Copernican Journal of Finance & Accounting

2019, volume 8, issue 4

e-ISSN 2300-3065
p-ISSN 2300-1240

Bag, D. (2019). Information content of stocks in call auction of shorter duration in emerging market. Copernican Journal of Finance & Accounting, 8(4), 113–132. http://dx.doi.org/10.12775/CJFA.2019.020

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INFORMATION CONTENT OF STOCKS IN CALL AUCTION OF SHORTER DURATION IN EMERGING MARKET

Keywords: auction, information, duration, volatility.

J E L Classification: G10, G14, D53, G14.

Abstract: Pre-open auctions have been widely implemented across trading exchanges. Pre-open auctions tend to reduce information asymmetry and trading risks. Call auctions have been encouraged to enhance price discovery. This paper explores the shifts in information content of the pre-market auction session over time. We derive that the information content of the pre opening auction did improve little after a gap of two months. We conclude that the intraday 15 minutes realized volatility was influenced by information content in the pre-market. We demonstrate that volatility is the cause of order imbalance or a cause of poor information content. The investigation of the related volatility in the futures segment provides interesting insights on the unusual pre-market imbalances visualized on days close to expiry of futures.

Introduction

The design of market microstructure and testing of the efficient market hypothesis has drawn attention from empirical researchers in the literature. Pre-

Date of submission: December 14, 2019; date of acceptance: January 15, 2020.

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open auctions have been widely implemented across many trading exchanges. Pre-open auctions tend to reduce information asymmetry and trading risks. An auction can calibrate the information changes and signal the participants by reducing price discrimination for market players. The motivation comes from the fact that the important aspect of the impact on volatility due to call auctions had not been conclusively established across many markets.

This study covers the order generation process of the opening call auction at regional exchanges (e.g., NSE, National Stock Exchange) in India. The objectives of this study include, examining the order generation as market depth, during auction and measuring the changes to information content of the call auction.

We develop a measure of information content for the pre opening session using order imbalance at ticker level. Our major findings are two fold; Information content during preopening has improved little during the sample period which portrays improvement in efficiency of markets and, there is visible rise in intraday 15 minutes volatility during the first hour of the normal market trading. We also find whether volatility could be a cause of order imbalance and poor information content.

We explore the pattern of order flow, and deduce that the number of trades has risen. We find that, quantity traded in Pre-Opening remains a small portion of the total volume in normal trade (only 0.18%), Limit orders comprise over 98% of all orders, The Order Cancellation rate is only 3% of the total orders, and proportion of buy orders is more than that of sell orders. The number of sell type modified orders is higher than buy type modified orders. Further, we gather that the time interval of modification for sell type orders is lower than the interval of modification for buy type orders. Observing the corresponding impact in the normal market, we find the first 15 minutes realized volatility has increased. Testing for the Realised volatility for the day, and auction indicators, we observe that both the opening order imbalance and pre-market traded volume, influence end of the day volatility significantly.

The paper is divided into four different chapters. In the second chapter, a literature review is presented about the information models. The third chapter presents the empirical research, using hypotheses considering the final objective of this study, the final results and statistical tests, as well as its discussion. In the last chapter, the conclusions are specified.

The research methodology and the research process

The empirical issues concerning call auction in information and efficiency has drawn reasonable attention in literature. Broadly, the empirical literature on call auctions, have dwelt upon stock performance within the split sample test windows, attempts to devise measures to compare the market level changes to abnormal or excess returns across fixed windows.

Literature review

The literature on market microstructure forms the basis of efficiency testing which includes Madhavan and Panchapagesan (2000), who tested the variance ratio of normal price to opening price for US markets. Earlier, Madhavan (1992), Amihud, Mendelson, and Lauterbach (1997) and Kalay, Wei, and Wohl (2002) had shown that the normal markets could fail when information asymmetry was higher. The authors used a measure of IS (Information Share) to provide relative information content of individual markets. An indicative measure of information share component was also discussed by Booth, So and Tse (1999), Chu, Hsieh and Tse (1999) and Baillie, Booth, Tse, and Zabotina (2002), who detected the transitory components of volatility, as suggested in Gonzalo and Granger (1995). Schwartz and Wood (2001) comprehensively determined the impact of call auction in NASDAQ and found is significant and effective. Pagano and Schwartz (2003) used short return intervals of 1–20 days for Euro Next Paris to understand the changes to returns. Kalay et al. (2002) examined. Israel Stock Exchange and noted decline in traded volume for small stocks post the auction, compared to continuous trading. Ellul, Shin, and Tonks (2005) explored call auction performance at London Stock Exchange and found that call markets were good for price discovery. Chang, Rhee, Stone and Tang (2008) tested the scenarios of opening and closing of the market in Singapore Stock Exchange. Hanousek and Kopøiva (2011) covered the Prague Stock Exchange, analyzing the behaviour of market makers and their ability to maintain private information on large orders, using the modified Easley, Kiefer, O'Hara and Paperman (1996) method. These suggested measures of IS or information content (viz., Madhavan, 1992, Gonzalo & Granger, 1995) cannot be directly related or easily applied to Indian markets. This is because the nature of volume generation and distribution during pre open at NSE (National Stock Exchange) is discrete and less ordered since the order entry duration of 8 minutes is too short for the total auction duration of 15 minutes only.

There are few studies on the impact of call auction for Indian markets, particularly, Agrawalla and Pandey (2013), Acharya and Gaikwad (2014) and Camilleri (2015) respectively. Acharya and Gaikwad (2014), Agrawalla et al. (2013) summarised the variation in returns for 56 tickers using 6 months data for the year 2010. Agrawalla et al. (2013) tested the holding period return across intervals of 1-20 days, but could not establish any major effects of the opening auction on normal markets. Acharya and Gaikwad (2014) confined to call auctions to BSE & NSE and found no significant improvement in price discovery process. None of these authors (For example, Acharya & Gaikwad, 2014; Agrawalla et al., 2013), did focus on the information content of Indian markets exclusively. Camilleri (2015) suggested that call auctions had a negative effect on VEL (Volatility, Efficiency & Liquidity) in NSE. And therefore auctions could not be confirmed to reduce NSE volatility.

Meanwhile, across the globe, the specific literature on (PIN) Probability of Informed Trading developed and this led to further work on gauging the ability of non-parametric indicators to foresee market events. Informational probability measures developed by Cao, Ghysels and Hatheway (2000) and Tao (2011) such as the WQPC (weighted quoted price contribution) were applied to trace the changes to entropy. Easley et al. (1996) designed (VPIN) volume probability of information trade, with the sole aim to predict market crashes. Later, few other works highlighted PIN and its variations to many exchanges. Easley, De Prado and O'Hara (2012) suggested Variable Probability of Informed Trading (VPIN) that could detect order flow imbalance one hour prior to a flash crash. Octavian Cosmin and Mihai Filip (2016) in their study of the PIN, for the Bucharest Stock Exchange, derived the set of macroeconomic drivers for the PIN. Cosmin and Filip (2016) determined that the macro indicators of Exchange Rate, Interest rate, Oil Price changes influenced the PIN in Hungary. Zheng (2017), in a study of China, has found positive results where the VPIN could successfully monitor the PIN of the indices of IC 500, IF 300 and IH 50, and it provided a test of early warning against the "circuit-breaker". Abad, Massot and Pascual (2018) have found the major limitations of VIPN in the form of its poor signalling ability of abnormal illiquidity, or to foresee toxic outcomes. VPIN based market decisions could not do better than the ordinary limit order transactions. To summarize, the imbalance in the market is denoted as the equivalence of Probability of Information Trading (PIN). Thus, VPIN method is to apprehend the source of volatility or the order flow process. This means the imbalance is a result of a disproportionate number of buy trades versus sell trades, where the sale trades are more in number. The root cause of rise or fall in VPIN is the order flow pattern occurring during the auction.

The order flow in an auction is composed by a sequence of limit orders and market orders that can be modified or cancelled. The arrival of newer information generates orders, signals other agents to update their orders and causes change in price. If an order flow process is completely random, an incremental buy order will move up average prices. Hasbrouck (2002) had demonstrated that the volatility at market open is ordinarily driven by higher flow of public information. So long as the players perceive that the equilibrium price accurately reflects the fair price, they react rationally. The attempts of bidder to modify orders, cancelling an order after entry, or, for example, large buy orders against small sell orders, etc., are the portrayal of irrational behaviour by members, which aggravates the order imbalance. Hence, players may perceive the prices as unnatural because of imbalance in inventory and may overreact that causes volatility. Order imbalance is a classic case of a surplus of buy orders than sell orders for any given security. There are many instances when the peak order imbalance has made exchange managers to suspend and halt trading. The smaller stocks or illiquid stocks may make imbalances to persist longer which could be due to inventory issues. Most order imbalances are short-lived. Limit orders can provide temporary protection against price changes from order imbalances in the pre-opening session.

Objectives and hypothesis

The objectives of the study are to examine the order generation as market depth, during auction and measuring the changes to information content of the call auction, and arriving at the influence on the intraday volatility. We find whether volatility could be a cause of order imbalance and poor information content.

We formulate the following hypothesis to explore the importance of order flow generation;

Hypothesis 1: Information content of Pre Opening auction impacts the market.

1.1. The information content for each stock is impacted during auction.

1.2. Information content is impacted by volatility in the futures segment market.

Hypothesis 2: Intraday volatility of normal markets is higher
2.1. Intraday volatility is higher in the opening hours.
2.2. Auction volume impacts volatility.

Sample and data

Data

The NSE data includes daily traded data from pre-opening sessions. Pre-opening data includes both Limit price orders & Market orders. It also includes normal trade data for the same days of pre-market auction samples of stocks. The data had been collected in 2013. Table 1 describes the sample observation window.

Table 1. Sampling Design

Type	Number of stocks	Months
Pre-market	104	April to September
Normal Trades	104	April to September

Note: The sample included all 104 stocks traded on all days in the pre-market session. The normal trade data for the 104 stocks were collected for a 6 months period from April to September.

Source: National Stock Exchange (2013).

To calculate daily SPIN for each stock, the pre opening call auction data was collected for the period from April & May, and August & September for four months. The normal trading data includes trade data from the period April & May, and August & September for four months. The pre-opening data for June and July were not included in SPIN calculation because of noise in two months of trade data. We present this analysis as a split sample comparison between 2months which is separated by a gap of 2 months.

Model: PIN

Earlier works of Shannon (1948), who presented an entropy measure to summarize average information content associated with any random outcome.

Shannon (1948) showed that any definition of entropy could be expressed as:

Entropy= K x p(x_i) log[p(x_i)] Eq. (1)

Where, K is a constant and x_i is observed variate.

The continuity assumption in Shannon (1948) is moderated for auction markets, where, size of an order signals information to other market players, The Volume Synchronized Probability of Information (VPIN) (Easley, Hvidkjaer & O'Hara, 2002), which owes itself to basic PIN (Easley et al., 1996). Probability informed Trading (PIN) is computed from the expected probability of information that could cause a change in quoted price. Bayesian incidences or prior probabilities are used to arrive at the expected information content. Both PIN (Easley et al., 1996) and VPIN (Easley et al., 2002) include information on volume, time, classified trades and trade intensity, which cannot be easily applied to regional exchanges (e.g., NSE) because of its smaller scale and short duration interval in nature.

To simplify the VPIN to the setting of a regional exchange (e.g., NSE), we proceed as follows.

Let's denote a security's current price as S_0.

The arrival and transmission of new information causes the price, $S_{0\ to}$ be either S_B (due to bad news) or S_G (due to good news) with some Probability (p ≥ 0).

The probability (p ≥ 0) that the *news* is good news and a probability (1-p ≥ 0) that the *news* will be bad.

The expected price in time t, t, $E(S_t) = p \times S_B + (1-p) \times \ S_G$ Eq. (2)

A Poisson distribution would simulate the arrival of more informed specialist traders at a known rate μ, and normal traders at known rate ε.

The standard case of probability of arrival of information is ($p = \frac{1}{2}$), and probability of good or bad is ($p = \frac{1}{2}$) gives rise to Eq. (3)

$$PIN = \frac{\mu}{\mu + \epsilon}$$ Eq.(4)

Volume flow mimics the arrival of information during the auction. The sample of volume is divided into *volume buckets* such that each bucket comprises equal volume. The volume is classified as *buy*, and *sell*. Within a given volume bucket, the volume is the total of *buy volume* (V_B traded against the Ask), and sell volume (V_S).

All the buckets are of equal size, $\mathrm{V} = n \times (V_B + V_S) = n \times V_T$ Eq. (5)

Where n is the number of buckets.

V_T is the total volume per bucket where all buckets will contain an equal amount of volume V.

Order imbalance exists with the excess of buy orders over the sell orders for each stock.

We calculate Order Imbalance for each stock on day t, as:

Order Imbalance $_{i,t} = \left| V_B - V_S \right|$ Eq. (6)

Where V_B is volume of Buy Orders and V_S, volume of sell orders for stock i and time t,

Therefore Order Imbalance$_{i,t} \geq 0$ for all i, t.

The total order imbalance for each stock i trading day t equals sum total of ($\sum_t$) Order Imbalance$_{i,t}$ during the day t.

Hence, we define a measure of information content for pre-opening session to be known as *SPIN* (Simple Probability Information Ratio) as given below:

$$SPIN_{i,t} = \frac{|V_B - V_S|}{|V_B + V_S|}$$ Eq. (7)

Where, $SPIN_{i,t}$ follows a distribution that varies between (0,1).

Barclay and Warner (1993), (also Barclay & Hendershott, 2008), have mentioned that the normalization of imbalance numbers can reduce the heteroscedasticity in observations. Value of SPIN close to *0* represents higher information efficiency and *1* represents lowest information efficiency.

We compute $\mathrm{SPIN}_{i,t}$ for each ticker day during the trading months of April, May, August and September.

Model: IMPACT OF IMBALANCE

The next objective of evaluating the effect of volatility by choosing a commonly denominated indicator of intraday volatility, known as realised volatility.

RV, which is the daily (i.e., open-to-close) realized volatility:

$$RV = \log(P_n / P_{n-1}) \qquad \text{Eq. (8)}$$

A simple specification of the model for RVOL is given below:

$$RVOL_{it} = \alpha + \beta_m\, RVOL_{it-m} + \beta_{t-m}\, RVOL_{i,t-m} + \gamma_{it}\, OI_i + \mu_{it}\, VOLUME_i + \varepsilon_t \qquad \text{Eq. (9)}$$

Where, RVOL is the intraday realized volatility (end of the day) which is the cumulative realized volatility incremented at one minute interval, during the day, OI_i are order Imbalance of stock i, $VOLUME_i$ is the pre-market traded volume for stock i.

The specification in Equation (9) is a test of the resilience of beginning intraday variability, on the end of the day variability. It is also a test of the impact of information content on volatility. For example, it takes into consideration the earliest (foremost) lag of RVOL as a regressand (lagged dependent variable) in the model. This specification of the model which includes the lags of RVOL(t), is to ensure that persistence component is detected thoroughly. The model in Equation (9) is tested with two major specifications of 1) Pooled regression and 2) SUR (Seemingly Unrelated Regression), respectively. The SUR specification ignores fixed effects across stocks. For the sake of generality and simplicity, we ignore the presence of simultaneous cross correlations (of RVOL among stocks in our sample.

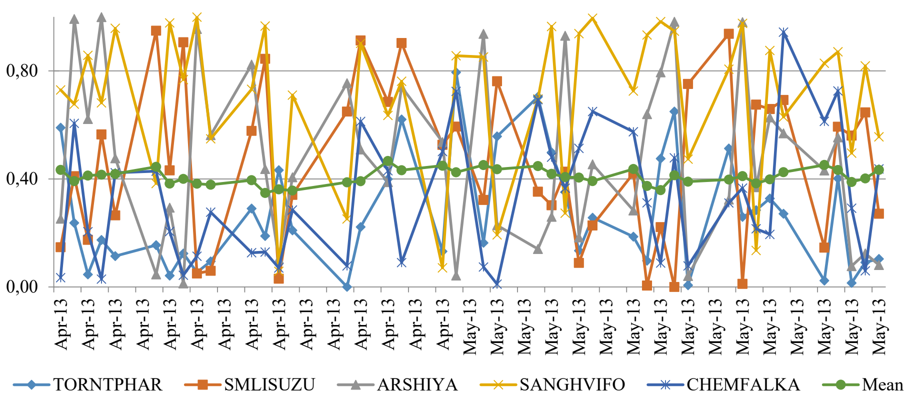
Results and conclusions of the research process

Model: PIN

Figure 1(a) and 1(b) provide the variation in the most minimum SPIN values of few stocks for the period for April, May, and August and September, respectively. Similarly, figure 2(a) and 2(b) provide the most maximum SPIN values of few stocks for April, May, and August and September, respectively. Minimum Imbalance (SPIN=0) reflects the absence of asymmetry and the maximum imbalance (SPIN=1) reflects the presence of asymmetry. Table 2 provides the descriptive statistics of SPIN (Simple Probability Information and Order Imbalance). It picturise the sample mean, extreme days of SPIN and the deviation from the mean values. It also provides the names of tickers and the dates alongside when these stocks displayed extreme values (minimum or maximum) of SPIN during the period. As shown in table 2, the mean SPIN value of 0.45 for the market reflects that the information content is somewhat better than 0.5, but it is still far away from attaining the value 0.

We sorted the individual SPIN values of each stock by descending order to find the dates on which they displayed the minimum information, and the dates on which they displayed maximum information. The average SPIN of five (5) minimum information stocks has not increased in the later period.

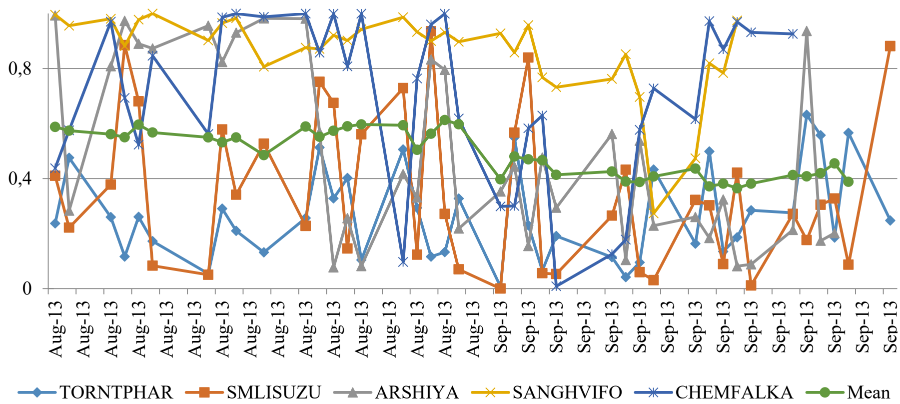
Figure 1 (a). Variation of Minimum Information Stocks (SPIN) (April to May)



N o t e : The stocks are illiquid and hence information content is lower.

S o u r c e : author's compilation.

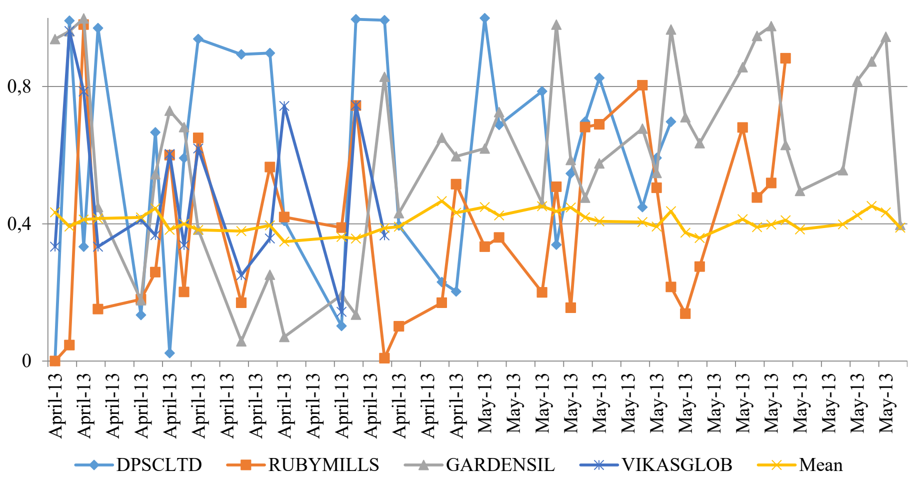
Figure 1 (b). Variation of Minimum Information Stocks (SPIN) (August to September)



N o t e : The stocks are illiquid and hence information content is lower.

S o u r c e : author's compilation.

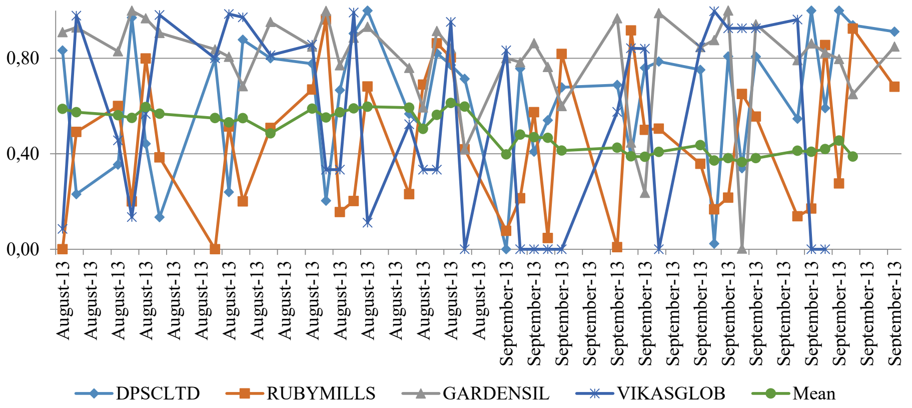
Figure 2 (a). Variation of Maximum Information Stocks (SPIN) (April to May)



N o t e : The 4 stocks are nifty stocks and information content is higher.

S o u r c e : author's compilation

Figure 2 (b). Variation of Maximum Information Stocks (SPIN) (August to September)



N o t e : The 4 stocks are nifty stocks and information content is higher.

S o u r c e : author's compilation

The reasons for poor information share are due to poor liquidity of the stocks in the sample.

Table 2. Descriptive Statistics SPIN (Simple Probability Information Ratio)

Period		SPIN			
2013	Number of Observations NT (6218) N (Stocks) 75	MAXIMUM	MINIMUM	Mean	STD
	T (Trade Days) 82	1	0	0.45	0.29
Extreme Event days- Maximum SPIN					
Date	symbol	SPIN		Mean	STD
10-May-13	ARSHIYA	1		0.39	0.30
13-Aug-13	SANGHVIFO	1		0.53	0.30
21-Aug-13	CHEMFALKA	1		0.57	0.29
21-Aug-13	GARDENSIL	1		0.57	0.29
24-Sep-13	DPSCLTD	1		0.41	0.28

Table 2. Descriptive…

Period		SPIN			
2013	**Number of Observations NT (6218) N (Stocks) 75**	**MAXIMUM**	**MINIMUM**	**Mean**	**STD**
	T (Trade Days) 82	**1**	**0**	**0.45**	**0.29**
25-Sep-13	DPSCLTD	1		0.42	0.26
26-Sep-13	DPSCLTD	1		0.45	0.29
27-Sep-13	DPSCLTD	1		0.39	0.28
Extreme Event days- MINIMUM SPIN					
Date	**symbol**		**SPIN**	**Mean**	**STD**
2-Apr-13	DPSCLTD		0	0.39	0.29
2-Apr-13	SUPRAJIT		0	0.39	0.30
5-Apr-13	HARITASEA		0	0.42	0.28
25-Apr-13	MOIL		0	0.47	0.30
3-May-13	ZODIACLOT		0	0.44	0.28
14-May-13	TORNT PHARMA		0	0.37	0.30
12-Aug-13	RUBYMILLS		0	0.55	0.29
2-Sep-13	SMLI SUZUKI		0	0.40	0.29
3-Sep-13	VIKAS GLOBAL		0	0.48	0.27
5-Sep-13	VIKASGLOBAL		0	0.47	0.30
6-Sep-13	VIKASGLOBAL		0	0.41	0.27
10-Sep-13	VIKAS GLOBAL		0	0.43	0.29
12-Sep-13	VIKAS GLOBAL		0	0.41	0.27
18-Sep-13	VIKAS GLOBAL		0	0.38	0.27
27-Sep-13	VIKAS GLOBAL		0	0.39	0.28
30-Sep-13	VIKAS GLOBAL		0	0.40	0.28

Note: Sample Mean of 0.45 is closer to 0 and is better than 1.0. No. of stocks which achieved full information share in the sample period were only 11. The reasons for poor information share are due to poor liquidity for those stocks.

Source: author's calculation.

Table 3. Volatility changes of Normal Trades

Minute	No. Observations	Average Spread	Average Realized Variance
1	2625	0.168	0.0005
2	2625	0.248	0.0006
3	2625	0.308	0.0006
4	2625	0.359	0.0007
5	2625	0.403	0.0007
6	2625	0.447	0.0008
7	2625	0.489	0.0008
8	2625	0.525	0.0008
9	2625	0.56	0.0009
10	2625	0.594	0.0009
11	2625	0.626	0.0009
12	2625	0.659	0.0010
13	2625	0.69	0.0010
14	2625	0.721	0.0010
15	2625	0.751	0.00104

Note: We find rise in both spread and realized volatility, where $Spread = \frac{(Trade\_Price - lag(Price)}{\frac{Price + lag(Price)}{2}}$ and, $Realised\,Variance = [Log(Price) - Lag(Log(Price))]$. Both spread and Realized volatility increases from 1 minute to the 15th minute during the first hour of trading.

Source : author's calculation.

For the corresponding period in our sample, table 3 provides the volatility changes which shows that the variance of normal trades has increased in the first 15 minutes of trading.

Model: IMPACT OF IMBALANCE

Table 4 shows the realised variance (RV) model estimates. The results reflect that the influence of pre-market indicators on the end of the day variance is significant. We also find that Order Imbalance, pre-market trading Volume seem to impact the end of the day RVOL significantly.

Table 4. Impact of SPIN on Realized Volatility (RVOL)

Dependent variable	RVOL	
Estimation Method	(1) Pooled Regression	(2) SUR
Intercept	0.01(.2)	0.01(.2)
RVOL(23)	0.7 (<.0001)	0.7 (<.0001)
RVOL(22)	0.4 (<.0001)	0.4 (<.0001)
Order Imbalance	8.61E-06 (<.0001)	8.61E-06 (<.0001)
Pre-Market Trade Quantity	3.5E-06 (<.0001)	3.5E-06 (<.0001)
NT (Total Observation)	3,381	3,381
N (stocks)	104	104
T (Traded Days)	48	48
SSE	127	127
MSE	0.1246	0.1246
R-Square	0.9305	0.9305

Note:
1. (21) Indicates the lag number of the indicator, 21 times of 15 minutes which is the RVOL at 5 hours 15 minutes before the end of the day. (22) Indicates 22 times of 15 minutes each which is the RVOL at 5 hours 30 minutes before the end of the day.
2. Parenthesis indicates the significance of P-values of the parameter coefficients. Pre-opening indicators are significant.
3. The SUR Model is estimated without fixed effects.
4. We ignore simultaneous cross correlations of RVOL (in our sample).

Source: author's calculation with the sample of normal trade tickers for 2013.

It shows that the influence of order imbalance is about 2.5 times the traded volume on the realized variance. Our results are in consonance with previous findings with respect to regional exchanges (e.g., NSE), namely, Bacidore, Polidore, Xu and Yang (2012) who established that volume imbalance during pre-open auction led to enhanced volatility. Kehr, Krahnen and Theissen (2001) concluded that intervention in the auction could enhance order flow, reduce volatility and increase price efficiency. This is in concordance with the previous findings of Octavian Cosmin and Mihai Filip (2016) who had used VPIN as a dependent variable to detect Exchange Rate, Interest rate and Oil Price changes as independent variables in their test model.

We carry out a second test of the model parameter estimates from the reported volatility of the future segment for the corresponding days of minimum information. For this test, as shown in Table 5 we report the order imbalance and the corresponding daily NSE futures volatility. This is the related observation on the phenomenon of spikes in the futures segment. We find that the market displays over reaction of players on the date of expiry[1] of index futures. The spikes are also observable one day ahead of the day of expiry (Wednesdays).

Table 5. NIFTY Index Futures Volatility against matching pre-market dates

Trading Date	Number of Contracts	Nearest Expiry Date	Futures Daily Volatility+	Pre-Open Auction date	Number of pre-market TRADEs	Pre-Market Order Imbalance in Pre-open auction
23-Apr-13 (Wednesday)	410,634	25-Apr-13	0.0100	4/23/2013	16,078	75,606
25-Apr-13 (Thursday)	602,387	25-Apr-13	0.0102	4/25/2013	59,373	62,886
30-Apr-13 (Wednesday)	430,430	30-May-13	0.0094	04/30/2013	N.A.	63,679
29-May-13 (Wednesday)	350,560	30-May-13	0.0107	5/29/2013	27,272	84,403
30-May-13 (Thursday)	533,435	30-May-13	0.0105	5/30/2013	15,047	69,584
16-Aug-13 (Friday)	338,425	29-Aug-13	0.0151	8/16/2013	N.A.	376,380
28-Aug-13 (Wednesday)	883,258	29-Aug-13	0.0161	8/29/2013	10,504	442,518
29-Aug-13 (Thursday)	876,965	25-Sep-13	0.0166	9/25/2013	9,811	82,712
19-Sep-13 (Thursday)	413,400	26-Sep-13	0.01900	9/19/2013	N.A.	45,175

[1] Normally, the expiry date is the last Thursday of each Month unless it is a holiday, NSE.

Table 5. NIFTY...

Trading Date	Number of Contracts	Nearest Expiry Date	Futures Daily Volatility+	Pre-Open Auction date	Number of pre-market TRADEs	Pre-Market Order Imbalance in Pre-open auction
25-Sep-13 (Wednesday)	526,516	26-Sep-13	0.0179	9/26/2013	1,36,466	76,117

Note: On days of settlement (Last Thursday) and one day before the settlement (Wednesday), we find significant activity in Pre-open session in the form of high Traded volume and Order Imbalances. Days which are not close to days of future settlement dates (last Thursdays), the volume imbalances are lower than other days.

Source: author's compilation from National Stock Exchange, 2013.

Further we find higher trading volume during pre-opening sessions on these days as compared to other days. We also find higher volume imbalance on days on or ahead of NIFTY futures expiry dates[2]. For example, May 29th, NIFTY volatility is 0.107 which is higher than April 23rd, and so also on August 28th and August 29th of 2013. These results reinforce our confidence in the analysis. Probably, one way to curtail volatility could be a separate pre-opening auction for futures.

Conclusions

Overall, we conclude with our findings on the lower average SPIN value of 0.45 for the market which is due to shorter duration of the auction and also lower liquidity. Therefore, a longer duration of auction (Pagano & Schwartz, 2003) could lead to better discovery and lower volatility. Euronext Paris already incorporates order imbalance in its call auction summary that allows market makers to remain active. Our results are in consonance with previous findings with respect to regional exchanges (e.g., NSE), namely, Bacidore et al. (2012) who established that volume imbalance during pre-open auction led to enhanced volatility. Kehr, Krahnen and Theissen (2001) concluded that intervention in the auction could enhance order flow, reduce volatility and increase price efficiency.

[2] For dates away from the expiry dates, which are not the last Thursdays of the month, the volume imbalances are much lower.

This study covered to envisage information content of the short duration pre-opening session. Call auctions have drawn worldwide attention across exchanges and have been implemented successfully. We demonstrated few significant empirical issues in relation to the impact, mainly the order imbalance effect, increased volatility in the normal market. The reliable measures of SPIN developed by us is much simpler to implement as compared to both the VPIN[3] and PIN which are applied to situations of discrete prices such as the pre-opening call. There are few questions that emerge from this analysis, which are interesting to verify, such as, a large number of non-NIFTY tickers are not traded during pre opening. Similarly, the duration of the auction plays a big role since a longer duration of the pre-opening session from 7 minutes will also allow more players to participate.

In this study, we adopted a simple innovation to the basic PIN model to detect information content of NSE pre-market. Our SPIN measure is an approximation for a discontinuous market which may not be as accurate as a continuous market. One cannot use SPIN to foresee flash crashes. Further research should include deeper innovation of PIN that can be applied to high frequency data, recent period data to emerging markets.

References

Abad, D., Massot, M., & Pascual, R. (2018). Evaluating VPIN as a trigger for single-stock circuit breakers. *Journal of Banking and* Finance, 86(C), 21-36.

Acharya, H.R., & Gaikwad, V. (2014). Pre Open call auction and price discovery: Evidence from India. *Cogent Economics & Finance* (*Taylor and Francis Group*), 2(1). http://dx.doi.org/10.1080/23322039.2014.944668.

Agarwalla, S., & Pandey, A. (2013). Expiration Day Effects and the Impact of Short Trading Breaks on Intraday Volatility: Evidence from the Indian Market. *Journal of Futures Markets*, 33(11).

Amihud, Y., Mendelson, H., & Lauterbach, B. (1997). Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange. *Journal of financial Economics*, 45(3), 365-390.

Bacidore, J., Polidore, B., Xu, W., & Yang, C. (2012). Order submission strategies, liquidity supply, and trading in pennies on the New York Stock Exchange. *The Journal of Trading*, 8(1), 48-57.

Barclay, M.J., & Warner, J.B. (1993). Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics*, 34(3), 281-305.

Barclay, M.J., & Hendershott, T. (2008). A comparison of trading and non-trading mechanisms for price discovery, *Journal of Empirical Finance*, 15(5), 839-849.

Baillie, R.T., Booth, G.G., Tse, Y., & Zabotina, T. (2002). Price discovery and common factor models. *Journal of Financial Markets*, 5, 309-321.

Booth, G.G., So, R.W., & Tse, Y. (1999). Price discovery in the German equity index derivatives markets. *Journal of Futures Markets*, 19, 619-643.

Cao, C., Ghysels, E., & Hatheway, F. (2000). Price discovery without trading: Evidence from the NASDAQ pre opening. *The Journal of Finance*, 55(3), 1339-1365. http://dx.doi.org/10.1111/0022-1082.00249.

Camilleri, S.J. (2015). Do call auctions curtail price volatility? Evidence from the National Stock Exchange of India. *Managerial Finance*, 41(1), 67-79. http://dx.doi.org/10.1108/MF-10-2013-0292.

Chang, R.P., Rhee, S.G., Stone, G.R., & Tang, N. (2008). How does the call market method affect price efficiency? Evidence from the Singapore Stock Market. Jo*urnal of Banking* & *Finance*, 32(10), 2205-2219.

Chu, Q.C., Hsieh, W.G., & Tse, Y. (1999). Price discovery on the S&P 500 index markets: an analysis of spot index, index futures and SPDRs. *International Review of Financial Analysis*, 8, 21-34.

Cosmin, O., & Filip, M. (2016). Estimating Probability of Informed Trading on the Bucharest Stock Exchange. *Finance a úvěr-Czech Journal of Economics and Finance*, 66(2), 140-160.

Easley, D., Kiefer, N., O'Hara, M., & Paperman, J. (1996). Liquidity, Information, and Infrequently Traded Stocks. *The Journal of Finance*, 51(4), 1405–1436.

Easley, D., Hvidkjaer, S., & O'Hara, M. (2002). Is Information Risk a Determinant of Asset Returns? *Journal of Finance*, 57, 2185-2221. http://dx.doi.org/10.1111/1540-6261.00493.

Easley, D., De Prado, M.L., & O'Hara, M. (2012). Flow toxicity and liquidity in a high frequency world. *Review of Financial Studies*, 25(5), 1457-1493. http://dx.doi.org/10.1093/rfs/hhs053.

Ellul, A., Shin, H. S., & Tonks, I. (2005). Opening and closing the market: Evidence from the london stock exchange. *Journal of Financial and Quantitative Analysis*, 40(4), 779.

Gonzalo, J., & Granger, C. (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business and Economic Statistics*, 13, 27-35.

Hanousek, J., & Kopøiva, F. (2011). Detecting Information-Driven Trading in a Dealers Market. Czech Journal of Economics and Finance (Finance a uver), Charles University Prague, Faculty of Social Sciences, 61(3), 204-229.

Hasbrouck, J. (2002). Stalking the efficient price in empirical microstructure specifications. *Journal of Financial Markets*, 5, 329-339.

Kalay, A., Wei, l., & Wohl, A. (2002). Continuous Trading or Call Auctions: Revealed Preferences of Investors at the Tel Aviv Stock Exchange. *Journal of Finance*, 57(1),523-542.

Kehr, C.H., Krahnen, J.P., & Theissend, S. (2001). The Anatomy of a Call Market. *Journal of Financial Intermediation*, 10(3-4), 249-270. http://dx.doi.org/10.1006/jfin.2001.0314.

Madhavan, A. (1992). Trading mechanisms in securities markets. *Journal of Finance*, 47(2), 607-641.

Madhavan, A., & Panchapagesan, V. (2000). Price discovery in auction markets: A look inside the black box. *Review of Financial Studies*, 13(3), 627-658. http://dx.doi.org/10.1093/rfs/13.3.627.

Pagano, M.S., & Schwartz, R.A. (2003). A closing call's impact on market quality at Euronext Paris. *Journal of Financial Economics*, Elsevier, 68(3), 439-484.

Schwartz, R. A., & Wood, R.A. (2001). Calling the open: Price discovery evidence from nasdaq. Working Paper, The Nasdaq Stock Market, Inc. Economic Research.

Shannon, C.E. (1948). A Mathematical Theory of Communication. *The Bell System Technical Journal*, 27, 379–423.

Tao, C. (2011). Price discovery with and without trading on the Tokyo Stock Exchange. *International Journal of Behavioural Accounting and Finance*, 2(1), 56-78.

Theissen, E. (2000). Market structure, informational efficiency and liquidity: An experimental comparison of auction and dealer markets. *Journal of Financial Markets,* 3(4), 333-363.

Zheng, Y. (2017). VPIN and China's circuit-breaker. *International Journal of Economics and Finance*, 9(12), 126-133. http://dx.doi.org/10.5539/ijef.v9n12p126.