Trading Patterns Centered Around Large Institutional Purchase Events in the Indian Stock Markets

Vikram Gulati

The Leonard N. Stern School of Business

Glucksman Institute for Research in Securities Markets

Faculty Advisor: Marti G. Subrahmanyam

April 10, 2019

I. INTRODUCTION

The Indian stock market is unique in that it contains one very large institutional investor – the Life Insurance Corporation of India ("LIC"). This is the state-run insurance company and is by far the largest investor in the stock markets (owing to its outsized presence in the Insurance market). LIC sometimes buys significant stakes in a company, and therefore, an investment (or conversely a sale) is usually enough to move the stock price by a significant amount. The hypothesis that this paper looks to examine is whether LIC's trades are leaked to market participants beforehand, and whether such information is used to profit by front-running LIC's trades in the market.

We believe that the front running would likely be in two main markets: the first via a trade in the options of the stock, specifically call options. There are well-traded options for each major stock, and these are also traded on the two national stock exchanges. Options allow for an increase in leverage, and therefore allow outsized returns with minimal upfront capital invested.

The second market could be via the purchase of shares on major stock exchanges. The advantages this method presents are mainly liquidity and depth. There are no restrictions around the maturity of options and the relatively thin trading volumes associated with later-expiry options could tilt investor preferences toward stock exchanges.

II. ANALYSIS OF STOCK TRADING VOLUME ON MAJOR EXCHANGES

1. Methodology – Data Sources

The CMIE (Center for the Monitoring of the Indian Economy) maintains a comprehensive database with trading information from the two major Indian indices – the National Stock Exchange ("NSE") and the Bombay Stock Exchange ("BSE"). Major stocks trade on both indices, and this paper uses the data from one/both indices as and where needed. A subset of this data essentially identifies all major purchase events – i.e. when a significant percentage of a listed company's stock was bought by an institutional investor. The day on which the purchase was made is available to us. Therefore, the first set of data used in the analysis is from CMIE's PROWESS database, which lists major purchase events where LIC is the buyer.

Once the LIC purchase events were identified, stock trading volume was obtained from S&P's CapitalIQ database for a period of five months prior to the date of the event, and for a period of one month after the event – the total timeframe being approximately six months. We did not extend this as trading volumes tend to drift with time, given changes in the company and/or the overall market. The trading volume for the broader market (BSE and NSE) was obtained from the CMIE Prowess Database, a sample of which is shown in Table 1.

Company Name	Purchase Date	Method of Acquisition	Percentage of Shares Acquired	Percentage of Shares After Transaction
ADANI PORTS	07-12-17	Open Market	2.05	9.63
ITC LTD.	07-02-17	OTHERS	2	16.29

Table 1: Sample purchase event data (26 events were identified between 2014 and 2018)

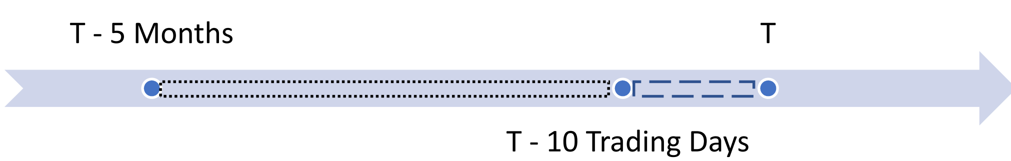
2. Event Study Definition and Procedure

The LIC Purchase event is identified by using CMIE Prowess data. This date is designated as “T”. Filters were applied to restrict the data points to single-day events (or at the maximum a few days). This simplifies the analysis by excluding factors like momentum buying (once it is apparent that LIC is purchasing stock), copy-cat purchasing (as LIC tends to buy and hold) etc., which are all legitimate trading strategies, and as such are not illegal.

Next, two sets of daily trading volume data are then downloaded: one for the stock bought by LIC and the other for the broader index. The date range for the data was from T – 5 months to T + 1 month (using calendar months).

Our analysis of volume data is then been broken down into two parts:

Volume trends: The average daily trading volume for T – 10 days (trading days) is compared with the average trading volume for T – 10 days to T – 5 Months (dotted vs. dashed in the figure below).



Predicted vs. Actual volume: Using the six months’ of volume data for the broader index and for the stock, a regression is run with stock volume as the dependent variable and market volume as the independent volume. The equation being checked is Y = A + B(M) where Y is the individual stock volume and M is the market volume. M is estimated by looking at the Nifty 50 stocks or the BSE 100 (depending on whether the stock volume data is from the

NSE or BSE). Once the coefficients (A, B) have been determined, the market volume during the period T -20 (trading) days to T is used to obtained a "predicted" volume for each day. Next, the actual volume is compared with the "predicted" volume, and a variation for each day is determined. This variation is then normalized by using the average daily trading volume for the six-month period.

We are looking for anomalies in trading volume in the days leading up to T, i.e. a larger-than-expected or a larger-than-average trading volume during the period just before T, as opposed to what would be an otherwise "normal" activity period, i.e. T – 5 months to T – 20/10 days. The reasoning is that participants with information on LIC's future trades would act upon that information during the days leading up to the actual purchase of stock by LIC.

3. Results

A. Volume Trends

We collected a sample set of 26 purchase events, and analysed the trading volume as described in the previous section. The results are as follows (below section and Figures 1 and 2):

Sl. No.	Stock/Company Name	Event Date	Percentage Above/Below Avg. Trading Vol	Avg. Trading Vol around Event (number of shares)
1	National Fertilizers	26-Jul-17	-41%	251,596
2	Uco Bank	29-Nov-16	-20%	218,409
3	NBCC	20-Oct-16	49%	627,212
4	Oriental Bank of Commerce	01-Apr-16	7%	454,278
5	Welspun	01-Feb-10	-60%	623,217
6	Welspun	29-Dec-09	-64%	478,066
7	PTC India	03-Jul-09	42%	485,213
8	NHPC	27-Apr-16	-40%	741,839
9	Bank of India	15-Jan-16	25%	539,924
10	Bank of India	28-Jun-17	-6%	555,629
11	Dredging Corporation of India	21-Aug-15	103%	24,827
12	Castrol India	10-Nov-09	24%	452,708
13	Castrol India	16-Mar-17	-91%	805,031
14	Corporation Bank	13-Jan-16	59%	45,968
15	Hindustan Copper	02-Aug-17	60%	468,886
16	Hindustan Copper	30-Sep-16	-19%	185,596
17	MOIL	24-Jan-17	0%	126,282
18	Vedanta	28-Apr-17	26%	12,139,821
19	Tata Steel	29-Jun-17	-38%	730,656
20	Adani Ports	07-Dec-17	12%	3,741,241
21	SBI	13-Jun-17	-33%	15,020,043
22	NTPC	28-Aug-17	1%	5,520,980
23	Nalco	19-Apr-17	-53%	433,629
24	Mahindra and Mahindra	05-Jul-17	7%	2,068,062
25	ITC	07-Feb-17	73%	10,143,763
26	Infosys	25-Jan-17	66%	7,372,177

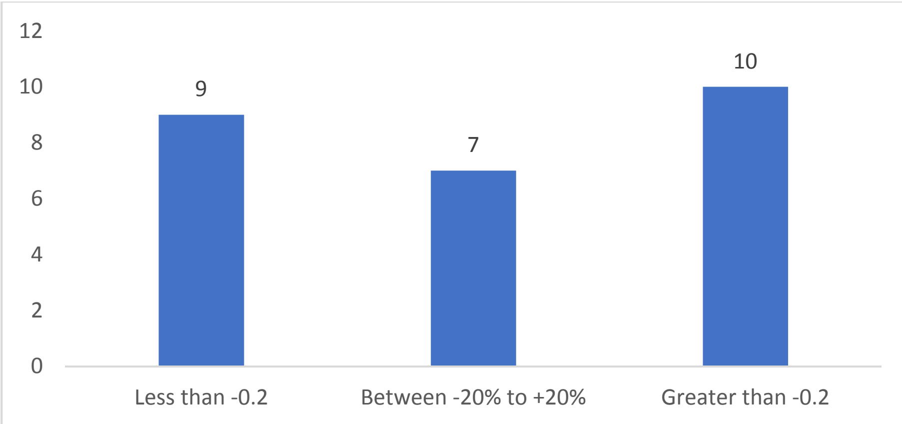


Figure 1: Immediately Prior (10 trading days) Trading Volume vs. Average Trading Volume

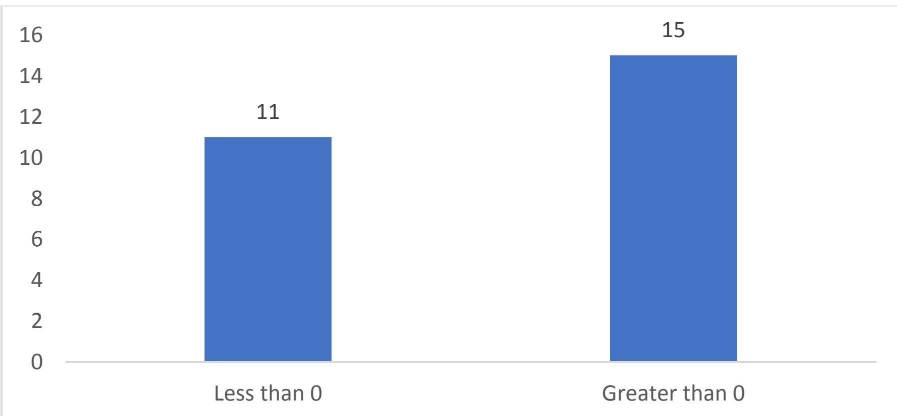


Figure 2: Immediately Prior (10 trading days) Trading Volume vs. Average Trading Volume

As we can see in the above figures (1 and 2), the majority of stocks purchased by LIC (15 of 26) show an increased trading volume just prior to the purchase event. Setting a threshold of +20% increased volume, we see that 10 of the 26 firms show an increase of >20% in trading volume prior to the purchase event.

Given that some stocks are much more liquid than others in our sample set (as evidenced by the daily trading volume), we examined the relationship between average trading volume and the percentage change in trading volume prior to the purchase event. We ran a regression with the percentage change in trading volume prior to the purchase event ("TVP") as the dependent variable and average trading volume ("AVG") as the independent variable. Our sample size was 17 and we used the following equation: AVG = M*TVP + C

Below are the results:

Regression Statistics				
Multiple R	0.47			
R-Square	**0.22**			
	Coefficients	*Standard Error*	*t-Stat*	*P-value*
Intercept	0.449	0.239	1.878	0.080
X Variable 1	-1E-06	5.02E-07	-2.065	0.057

We can see that there is a weak correlation between the trading volume and percentage change in trading volume prior to the purchase event. We believe that this is because liquid stocks provide better opportunities to enter and exit positions, thereby reducing friction in executing trading strategies.

B. Predicted vs. Actual Volume

We carried out the regression analysis (as described section II.2) for the 26 purchase events. However, we found a non-zero R^2 in only 7 cases, all of them on the National Stock Exchange. None of the stocks for which we used information from the Bombay Stock Exchange ended up with any significant R^2 value. We believe that this is due to the nature of the two indices and their composition – which can have different trading patterns to individual stocks. The data for these seven cases appears as below:

Stock	Cumulative percentage deviation vs. predicted volume for prior period	R^2
ITC	168%	0.24
SBI	-126%	0.22
Vedanta	25%	0.15
M&M	385%	0.12
Infosys	799%	0.095
Adani Ports	150%	0.07
NTPC	140%	0.065

Except for SBI, we can see that there is a large positive percentage deviation between the predicted trading volume and actual trading volume for the 20 trading days prior to the purchase event. This would support the hypothesis that at least some of the trading is happening basis material non-public information (in this case it could be the impending purchase by LIC).

We also looked at the deviation in trading volume during the days immediately after the purchase event. Given the way Indian indices function, LIC's purchases become public information in a matter of days, if not hours (due to the size of the purchase). Therefore, we expect to see positive deviation in purchase volumes for the days immediately after the purchase event. Our data for the seven non-zero R^2 is as follows:

Stock	Cumulative percentage deviation vs. predicted volume for future period	R^2
ITC	-516%	0.24
SBI	163%	0.22
Vedanta	317%	0.15
M&M	-75%	0.12
Infosys	532%	0.095
Adani Ports	208%	0.07
NTPC	1735%	0.065

As we can see, there is a largely positive deviation. This is along expected lines, where the market realizes that LIC has made a purchase and therefore is likely to positively affect prices of the stock in the medium term.

4. Further Work

In order to improve this study, we have outlined potential future areas of work as follows:

1. Analysis of hourly trading data: In this paper, we were able to obtain only daily trading data. Therefore, we were restricted to looking at patterns in the days leading up to the purchase event. If we can obtain hourly or by minute trading data, it would allow us to have a closer look at intra-day trends on the day of purchase.
2. Regression model for predicted trading volume: We have used the simplest regression model to predict stock trading volumes – a linear, single-variable model. The use of a more sophisticated model with more independent variables may provide a larger R^2 value, and hence greater predictive power.
3. Increased sample: We looked at only 26 purchase events. Being able to increase this sample to 50 or more would allow us to obtain a more precise idea of the volume and regression relationship.
4. Analysis of stock prices around purchase events: The primary motivation in trading with non-public information is to make outsized returns. An analysis of stock prices around purchase events can provide valuable evidence of insider trading. The patterns around returns can also be analysed to support or negate the overall hypothesis. Price information can be subjected to the same analysis as volume information, namely a basic study of

movements before the purchase event, and a regression with the market movements using the CAPM model.

III. ANALYSIS OF CALL OPTIONS

1. Methodology – Data Sources

The purchase event data was identified using the same process as in the previous section. Once the events were identified, we obtained the aggregate trading data for options (corresponding to the specific stock) on the NSE. This data has been analysed to look for patterns, such as increased trading volume prior to the purchase event. There are complicating factors that make this analysis tricky. We will outline these in later sections.

The options trading data has been obtained from NSE's website, where it is freely available for download upon query requests. A sample of this data is shown in Table 2.

Row Labels	**Sum of Turnover in INR Millions**	**Sum of No. of contracts**
28-Nov-17	440.92	41
29-Nov-17	652.09	61
30-Nov-17	1282.41	120
01-Dec-17	8702.5	814
04-Dec-17	7763.87	745
05-Dec-17	5291.7	513
06-Dec-17	5374.9	525
Grand Total	**31034.39**	**2958**

Table 2: Sample Options trading data (after adding turnover and volume across all strike prices)

2. Event Study Definition and Procedure

The preliminary analysis carried out is complicated by the nature of the options market. Stock options (specifically European Calls) on the NSE are written in a manner that ensures that there is only one expiry for each month – i.e. each stock will have many call options (based on the strike price) that expire on the same date in a given calendar month. The expiry date is sometime in the last week of each month, and all options (for different underlying stocks) in a given month expire on the same date.

The purchase events data is more straightforward making it simple to identify large stock purchases by LIC. Filters were applied to restrict the data points to single-day events (or at most a few days). This simplifies the analysis by excluding factors like momentum buying (once it is apparent that LIC is purchasing stock), copy-cat purchasing (as LIC tends to buy and hold) etc., which are all legitimate trading strategies, and as such not illegal.

This paper has followed the below process for analyzing data to create an event study:

1. The purchase event date ("T") is identified from CMIE's PROWESS data. Filters on the buying entity allow for the identification of LIC and duration filters restrict the sample set to single-day events.
2. Once the purchase event date is identified, four sets of options data are prepared. The data for options that have the same expiry date (for the same underlying stock) but different strike prices are summed together, in a simple addition operation
    a. First Set: this data set contains trading information (turnover and number of options traded) for all the options with the expiry date *just after* the purchase

event (i.e. T + X days, where X is the difference between the option expiry date and the purchase event date)

b. Second Set: this data set contains trading information (turnover and number of options traded) for all the options with the expiry date *just prior to* the purchase event (i.e. T – Y days, where Y is the difference between the purchase event and the option expiry date)
c. Third Set: this data set contains trading information (turnover and number of options traded) for all the options with the expiry date T – Y – 30 (approx.). Essentially, this is the option with an expiry between a month and two months prior to the purchase event
d. Fourth Set: this data set contains trading information (turnover and number of options traded) for all the options with the expiry date T – Y – 60 (approx.). Essentially, this is the option with an expiry between two months and three months prior to the purchase event

3. Once the data sets are ready, turnover and number of options traded (summed across all strike prices) are calculated for all the data sets, setting X as the standard number of days. This ensures a like-for-like comparison across the four data sets
4. The turnover (and number of options) data for sets 2-4 is indexed to set 1, by setting data set 1 as 100% and expressing sets 2-4 in terms of set 1.

The purpose to the above steps is to check for unusual trading volume spikes, to see whether any of the months prior to the purchase event show higher/lower trading volumes when compared to the month in which the purchase event has occurred. The option with an expiry *just after* the purchase event (data set 1) will be influenced by post-facto information, namely the fact that LIC has *already* bought the stock in question. This is not illegal, as there are several public indicators that can give this away – such as price, share trading volume information etc.

Therefore, non-public trading is likely to show up in the months leading to the actual purchase event. Presumably, this is when actors can use non-public information to profit from the upcoming purchase event.

3. Results

We have analysed the purchase event and corresponding options data for five stocks – Adani Ports, ITC, Infosys, Mahindra and Mahindra and NTPC. Below are the graphs for the indexed turnover data and number of options traded data (Figures 3 and 4).

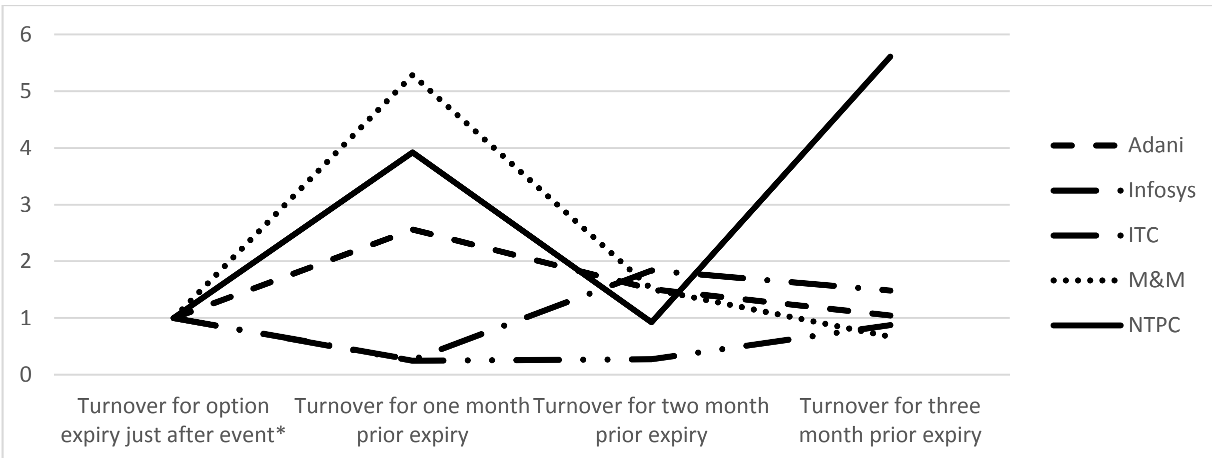


Figure 3: (Indexed) Turnover in INR

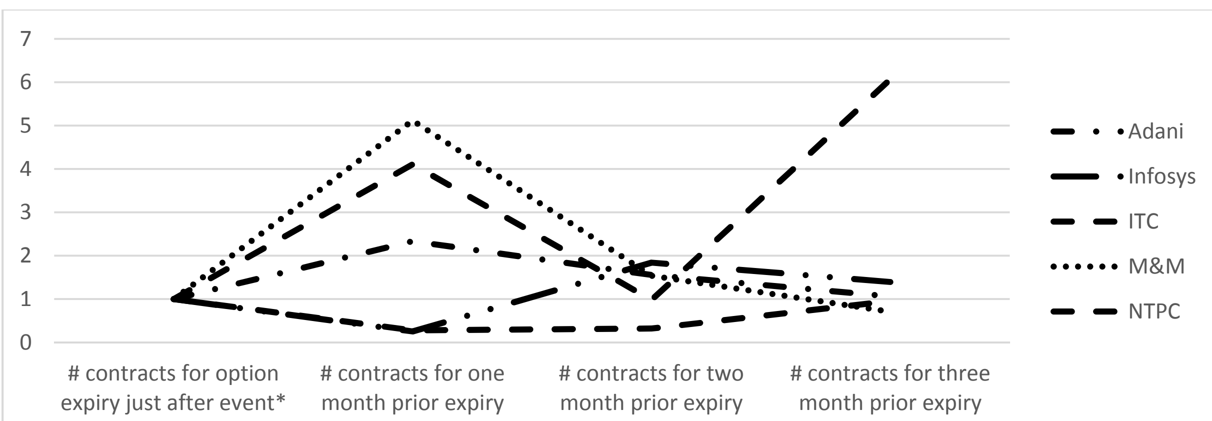


Figure 4: (Indexed) Number of Options Traded

As can be seen, there is no consistency in the data. The same pattern cannot be seen in all five firms. If anything, the turnover seems to increase for the T – Y expiry, i.e. the option that expires *just prior* to the purchase event. However, this is only in three of the five firms. More data is needed before this conclusion can be drawn. If supported, this result would appear to confirm the hypothesis of some form of insider (or non-public information) trading.

4. Further Work

We have analysed five purchase events in our study. This needs to be extended to a larger number of firms, in order to establish a pattern, if any. Also, to ensure that other events are not driving the changes in turnover/number of options traded, we need to cross-check trading volume information for the days in question. This will help remove other drivers of volume such as earnings announcements and company-specific news. An easy way to do this is to benchmark the options data for each day with the corresponding shares traded on the exchange, and thereby have an indexed number for each day (akin to a percentage figure).

Further work undertaken by us would be to complete the above steps, and then see if there is an established pattern of spikes in trading volumes *before* purchase events occur.

There is also an element of refining that needs to be done – right now, the event study is based on the simple addition of trading volume for different strike prices on any given day, and in turn adding up the cumulative trading volume for a fixed number of days prior to the option expiry. This method may result in granular information being lost in the two consecutive addition operations. An improvement to the current data would be a cumulative view of trading data across all options (with different expiry dates) for a particular underlying stock. This would allow a more comprehensive analysis to be undertaken, without the need to check different options for trading anomalies.

We also need to analyse intra-day trading information, both for options as well as the underlying stocks. There may very well be the case that the information of the purchase event is leaked on the day of the event, with a relatively shorter window for front-running to happen.

Further, the instrument used for such activities may also be the actual stock itself, as opposed just the call options. Increasingly, we are leaning towards this last hypothesis, as the volume of options traded is much lower than the underlying stock's trading volumes.

III. CONCLUSION

The analysis of stock trading volume data is inconclusive. While there is limited evidence that suggests that there is some form of trading that appears to be front-running LIC market purchases, there isn't a clear and definite "smoking gun" that proves the hypothesis. More work needs to be done with a larger sample set, hourly trading data, more sophisticated market-volume models and by building price analysis into the process.

The analysis of options trading volume data is similarly inconclusive. There isn't a clear trend that emerges from the data. A larger sample set may help prove the hypothesis one way or the other, but it is unlikely given the relative thinness of each option's trading volume.

IV. REFERENCES

Acharya, V. V., Johnson, T. C., 2010. More insiders, more insider trading: Evidence from private-equity buyouts. Journal of Financial Economics 98 (3), 500–523

Augustin, P., Brenner, M., Hu, J., Subrahmanyam, M. G., 2015. Are corporate spinoffs prone to insider trading? ISSN 2164-5744; DOI 10.1561/104.XXXXXXXX

Augustin, P., Brenner, M., Subrahmanyam, M. G., 2018. Informed options trading ahead of takeover announcements: Insider trading? https://doi.org/10.1287/mnsc.2018.3122

Augustin, P., Brenner, M., Subrahmanyam, M. G., 2018. How do Informed Investors Trade in the Options Market?

Bhattacharya, U., 2014. Insider trading controversies: A literature review. Annual Review of Financial Economics 6 (1), 385–403. https://doi.org/10.1146/annurev-financial-110613-034422

Chakravarty, S., Gulen, H., Mayhew, S., 2004. Informed trading in stock and option markets. The Journal of Finance 59 (3), 1235– 1258. https://doi.org/10.1111/j.1540-6261.2004.00661.x

John, K., Koticha, A., Narayanan, R., Subrahmanyam, M. G., 2003. Margin rules, informed trading in derivatives and price dynamics. NYU Working Paper No. FIN-01-038. http://people.stern.nyu.edu/msubrahm/papers/RangaMar00.pdf