77
4	-512,836.662	723,446.57	-925,204.47	351,054.36
5	-28,286.379	-54,732.76	-127,274.47	-118,721.41
Totals	301,481.038	-111,538.35	-1,480,899.89	-802,174.06
		NCNP		
1	-102,033.920	-13,972.63	-36,842.78	-72,223.08
2	128,287.588	-190,053.53	-300,297.15	157,088.24
3	-41,676.501	-45,721.41	387,729.16	74,745.35
4	-117,279.676	156,600.00	185,779.54	-290,448.27
5	-8,503.009	27,835.88	94,107.34	-155,380.43
Totals	-141,205.516	-65,311.70	330,476.11	-286,218.18

Figure 3 Relationship between net buying pressure of calls and puts, AT

The figures show the scatter diagrams between the net buying pressure of calls and net buying pressure of puts for all AT and each investor type: custodians (C), proprietary (P) and non-custodian non-proprietary (NCNP) within AT. Each point denotes a pair of net buying pressures of calls and puts over a five-minute interval. The relationship appears to be negative all AT. For each investor within AT, it appears to be negative for the proprietary and NCNP investor categories but marginally positive for the custodians.

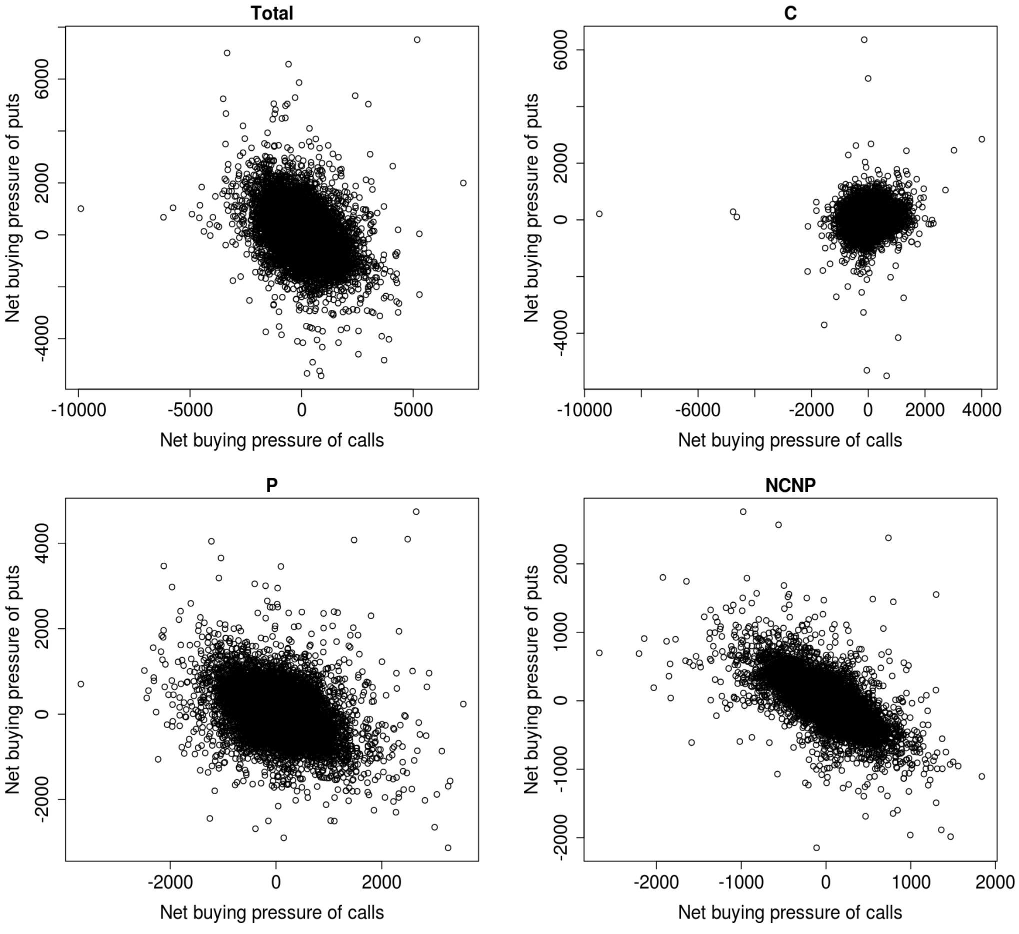
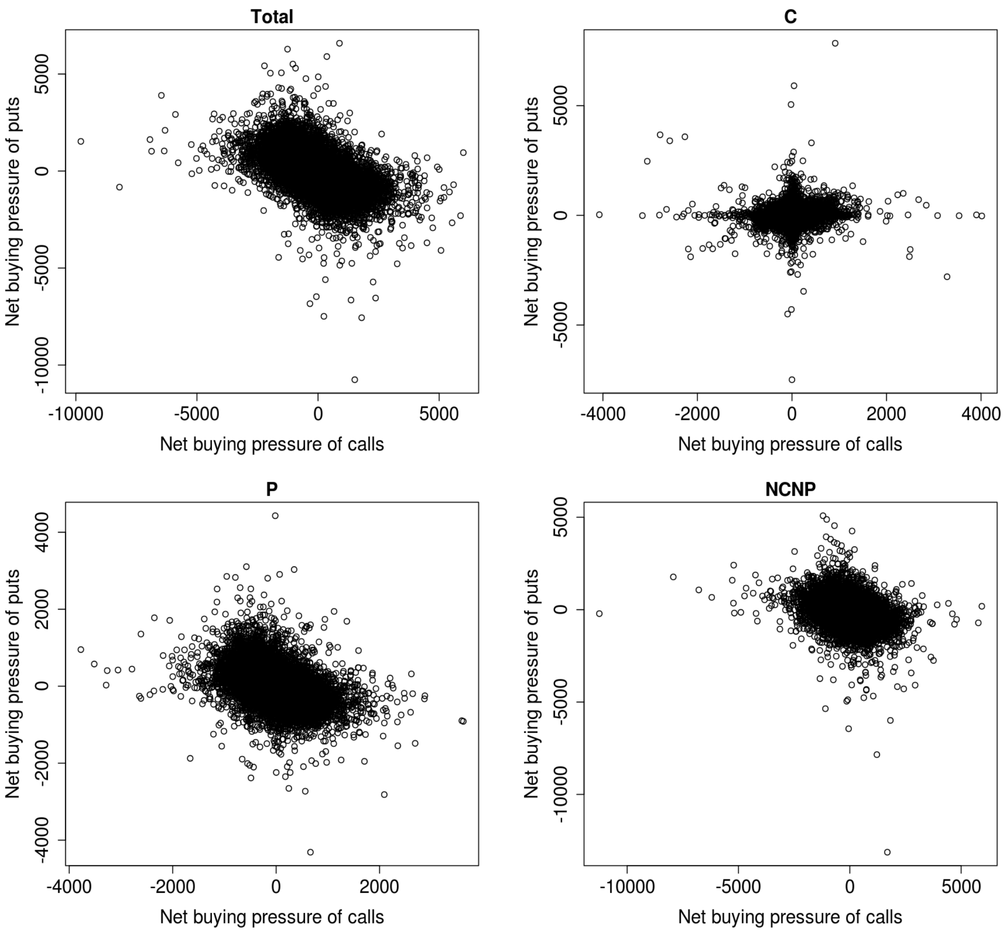


Figure 4 Relationship between net buying pressure of calls and puts, non-AT

The figures show the scatter diagrams between the net buying pressure of calls and net buying pressure of puts for all non-AT and each investor type: custodians (C), proprietary (P) and non-custodian non-proprietary (NCNP) within AT. Each point denotes a pair of net buying pressures of calls and puts over a five-minute interval. The relationship appears to be negative for all AT. For each investor type within non-AT, it appears to be negative for the proprietary and NCNP investor categories but marginally positive for the custodians.



For AT, the correlation between net buying pressure of calls and puts is at -0.5 for total investors, 0.09 for custodians, -0.52 for props, and -0.66 for NCNP. For non-AT, it is -0.66 for total investors, 0.18 for custodians, -0.51 for props, and -0.53 for NCNP. A relatively strong negative relation emerges for proprietary and NCNP categories and a weak positive one for custodian.

4 Empirical specification

Bollen and Whaley (2004) suggest two hypotheses to account for the relationship between net buying pressure and implied volatility: limits to arbitrage and volatility-learning. They use regression methods to test these hypotheses on daily SPX index options data. Both these hypotheses, predict a positive relation between demand for options and their corresponding implied volatilities. Kang and Park (2008) find that this relation is not always positive. They find that the implied volatility of a call (put) option exhibits a positive (negative) relation with demand for call option but a negative (positive) relation with demand for put option. They suggest a third hypothesis, the direction-learning hypothesis to explain these results, and apply the same regression method to the five minute intraday KOSPI 200 index options data to examine the information effect of net buying pressure on implied volatility.

This section empirically tests these three hypotheses using the same regression methods on five minute intervals of intraday Nifty index options data. The analysis is conducted separately for AT/non-AT and different investor groups within these categories. I find evidence to support direction-learning hypothesis for non-AT while none of the hypotheses hold for AT.

4.1 Hypotheses testing and regression models

The impact of net buying pressure on implied volatilities is assessed by regressing changes in average implied volatility of options in a moneyness category on index return, index trading volume, net buying pressure, and lagged change in the average implied volatility. The index return and trading volume are included as control variables for leverage and information flow effects. According to the leverage hypothesis by Black (1976), index returns are expected to be negatively correlated with changes in implied volatility. Also, trading volumes and changes in implied volatilities are expected to be contemporaneously related since both the variables capture information flow in the market (Epps and Epps, 1976; Tauchen and Pitts, 1983).

The limits to arbitrage and the direction-learning hypotheses predict a negative coefficient on the lagged change in implied volatility. In contrast, the volatility-learning hypothesis predicts an insignificant coefficient on the lagged change in implied volatility. Under the limits to arbitrage, the temporary nature of net buying pressure implies this negative relation while under direction-learning its a result of option prices leading underlying asset prices. Under the volatility-learning hypothesis, changes in implied volatilities are only driven by new changes in the information regarding market volatility implying no relation between the current and lagged changes in implied volatility.

4.1.1 Regression models

Regressions are run for ATM calls, ATM puts, OTM calls, and OTM puts. They are specified as follows:

$$\Delta \text{ATM\_}\sigma_t = \alpha_0 + \alpha_1 RS_t + \alpha_2 VS_t + \alpha_3 \text{ATM\_}D_{1,t} + \alpha_4 \text{ATM\_}D_{2,t} + \alpha_5 \Delta\sigma_{t-1} + \epsilon_t \quad (1)$$

$$\Delta \text{OTM\_}\sigma_t = \alpha_0 + \alpha_1 RS_t + \alpha_2 VS_t + \alpha_3 \text{OTM\_}D_{1,t} + \alpha_4 \text{ATM\_}D_{2,t} + \alpha_5 \Delta\sigma_{t-1} + \epsilon_t \quad (2)$$

where $\Delta\text{ATM\_}\sigma_t$ is the change in average implied volatility of ATM calls (or puts), $\Delta\text{OTM\_}\sigma_t$ is the change in average implied volatility of OTM calls (or puts) at five minute time interval t, RS_t is index return during the time interval t, VS_t is summed trading volume of Nifty index over time-t interval expressed in million of rupees, and $\text{ATM\_}D_t$ and $\text{OTM\_}D_t$ is the summed net buying pressure of ATM calls or puts and OTM calls or puts during t.

The regressions (1) and (2) are run for the AT subgroup in each investor group – the custodian, the proprietary, and the non-custodian non proprietary – as well as the entire AT investor group and for each non-AT investor subgroup in an investor group as well as the entire non-AT investor group. For instance, if the effect of net buying pressure of AT in the custodian group on ATM calls is examined, then $\text{ATM\_}D_{1,t}$ is the AT custodian ATM call net buying pressure and $\text{ATM\_}D_{2,t}$ is AT custodian ATM put net buying pressure in (1).

4.1.2 Differentiating hypotheses

To distinguish the three alternative hypotheses, the size and the sign of coefficients of net buying pressure are compared for ATM and OTM call options using equations (1) and (2) respectively.

ATM options

For changes in ATM call or put implied volatility as dependent variable in (1), the three hypotheses imply:

Limits to arbitrage: The effect of net buying pressure of ATM calls and puts will be positive but not equal since trading in these options have no relation to the expectations of changes in volatility i.e. α_3, $\alpha_4 > 0$ and $\alpha_3 \neq \alpha_4$.

Volatility-learning: The effect of net buying pressure of ATM calls and puts will be positive and equal. Both ATM calls and puts have same vega and thus are equally sensitive to changes in expectation of future volatility i.e. α_3, $\alpha_4 > 0$ and $\alpha_3 = \alpha_4$.

Direction-learning: For changes in ATM call (put) volatility, the net buying pressure of ATM calls will be positive (negative), and net buying pressure of ATM puts will be negative (positive).

OTM options

For changes in OTM call or put implied volatilities as dependent variable in (2), the three hypotheses imply:

Limits to arbitrage: The effect of net buying pressure of OTM options will be higher than those of the ATM options. All coefficients on net buying pressure will be positive. $\alpha_3 > \alpha_4$ and $\alpha_3, \alpha_4 > 0$.

Volatility-learning: The impact of net buying pressure of ATM options will be higher than that of OTM options own net buying pressure. Since ATM options have higher vegas than OTM options, the investors will react more rapidly in ATM options market. All coefficients on net buying pressure will be positive. $\alpha_4 > \alpha_3$ and $\alpha_3, \alpha_4 > 0$.

Direction-learning: The effect of net buying pressure of call (put) options will be positive and the effect of net buying pressure of put (call) will be negative, regardless of moneyness, on changes in the implied volatility of OTM call (put) options.

4.2 Regression Results

Table 7 reports the robust intraday regression results for equation (1) It includes estimation results for the regressions of changes in ATM Call volatility in Panel A and changes in ATM put implied volatility in Panel B. Each Panel presents estimation results for AT and non-AT respectively. Under each of

Table 7 Impact of net buying pressure on changes of ATM volatility

The table presents the coefficients from the robust regression model:

$$\Delta\sigma_t = \alpha_0 + \alpha_1 RS_t + \alpha_2 VS_t + \alpha_3 D_{1,t} + \alpha_4 D_{2,t} + \epsilon_t$$

where $\Delta\sigma_t$ is the change in the ATM option's implied volatility in over five minute t, RS_t is the Nifty index return over five minute interval t, VS_t is the summed trading volume of the index over five minute interval t expressed by millions of rupees, and $D_{1,t}$ and $D_{2,t}$ are summed net buying pressure over five minute interval t divided by one thousand. Panel A contains results for change in implied volatility of ATM call options and Panel B contains results for change in implied volatility of ATM put options. A coefficient significant at 5% level of significance is represented in bold face. The sample period is from January 2009 to August 2013.

Category	D_1	D_2	α_0	α_1	α_2	α_3	α_4	α_5
	Panel A: Changes in ATM Call volatility as a function of D_1 and D_2							
AT	TNBP_ATMC	TNBP_ATMP	**0.004**	**-0.985**	**-0.010**	**-0.027**	**-0.035**	**-0.291**
	CNBP_ATMC	CNBP_ATMP	**0.004**	**-0.989**	**-0.011**	-0.014	**-0.037**	**-0.291**
	PNBP_ATMC	PNBP_ATMP	**0.004**	**-0.991**	**-0.010**	**-0.055**	**-0.051**	**-0.291**
	NNBP_ATMC	NNBP_ATMP	**0.004**	**-1.005**	**-0.011**	-0.006	**-0.078**	**-0.290**
NON-AT	TNBP_ATMC	TNBP_ATMP	**0.004**	**-1.190**	**-0.012**	**0.072**	**-0.038**	**-0.283**
	CNBP_ATMC	CNBP_ATMP	**0.004**	**-1.002**	**-0.013**	**0.098**	0.010	**-0.290**
	PNBP_ATMC	PNBP_ATMP	**0.004**	**-1.084**	**-0.011**	**0.044**	**-0.110**	**-0.287**
	NNBP_ATMC	NNBP_ATMP	0.002	**-1.148**	**-0.009**	**0.100**	**-0.037**	**-0.285**
	Panel B: Changes in ATM Put volatility as a function of D_1 and D_2							
AT	TNBP_ATMP	TNBP_ATMC	**-0.012**	**-0.224**	**0.016**	**-0.054**	**-0.068**	**-0.327**
	CNBP_ATMP	CNBP_ATMC	**-0.012**	**-0.206**	**0.016**	**-0.088**	**-0.146**	**-0.326**
	PNBP_ATMP	PNBP_ATMC	**-0.012**	**-0.250**	**0.015**	**-0.060**	**-0.049**	**-0.328**
	NNBP_ATMP	NNBP_ATMC	**-0.012**	**-0.224**	**0.014**	0.029	**-0.130**	**-0.326**
NON-AT	TNBP_ATMP	TNBP_ATMC	**-0.012**	0.036	**0.015**	**0.078**	**-0.094**	**-0.325**
	CNBP_ATMP	CNBP_ATMC	**-0.012**	**-0.239**	**0.014**	**0.091**	**-0.062**	**-0.328**
	PNBP_ATMP	PNBP_ATMC	**-0.014**	**-0.098**	**0.017**	**0.077**	**-0.177**	**-0.327**
	NNBP_ATMP	NNBP_ATMC	**-0.011**	**-0.052**	**0.014**	**0.110**	**-0.096**	**-0.326**

Note: TNBP_ATMC stands for total investor's net buying pressure on at-the-money call options, CNPB_ATMC stands for custodians net buying pressure on at-the-money call options, PNBP_ATMC stands for proprietary net buying pressure on at-the-money call options, and NNBP_ATMC stands for non-custodian non-proprietary net buying pressure on at-the-money call options. In the same way, TNBP_ATMP stands for total investors' net buying pressure on at-the-money put options.

Table 8 Impact of net buying pressure of AT on changes of OTM volatility

The table presents the coefficients from the robust regression model:

$$\Delta\sigma_t = \alpha_0 + \alpha_1 RS_t + \alpha_2 VS_t + \alpha_3 D_{1,t} + \alpha_4 D_{2,t} + \epsilon_t$$

where $\Delta\sigma_t$ is the change in the OTM option's implied volatility in over five minute t, RS_t is the Nifty index return over five minute interval t, VS_t is the summed trading volume of the index over five minute interval t expressed by millions of rupees, and $D_{1,t}$ and $D_{2,t}$ are summed net buying pressure over five minute interval t divided by one thousand. Panel A contains results for change in implied volatility of OTM call options and Panel B contains results for change in implied volatility of OTM put options. A coefficient significant at 5% level of significance is represented in bold face. The sample period is from January 2009 to August 2013.

D_1	D_2	α_0	α_1	α_2	α_3	α_4	α_5
Panel A: Changes in OTM Call volatility as a function of D_1 and D_2							
TNBP_OTMC	TNBP_ATMC	0.001	**-0.782**	**-0.007**	-0.005	**-0.008**	**-0.276**
TNBP_OTMC	TNBP_ATMP	0.001	**-0.789**	**-0.007**	-0.007	**-0.018**	**-0.275**
CNBP_OTMC	CNBP_ATMC	0.001	**-0.781**	**-0.007**	**-0.024**	**-0.014**	**-0.275**
CNBP_OTMC	CNBP_ATMP	0.001	**-0.784**	**-0.007**	**-0.025**	**-0.026**	**-0.275**
PNBP_OTMC	PNBP_ATMC	0.001	**-0.782**	**-0.007**	**-0.017**	**-0.016**	**-0.276**
PNBP_OTMC	PNBP_ATMP	0.001	**-0.787**	**-0.007**	**-0.013**	**-0.023**	**-0.275**
NNBP_OTMC	NNBP_ATMC	0.001	**-0.797**	**-0.007**	**0.091**	0.010	**-0.274**
NNBP_OTMC	NNBP_ATMP	0.000	**-0.799**	**-0.007**	**0.082**	**-0.034**	**-0.274**
Panel B: Changes in OTM Put volatility as a function of D_1 and D_2							
TNBP_OTMP	TNBP_ATMC	**-0.010**	**-0.279**	**0.013**	**-0.023**	**-0.021**	**-0.309**
TNBP_OTMP	TNBP_ATMP	**-0.010**	**-0.296**	**0.013**	**-0.021**	**-0.019**	**-0.310**
CNBP_OTMP	CNBP_ATMC	**-0.010**	**-0.263**	**0.014**	**-0.087**	**-0.088**	**-0.309**
CNBP_OTMP	CNBP_ATMP	**-0.010**	**-0.292**	**0.014**	**-0.096**	**-0.068**	**-0.310**
PNBP_OTMP	PNBP_ATMC	**-0.010**	**-0.288**	**0.013**	**-0.017**	0.001	**-0.310**
PNBP_OTMP	PNBP_ATMP	**-0.010**	**-0.292**	**0.013**	**-0.026**	**-0.022**	**-0.310**
NNBP_OTMP	NNBP_ATMC	**-0.009**	**-0.269**	**0.013**	**0.115**	**-0.052**	**-0.309**
NNBP_OTMP	NNBP_ATMP	**-0.009**	**-0.273**	**0.013**	**0.129**	0.022	**-0.309**

Note: TNBP_OTMC stands for total investor's net buying pressure on out-of-the-money call options, CNPB_OTMC stands for custodians net buying pressure on out-of-the-money call options, PNBP_ATMC stands for proprietary net buying pressure on at-the-money call options, and NNBP_OTMC stands for non-custodian non-proprietary net buying pressure on out-of-the-money call options. In the same way, TNBP_OTMP, TNBP_ATMC, TNBP_ATMP stands for total investors net buyer pressure on out-of-money put options, at-the-money call options, and at-the-money put options respectively.

Table 9 Impact of net buying pressure of non-AT on changes of OTM volatility

The table presents the coefficients from the robust regression model:

$$\Delta\sigma_t = \alpha_0 + \alpha_1 RS_t + \alpha_2 VS_t + \alpha_3 D_{1,t} + \alpha_4 D_{2,t} + \epsilon_t$$

where $\Delta\sigma_t$ is the change in the OTM option's implied volatility in over five minute t, RS_t is the Nifty index return over five minute interval t, VS_t is the summed trading volume of the index over five minute interval t expressed by millions of rupees, and $D_{1,t}$ and $D_{2,t}$ are summed net buying pressure over five minute interval t divided by one thousand. Panel A contains results for change in implied volatility of OTM call options and Panel B contains results for change in implied volatility of OTM put options. A coefficient significant at 5% level of significance is represented in bold face. The sample period is from January 2009 to August 2013.

D_1	D_2	α_0	α_1	α_2	α_3	α_4	α_5
Panel A: Changes in OTM Call volatility as a function of D_1 and D_2							
TNBP_OTMC	TNBP_ATMC	0.001	**-0.948**	**-0.006**	**0.091**	**0.036**	**-0.267**
TNBP_OTMC	TNBP_ATMP	0.001	**-0.924**	**-0.006**	**0.094**	**-0.029**	**-0.269**
CNBP_OTMC	CNBP_ATMC	0.001	**-0.799**	**-0.009**	**0.135**	**0.047**	**-0.275**
CNBP_OTMC	CNBP_ATMP	0.001	**-0.794**	**-0.008**	**0.135**	0.015	**-0.276**
PNBP_OTMC	PNBP_ATMC	0.002	**-0.828**	**-0.008**	**0.044**	**0.036**	**-0.273**
PNBP_OTMC	PNBP_ATMP	0.001	**-0.842**	**-0.006**	**0.033**	**-0.073**	**-0.273**
NNBP_OTMC	NNBP_ATMC	-0.001	**-0.910**	**-0.004**	**0.110**	**0.046**	**-0.269**
NNBP_OTMC	NNBP_ATMP	-0.000	**-0.880**	**-0.006**	**0.120**	**-0.026**	**-0.271**
Panel B: Changes in OTM Put volatility as a function of D_1 and D_2							
TNBP_OTMP	TNBP_ATMC	**-0.010**	**-0.044**	**0.015**	**0.140**	**-0.052**	**-0.306**
TNBP_OTMP	TNBP_ATMP	**-0.010**	**-0.052**	**0.015**	**0.148**	**0.060**	**-0.306**
CNBP_OTMP	CNBP_ATMC	**-0.010**	**-0.277**	**0.012**	**0.126**	-0.024	**-0.310**
CNBP_OTMP	CNBP_ATMP	**-0.009**	**-0.272**	**0.010**	**0.135**	**0.105**	**-0.311**
PNBP_OTMP	PNBP_ATMC	**-0.010**	**-0.183**	**0.016**	**0.128**	**-0.080**	**-0.308**
PNBP_OTMP	PNBP_ATMP	**-0.008**	**-0.180**	**0.013**	**0.150**	**0.079**	**-0.308**
NNBP_OTMP	NNBP_ATMC	**-0.010**	**-0.115**	**0.014**	**0.164**	**-0.065**	**-0.307**
NNBP_OTMP	NNBP_ATMP	**-0.013**	**-0.154**	**0.018**	**0.165**	**0.051**	**-0.307**

Note: TNBP_OTMC stands for total investor's net buying pressure on out-of-the-money call options, CNPB_OTMC stands for custodians net buying pressure on out-of-the-money call options, PNBP_ATMC stands for proprietary net buying pressure on at-the-money call options, and NNBP_OTMC stands for non-custodian non-proprietary net buying pressure on out-of-the-money call options. In the same way, TNBP_OTMP, TNBP_ATMC, TNBP_ATMP stands for total investors net buyer pressure on out-of-money put options, at-the-money call options, and at-the-money put options respectively.

these, regressions are run for total investors that include investors of all categories and for each individual investor category.

Table 8 and 9 report the robust intraday regression results for equation (2) for AT and non-AT respectively. Each table includes results for the regressions of changes in OTM call volatility in Panel A and changes in OTM put implied volatility in Panel B. Each panel includes results for all investors and for each individual investor category.

The coefficients of index returns, volumes, and lagged volatility

All coefficients of index returns, α_1's in the regressions of changes in implied volatility of ATM and OTM calls in Panel A of all the tables are negative and significant at 5%. This is consistent with the leverage hypothesis. The same coefficients for ATM and OTM puts in Panel B of all tables are also negative which is again consistent with the leverage hypothesis. Bollen and Whaley (2004) also find the leverage hypothesis to hold for SPX options. In contrast, Kang and Park (2008) find positive coefficients for KOSPI 200 index returns in regressions of changes in implied volatility of ATM and OTM puts. They explain these positive coefficients using the direction-learning hypothesis. The coefficients of traded volume, α_2's are negative and significant at 5% for calls while they are positive and significant at 5% for puts. This implies that price of a call (put) option tends to decrease (increase) if stocks are more actively traded. In contrast, Bollen and Whaley (2004) find this relation to be positive for calls and puts while Kang and Park (2008) find it to be negative for calls and puts. All coefficients of lagged implied volatilities, α_5's, in all regressions are negative and significant at 5%. This is consistent with the limits to arbitrage and direction-learning hypotheses.

The coefficients of net buying pressure

The coefficients of net buying pressure, α_3's and α_4's in Tables 7 to 9 are the main tests for the information effect of net buying pressure.

The coefficients of option series' own net buying pressure i.e. ATM calls for ATM calls, ATM puts for ATM puts, OTM calls for OTM calls, and OTM puts for OTM puts, are presented as α_3's in Tables 7 to 9. Under the AT category (Table 7 and 8), the coefficients are negative and significant at 5% across all categories of investors except for NCNP in OTM calls and puts. Under the non-AT category (Table 7 and 9) they are positive and significant at 5% for all categories of investors.

The coefficients of net buying pressure of ATM calls for OTM calls and ATM puts for OTM puts, $\alpha_4's$, are presented in Panel A and B of Tables 8 to 9 respectively. Under the AT category, they are mostly negative and significant at 5%. Under the non-AT category, they are all positive and significant at 5%.

The coefficients of net buying pressure of other options: ATM puts for ATM and OTM calls (Panel A), and ATM calls for ATM and OTM puts (Panel B), α_4's, are presented in Tables 7 to 9. Under AT and non-AT category, they are negative and significant at 5% level of significance.

These results are not consistent with the limits to arbitrage or the volatility learning hypothesis. The direction-learning hypothesis can account for some of these results. It explains the results for non-AT but not AT. The non-AT in the Nifty index options market are directional traders. If they acquire information regarding future movements in the stock prices, they exploit their private information by taking positions in the options market prior to the underlying stock market. If the information acquired indicates upward (downward) movement in prices, they place buy orders in calls (puts) or sell orders in puts (calls). The net buying pressure of calls (puts) causes price and implied volatility of calls (puts) to increase while the net selling pressure of puts (calls) decreases the price and implied volatility of puts (calls).

Researchers have argued that AT may engage in information-based trading by using fast automated technology which essentially facilitates information processing and helps them become informed by identifying trading patterns of informed investors. The results above suggest that the aggregate behaviour of AT and also investor categories within AT are not in favour of information-based trading in the Nifty index option market. On the contrary, I find evidence for (directional) informed trading by non-AT. This is contrary to evidence found in other studies (Frino *et al.*, 2012; Viljoen *et al.*, 2014).

4.3 Directional trading vs noise trading

Kang and Park (2008) suggest the possibility that results supporting the direction-learning hypothesis may be a consequence of noise trading in the index. Noise traders anticipate movements in underlying stock prices based on intuition rather than superior information. If they think that the index will rise, they will buy calls and sell puts. This will increase the prices and implied volatilities of calls and decrease the same for puts. If the index does not rise then the implied volatilities of calls drops back and implied volatilities of puts rises back. This implies same signs for coefficients as under direction-learning hypothesis. Following Kang and Park (2008), I test whether current net buying pressure has any predictive power for future index returns to distinguish between the two explanations.

The following regression model is run to examine the ability of net buying pressure of Nifty index options to predict future index returns:

$$\mathrm{NBP}_t = \alpha_0 + \sum_{i=-2}^{2} \alpha_{i+3} r_{t+i} + \alpha_6 \mathrm{NBP}_{t-1} + \epsilon_t \tag{3}$$

where NBP_t is net buying pressure over a five minute interval t and r_t is the Nifty index return over the five minute interval t. Here, noise trading or limits to arbitrage would imply that α_4=0 and α_5=0. For direction-learning hypothesis, these coefficients would differ from zero and their signs would depend on whether the option series is a call or a put. When there is net buying of calls, the stock price rises over the next five intervals while it falls when there is net buying of puts. Thus, $\alpha_4 > 0$ for calls and $\alpha_4 < 0$ for puts.

The regression is estimated for three option categories: in-the-money (ITM), at-the-money (ATM), and out-of-the-money (OTM) options. Under each category, the regressions are run for the AT investor subgroup in each investor group – custodian, proprietary, and non-custodian non proprietary – as well as the entire AT investor group; and for each non-AT investor subgroup in an investor group as well as the entire non-AT investor group.

Tables 10 and 11 report the robust regression results for equation (3) for AT and non-AT respectively. Each table includes the results for the regressions of net buying pressure of calls in Panel A and net buying pressure of puts in Panel B. Each panel includes results for the three option categories (ITM, ATM, and OTM) and under each category, the regression results for each AT/non-AT investor subgroup in an investor group and for the entire AT/non-AT investor group.

For AT investors (Table 10), most of the coefficients for r_{t+1} are insignificant at 5% for calls and puts with the exception of ATM and OTM calls and ITM, ATM, and OTM puts under the total AT investor group. This implies that the net buying pressure of AT calls or puts have no predictive power. This is consistent with the results found in Section 4.2 that AT do not follow the direction-learning hypothesis.

For non-AT investors (Table 11), all coefficients are positive and significant at 5% for calls with the exception of ATM calls under the custodian group.

Table 10 Relation between net buying pressure of AT and Nifty index returns

The table presents the coefficients from the robust regression model:

$$NBP_t = \alpha_0 + \sum_{i=-2}^{2} \alpha_{i+3} r_{t+i} + \alpha_6 NBP_{t-1} + \epsilon_t$$

where NBP_t is net buying pressure over a five minute interval t and r_t is the Nifty index return over the five minute interval t. The regression is run for three option categories: in-the-money (ITM), at-the-money (ATM), and out-of-the-money (OTM). Under each category, the model is estimated for each AT investor group – custodian (C), proprietary (P), and non-custodian non-proprietary (NCNP) as well as the entire AT investor group (TOT). Panel A and B present these results for call and put options respectively. A coefficient significant at 5% level of significance is represented in bold face. The sample period is from January 2009 to August 2013.

Category	Type	α_0	α_1	α_2	α_3	α_4	α_5	α_6
Panel A: Relationship between call option's net buying pressure and index returns								
ITM	TOT	**0.051**	**-0.088**	**-0.116**	**1.363**	0.005	-0.024	**0.176**
	C	**0.002**	-0.002	-0.005	**0.044**	0.003	-0.000	**0.028**
	P	**0.029**	-0.021	-0.032	**0.734**	0.008	-0.018	**0.190**
	NCNP	**0.005**	-0.012	**0.016**	**0.267**	0.006	-0.006	**0.156**
ATM	TOT	**0.027**	-0.082	0.169	**17.909**	**0.917**	-0.077	**0.191**
	C	**-0.006**	0.006	0.020	**0.666**	0.015	-0.001	**0.089**
	P	0.001	-0.045	**0.136**	**0.651**	-0.067	-0.020	**0.244**
	NCNP	0.003	**-0.063**	**0.047**	**0.479**	-0.008	**-0.031**	**0.193**
OTM	TOT	**-0.099**	**0.434**	**0.752**	**9.898**	**0.641**	0.000	**0.148**
	C	**-0.009**	-0.006	**-0.073**	**0.328**	0.011	-0.006	**0.096**
	P	**-0.023**	**0.075**	0.005	**1.207**	0.040	-0.017	**0.228**
	NCNP	-0.001	**0.013**	**0.040**	**0.209**	0.008	0.001	**0.100**
Panel B: Relationship between put option's net buying pressure and index returns								
ITM	TOT	**0.015**	-0.023	-0.043	**-2.890**	**-0.184**	0.008	**0.142**
	C	0.000	0.000	-0.000	-0.000	0.000	-0.000	0.000
	P	**0.012**	-0.027	**-0.042**	**-0.583**	-0.015	0.004	**0.180**
	NCNP	-0.000	**-0.011**	**-0.024**	**-0.137**	-0.005	0.000	**0.114**
ATM	TOT	**0.036**	**0.298**	**0.483**	**-10.926**	**-0.666**	0.108	**0.194**
	C	**-0.007**	-0.000	0.003	**-0.034**	0.013	0.004	**0.120**
	P	**0.016**	-0.008	**-0.183**	**-0.328**	0.053	0.036	**0.235**
	NCNP	**-0.004**	**0.059**	**-0.035**	**-0.404**	0.019	0.019	**0.203**
OTM	TOT	**-0.149**	**-0.158**	**-0.342**	**-9.017**	**-0.502**	-0.042	**0.167**
	C	0.001	**-0.028**	0.002	**-0.081**	0.001	-0.016	**0.123**
	P	**-0.085**	**-0.051**	-0.018	**-0.665**	0.008	-0.002	**0.271**
	NCNP	**-0.010**	**0.019**	-0.010	**-0.177**	0.002	0.006	**0.134**

Table 11 Relation between net buying pressure of non-AT and Nifty index returns

The table presents the coefficients from the robust regression model:

$$NBP_t = \alpha_0 + \sum_{i=-2}^{2} \alpha_{i+3} r_{t+i} + \alpha_6 NBP_{t-1} + \epsilon_t$$

where NBP_t is net buying pressure over a five minute interval t and r_t is the Nifty index return over the five minute interval t. The regression is run for three option categories: in-the-money (ITM), at-the-money (ATM), and out-of-the-money (OTM). Under each category, the model is estimated for each non-AT investor group – custodian (C), proprietary (P), and non-custodian non-proprietary (NCNP) as well as the entire non-AT investor group (TOT). Panel A and B present these results for call and put options respectively. A coefficient significant at 5% level of significance is represented in bold face. The sample period is from January 2009 to August 2013.

Category	Type	α_0	α_1	α_2	α_3	α_4	α_5	α_6
Panel A: Relationship between call option's net buying pressure and index returns								
ITM	TOT	**-0.010**	**-0.163**	-0.049	**2.623**	**0.174**	0.018	**0.088**
	C	**0.003**	**-0.008**	**-0.016**	**0.054**	**0.007**	0.002	**0.078**
	P	**-0.004**	-0.003	**-0.040**	**1.005**	**0.090**	0.010	**0.113**
	NCNP	**-0.017**	**-0.116**	0.038	**1.401**	**0.072**	0.002	**0.058**
ATM	TOT	**0.027**	-0.082	0.169	**17.909**	**0.917**	-0.077	**0.191**
	C	**0.005**	**0.031**	**0.065**	**0.378**	0.009	**0.023**	**0.131**
	P	**-0.072**	**0.187**	0.019	**4.481**	**0.408**	0.015	**0.151**
	NCNP	**0.101**	**-0.143**	**0.453**	**8.846**	**0.497**	-0.034	**0.116**
OTM	TOT	**-0.099**	**0.434**	**0.752**	**9.898**	**0.641**	0.000	**0.148**
	C	**0.003**	0.012	**0.021**	**0.212**	**0.019**	0.001	**0.138**
	P	**-0.085**	**0.286**	**0.255**	**2.537**	**0.186**	0.010	**0.163**
	NCNP	**0.031**	**-0.088**	**0.328**	**3.900**	**0.262**	-0.003	**0.122**
Panel B: Relationship between put option's net buying pressure and index returns								
ITM	TOT	**0.015**	-0.023	-0.043	**-2.890**	**-0.184**	0.008	**0.142**
	C	**0.001**	0.001	-0.002	**-0.028**	**-0.005**	-0.000	**0.026**
	P	**0.003**	**-0.040**	**-0.058**	**-0.608**	**-0.061**	-0.007	**0.089**
	NCNP	**-0.007**	**0.098**	**0.023**	**-0.585**	-0.018	-0.001	**0.046**
ATM	TOT	**0.036**	**0.298**	**0.483**	**-10.926**	**-0.666**	0.108	**0.194**
	C	0.001	**-0.041**	**-0.070**	**-0.193**	-0.006	**-0.021**	**0.128**
	P	**-0.022**	**-0.131**	-0.052	**-3.743**	**-0.360**	0.021	**0.144**
	NCNP	**0.054**	**0.532**	**0.560**	**-5.418**	**-0.339**	0.009	**0.130**
OTM	TOT	**-0.149**	**-0.158**	**-0.342**	**-9.017**	**-0.502**	-0.042	**0.167**
	C	**0.020**	**-0.022**	**-0.073**	**-0.192**	-0.008	-0.008	**0.167**
	P	**-0.095**	**-0.207**	**-0.169**	**-2.917**	**-0.275**	0.015	**0.149**
	NCNP	**0.041**	**0.272**	**-0.059**	**-3.961**	**-0.184**	0.012	**0.132**

They are negative and significant at 5% for puts except for the cases of ITM put options in the NCNP category and ATM and OTM put options in the custodian category. Therefore, the call and put net buying pressure for non-AT has predictive power for future index returns implying that they are direction traders and not noise traders. In addition, we also find that the net buying pressure of the custodian group (which include foreign institutional investors) within the non-AT category has the lowest degree of predictability for future index returns (smallest coefficient). In some cases such as ATM calls, ATM puts, and OTM puts, it has no predictability. This is in contrast to other studies that find a strong informational role played by foreign institutional investors in many emerging derivatives markets (Ahn *et al.*, 2008; Chou and Wang, 2009; Chang *et al.*, 2009; Wen-liang and He, 2014). In India, there is limited participation by foreign investors due to several regulatory constraints that include onerous Know-Your-Customer (KYC) documentation and low position limits. For instance, we find that only 17.4% of trades in the Nifty index option market were initiated by institutional investors which would primarily be foreign institutional investors. This may explain the weak informational role of foreign investors in this market.

5 Conclusion

In this paper, I test whether AT engage in direction/volatility based informed trading by examining the linkages between their net demand for Nifty index options and implied volatilities. I also examine this relation for non-AT and investor categories within AT/non-AT. If AT are volatility traders, then under the volatility-learning hypothesis, their net demand for options and implied volatilities are always positively related. If AT are directional traders, then under the direction-learning hypothesis, their net demand for call (put) options would have a positive impact on implied volatilities of call (put) options and negative impact on implied volatilities of put (call) options.

I find that, in the Nifty index option market, the volatility-learning and direction-learning hypotheses do not hold for AT. In fact, none of the hypotheses in the extant literature explain the behaviour of AT. Also, the net buying pressure of AT exhibits no predictive power for future index returns. Hence, corroborating with results that find no evidence for direction-learning hypothesis among AT. On the contrary, direction-learning hypothesis holds for non-AT and their net buying pressure has predictive power for future index returns suggesting absence of noise trading. This implies that non-AT in the Nifty index option market are directional traders and exploit their private information regarding future movements in stock prices in the option market before trading in the spot market.

A direct extension of this work can be to apply the methodology in this paper to single stock options. Bollen and Whaley (2004) find that the motivation for trading in index and stock options may not be the same. For instance, they find that puts are more actively traded in index options while calls in the single stock options. I find that the Nifty index option market is dominated by proprietary investors who are primarily algorithmic traders. It may be useful to examine such characteristics for the Indian single stock option market and test for informed trading.

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