Liquidity and Price Discovery When Some Participants are Irrational: Evidence from the NSE

Padma Kadiyala

This Version: December 25, 2019

ABSTRACT: The paper examines the impact of irrational trading on price discovery, and liquidity of stocks listed on the Indian NSE exchange. The ability of a market to absorb irrational trading with little price impact is an important dimension of liquidity. Irrational trading in this study is driven by an exogenous event, namely, 90-minute periods during the trading day called Rahukalam, during which superstitious traders believe it is inauspicious to undertake commercial activity. Not all traders are superstitious however. The dynamic interaction between rational traders, superstitious traders and competitive market makers is measured using popular liquidity and price discovery measures. Our empirical evidence suggests that price discovery and liquidity are compromised during the Rahu period. Inclusion in the Nifty 50 stock index, and greater trading volume cushions the impact of the superstition on prices.

INTRODUCTION

The study examines trading on the National Stock Exchange of India to determine how rational traders interact with irrational traders and a competitive market maker. Irrationality on the part of some traders is driven by an exogenous non-information event called the Rahukalam. The Hindu calendar divides a 12-hour period each day from sunrise to sunset into eight intervals of approximately 90 minutes. One such interval is Rahukalam (referred to as 'Rahu' hereafter), which occurs at approximately the same time on each calendar day, but differs from one calendar day to the next. It is location-specific being determined by sunrise and sunset at that location. Hindus consider it inauspicious to travel, conduct commerce, or commence a new undertaking during this period. Trading is likely to be most vulnerable to the superstition since it is a speculative activity with a direct impact on the wealth of its participants. But not all traders hold the superstition. Foreign institutional investors' share of trading on the NSE has grown from 9.8% in 2009-2010 to 15.2% in 2013-2014.¹ Thus, trading on the NSE is driven by a mix of those who consider Rahu to be inauspicious and those who don't hold that belief. If the superstitious act on their beliefs and refrain from trading during the Rahu period, how is overall trading affected? The superstition being exogenous to financial markets allows us to measure its cross-sectional impact without the need to consider the fundamentals of the underlying stock. In other words, we expect the impact of the superstition to be governed by the market microstructure of the stock, rather than by its fundamentals.

Rational traders may be unable to exploit mispricing created by the unwillingness of superstitious traders to trade during Rahu. Shleifer and Vishny (1997) show that delegated money management creates a limit to arbitrage activity by restricting access to capital precisely when the expected return to the arbitrage strategy is at its highest. Lending may be constrained during the Rahu period, limiting the ability of rational traders to exploit mispricing. Market microstructure effects can also constrain the ability of the rational trader to trade aggressively ahead of superstitious traders during the Rahu. We build a simple sequential order model using the Glosten and Milgrom (1985) framework to determine market makers' and traders' incentives to trade during the Rahu and non-Rahu periods. Hypotheses derived from the model are tested using intra-day data on 1786 stocks listed on the National Stock Exchange. Our results confirm that trading

¹ Source: NSE accessed online on www.nseindia.com

is subdued during the Rahu period: The number of trades per minute falls to 7.13 on average during the Rahu period from 8.78 in the pre-Rahu period and 8.12 in the post-Rahu period. When liquidity is measured as the price impact of a trade, we find that a 1000 share trade has a 0.20 INR impact on price, compared to a price impact of 0.09 INR and 0.11 INR in the pre-Rahu and post-Rahu periods. Price discovery is noisy during the Rahu period, with a signal-to-noise ratio of 0.70 on average, compared to averages closer to 1.0 during the periods surrounding it. Stocks in the Nifty 50 index suffer a smaller impact from the Rahu superstition. The signal-to-noise ratio for these stocks is indistinguishable across the pre-Rahu, Rahu and post-Rahu periods. Close to 50% of trading in the index is due to foreign institutional investors. The diversity among investors reduces the impact of irrational investors on liquidity and price discovery. Finally, greater underlying liquidity in the stock reduces the impact of the Rahu bias.

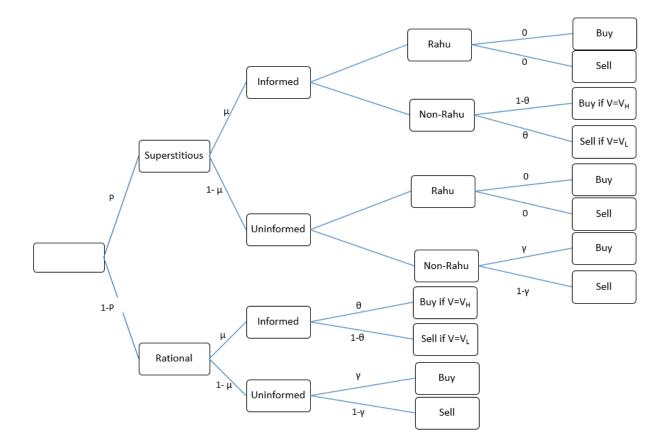
The study contributes to two strands of literature: behavioral finance, and market microstructure. Behavioral finance studies have to cross a significant hurdle to demonstrate that the reaction of market participants to information, or to an event, is indeed irrational; the classic joint hypothesis problem. For instance, Baker and Wurgler (2006) predict and test the hypothesis that investor sentiment affects valuation of stocks that are difficult to arbitrage. To be accepted as a proxy for irrational investor behavior, investor sentiment has to be independent of rational factors, such as risk aversion that affect the utility of wealth. The paper also contributes to the substantial literature on liquidity risk and expected returns. Chordia, Roll and Subrahmanyam (2008, 2002, 2000) show that order imbalance, and other measures of liquidity have a systematic component and are related to market-wide returns. Similary, Hasbrouck and Seppi (2001) study the importance of common factors in liquidity proxies. This paper suggests that the susceptibility of trading to irrational biases is an important dimension of liquidity risk. The rest of the paper is organized as follows: Section 2 describes the trading process and derives the hypotheses, Section 3 describes the data and the empirical design. Section 4 has the results, and Section 5 has the conclusions.

2. THE TRADING PROCESS

Trading occurs in an order-driven market where investors' buy and sell orders are crossed against each other. Investors have a choice of submitting a market order or a limit order. Models of limit order trading endogenize the choice between a market and a limit order by classifying traders into patient and impatient traders. Limit orders carry the advantage of receiving a better price, which comes at the cost of a lower execution probability. A trader incurs a waiting cost when her order is not immediately executed. Investors trade-off price against waiting costs to choose between submitting a market order or a limit order.

Overlaid on this order submission strategy are the motives and religious beliefs of traders. We consider a single traded asset which takes a high value V_H with a probability θ and a low value V_L with a probability (1- θ). There is a proportion μ of informed traders and a proportion (1- μ) of liquidity traders. Informed traders buy only if their information indicates $V=V_H$ and sell if $V=V_L$. Liquidity traders buy and sell randomly with probabilities γ and $(1-\gamma)$ respectively. Religious beliefs affect these trading motives by preventing a proportion ρ of sentimental traders from trading in the Rahu period. The proportion $(1-\rho)$ of rational traders are not similarly constrained. The trading activity of these participants is in Figure 1.





The trading day on the National Stock Exchange (NSE) can be divided into three periods: pre-Rahu, Rahu and post-Rahu. Let the lowest ask in the pre-Rahu period be A, and the highest bid be B, so that the bid-ask spread is A-B. Let the total volume on the offer side of the book be q, and the total volume on the bid side be p. There are three possible cases to consider with respect to p and q: i) p>q: Buy side imbalance, ii) p<q: sell side imbalance, and iii) p=q: no order imbalance.

Entering into the Rahu period, rational limit order traders will post less aggressive prices when a proportion, ρ , of traders are absent from the market. Spreads are also expected to widen as traders shield themselves against informed traders taking advantage of the absence of informed, but sentimental traders from the Rahu trading session. Wider spreads may not discourage rational informed traders from trading if: i) trader's private valuation is better than the unfavorable price; higher than A for a market buy, or lower than B for a market sell, and, or, ii) the trader is reluctant to postpone trading to the post-Rahu period. Thus, we expect order submission strategies of rational traders in the Rahu period to depend on market conditions in the post-Rahu period.

There is pent-up demand from sentimental liquidity traders in the post-Rahu period. The market is subjected to a series of liquidity shocks on the buy or sell side of the market depending on whether there is a pre-Rahu order imbalance on the buy or sell side. These liquidity motivated trades are executed against quotes posted by patient limit order traders. Patient traders capture larger rents from impatient traders by posting less aggressive orders. Impatient traders are willing to place market orders at ever more unfavorable prices, rather than place limit orders, since there is a risk of non-execution with limit orders. (Foucault, Kadan and Kandel (2005) and Rossu (2008) label a market where spreads do not revert to competitive levels following liquidity shocks as being not resilient.

When the post-Rahu period is not resilient, the informed trader is worried that the liquidity shock arising from order imbalance in the pre-Rahu period will move prices away from its equilibrium value. The trader prefers to move his trades to the Rahu period to avoid a liquidity driven drift in the price. Patient rational limit order traders are encouraged to post aggressive prices in the hope of attracting execution from the rational informed, but impatient, trader. Spreads should narrow as a result. Liquidity traders who would have preferred to postpone their trading to the post-Rahu period are drawn into the Rahu period when they observe spreads narrow.

The discussion here points to the crucial, but somewhat paradoxical, role played by market resilience in the post-Rahu period. In a resilient market, higher liquidity demands towards close should lead to higher volumes, and smaller spreads. A resilient post-Rahu market encourages all traders, rational and superstitious to shift their trading to the post-Rahu period. The shift away from the Rahu period reinforces the susceptibility of the market to sentimental traders. On the other hand, a less resilient post-Rahu market reduces the susceptibility of the market to sentimental traders are encouraging rational traders to trade during the Rahu period. Patient limit order traders are encouraged to post competitive prices in the Rahu period to attract impatient informed and liquidity driven traders.

The testable hypotheses that emerge from the discussion are:

 H_A : Volume of trading during Rahu is significantly lower than the volume of trading during non-Rahu in a resilient market

 H_B : There is less informed trading in the post-Rahu period than in the pre-Rahu period.

3. Empirical Methodology

The methodology is a modified version of the Madhavan, Richardson and Roomans (MRR, 1997). The stock's fundamental value can be written as:

$$\mu_t = \mu_{t-1} + \theta \left(x_t - E(x_t | x_{t-1}) \right) + \epsilon_t .$$
(1)

In the MRR model, the ask and bid prices are set by a competitive market maker whose profit is driven to zero. Thus, he sets the ask price at: $P_t^{ask} = \mu_t$ + inventory cost. In an order driven market, the trader has to decide whether to place a competitive price by trading off a better price against a lower probability of execution. Let the minimum tick size be Δ , and the limit order trader decides to place a j-tick order. The ask price set by the limit order is:

$$P_t^{ask} = \mu_t + j\Delta + \xi_t \tag{2}$$

where $j\Delta$ is the tick increment placed by the limit-order trader over the equilibrium price. $j\Delta$ is the expected value of the j-tick order = $j\Delta$ *pr(liquidity shock)*p(execution) + $j\Delta$ *(1-pr(liquidity shock)) *p(execution). To calculate p(execution), we assume that the order arrival rate is: $1/\Lambda$. If an order arrives with a probability $1/\Lambda$, it is assumed to be equally likely to be a buy or a sell order. Thus the p(execution)= 0.5/ Λ . When there is a liquidity shock, which is a series of market orders

on one side of the market, limit-order traders can post less competitive prices to extract rents from the impatient liquidity traders. The spread can widen as a result. When the order arrival rate slows down, limit order traders will post more competitive prices to attract order flow, and increase the likelihood of execution. Thus the price set by the limit order trader depends on the liquidity shock, the resilience of the market, and the order arrival rate.

Market resilience depends on the proportion of patient limit order traders, the volatility of the order arrival process. The proportion of patient limit order traders is not observable, so we model the market resilience as a parameter, $1/\omega$, to be estimated. We model liquidity shock as the posterior probability:

$$p_t = pr(x_{t+1} = 1, x_{t+2} = 1, \dots, x_{t+l} = 1 | x_t = 1, x_{t-1} = 1, \dots, x_{t-m} = 1)$$
(3)

Based on these modelling assumptions, we can write the ask price set by a limit order trader as:

$$P_t = \mu_t + \frac{1}{\omega} * \mathcal{P}_t * pr(execution) + (1 - \mathcal{P}_t) * p(execution) + \xi_t$$

The second term is the expected value of a j-tick order if there is a liquidity shock, while the third term is the expected value without a liquidity shock. Substituting for μ_t from equation (1) and replacing the unobservable μ_{t-1} with the observable P_{t-1}, in a manner similar to MRR, we get:

$$P_t - P_{t-1} = \left(\theta + \frac{1}{\Lambda} \left(\frac{1}{\omega} - 1\right) \rho\right) x_t - \theta \rho x_{t-1}$$
(4)

Equation (4) forms the basis for our empirical analysis. The key parameter is the market resilience, $1/\omega$, which determines whether investors' irrational biases are contagious. As in MRR, we shall use a GMM methodology by setting:

where $u_t = P_t - P_{t-1} - \left(\theta + \frac{1}{\Lambda}\left(\frac{1}{\omega} - 1\right)\rho\right)x_t + \theta\rho x_{t-1}$

3. DATA

Rahudata was gathered from an online source from Jan 2004 to March 2010 for the city of Mumbai, where the NSE is situated. Information about Rahukalam is summarized in Table 1. The average duration is 90 minutes, although the exact duration varies by no more than 5-10 minutes. For 57% of the sample period, Rahu occurs before noon. For 13% of the period, Rahu overlaps with market open which occurs at 9.15 am. During 27% of the period, Rahu overlaps with close of trading which occurs at 3.30 pm.

We collect capital market data from 2004 to 2010 from NSE-DOTEX. The data includes tick-by-tick transactions for all the tickers listed on the NSE at any time during that time period. The total number of tickers is 1786. The trading data has price, volume, and a date and time stamp to the second; microseconds are not identified, so two transactions in the ticker that occurred microseconds apart carry the exact same timestamp. There is no quote data, and trading participants are not identified. Table 2 has details on the sample. We deleted firms which traded for less than 30 days in a year, leaving us with a sample of 1304 tickers. The data does not suffer from survivorship bias because the NSE archives the data by year. 286 firms had data for the seven-year period, but a large number of firms (183) had only one-year of trading data. We also report the percent of the sample with trading days that begin earlier than 10 am. For 260 firms, trading never started before 10 am, and only 124 firms experienced trading that began before 10 am. Figure 2 has more details on trading frequency. Roughly 45% of the sample traded for fewer than 20% of the total number of trading days in the sample, and only 7% traded every day of the sample period. In total, Table 2 indicates that most firms that are listed on the NSE are thinly traded.

We merge trading data for these 1304 tickers with the Rahu data. For each day and each ticker, we identify the pre-Rahu, Rahu and post-Rahu periods.

3.2 EMPIRICAL DESIGN

Numerous liquidity measures have been proposed, which are based on the contribution of a particular time period to the volume and return over an entire trading day. Barclay and Hendershott (2003) calculate a weighted price contribution to measure the amount of price discovery by trade. These measures are harder to interpret in this paper since the pre-Rahu, Rahu

and post-Rahu time periods are not uniform. Indeed, the Rahu period is roughly 90 minutes long, with the pre- and post-Rahu periods covering the rest of the trading day.

We propose two simple measures of volume. The first is the size of a trade calculated as:

size_i =
$$\frac{V_i}{number of \ trades_i}$$
 i=1,2,3 (6)

where V_i is the volume in the pre-Rahu (i=1), Rahu (i=2), and post-Rahu (i=3) periods. The second measure is the intensity of trading calculated as:

Trading intensity_i =
$$\frac{V_i}{length_i}$$
 i=1,2,3 (7)

where length_i is the length of the trading interval i. The informativeness of trading is an important aspect of liquidity. We use two measures common in the liquidity literature: the first is the signal-to-noise ratio (Barclay and Hendershott (2003) and Biais, Hillion and Spatt (1999)). Efficiency of price discovery is measured as the signal-to-noise ratio estimated from a regression of the form:

$$\mathbf{r} = \alpha_i + \beta_i \, \mathbf{r}_{ci} + \varepsilon_i \tag{8}$$

where r is the return from the close of trading on the previous day to the close of the trading on the current day, and r_{ci} is the return from the close of trading on the previous day to the end of the period i on the current day. The slope coefficient is the ratio of signal to signal plus noise in the return process. A beta coefficient less than 1 indicates noisy price discovery, while estimates close to 1 indicate efficient price discovery. The second measure of informativeness is the Amihud (2002) illiquidity measure. It is calculated as:

Illiquidity_i =
$$\frac{|r_i|}{v_i}$$
 i=1,2,3 (9)

where $|r_i|$ is the absolute return. It measures the price impact of a share. Higher values of the Amihud measure indicate a greater price impact, or lower liquidity. Other measures of informativeness such as Kyle's Lambda require more computing power, and will be estimated in the next version of this paper.

4. **RESULTS**

The results are in Table 3. As expected, the average length of the trading interval is the smallest during the Rahu period. Even though Table 1 indicated that the average length of the

Rahu is 91 minutes, the length of the trading interval is smaller since the Rahu can overlap with market open and market close. The pre-Rahu period is roughly 1.5 times the length of the post-Rahu period. There is a rough correspondence between the number of trades during each period and the length of the trading interval, in that the pre-Rahu period has the largest number of trades, and it is also the period with the longest trading interval. When the number of trades is divided into the length of the trading interval, the Rahu period has the fewest trades per minute of 7.13 trades at the mean, and 5.77 trades at the median. The pre- and post-Rahu periods have about the same number of trades per minute. Turning to the volume of trading in each interval, there is no statistical difference in the size of a trade: In each of the three periods, roughly 170,000 shares are traded per order. The intensity of trading, or the volume traded per minute, is lowest during Rahu, both at the mean and at the median. The F-test for statistical significance indicates the difference is significant at the 10% level. When liquidity of trading during each period is measured using the Amihud illiquidity measure, the Rahu period is the most illiquid of the three. The Amihud measure indicates that every 1000 shares during the Rahu period has a mean price impact of 0.18 INR, relative to a price impact of 0.09 INR in the pre-Rahu period, and 0.13 INR in the post-Rahu period. The difference in the Amihud measure is statistically significant. Finally, the signal-tonoise ratio estimated as the beta coefficient in the unbiasedness regression (equation 4) is the highest in the pre-Rahu period both at the mean and at the median. A beta close to 1 indicates efficient price discovery, which is the case in the pre-Rahu period. The Rahu period has the lowest beta both at the mean and at the median, indicating that price discovery is noisy during the Rahu period. Lower betas in the post-Rahu period relative to the pre-Rahu period indicate that price discovery is less efficient in the post-Rahu period.

Table 3 showed that liquidity is compromised during Rahu. The trading process described in Section 2 explains the result as due to the unwillingness of informed rational traders to trade during the Rahu for fear of alerting the market maker. In Table 4, we examine whether liquidity worsens when Rahu occurs towards market opening. Numerous studies have shown that the level of information asymmetry is highest at market open, which tapers down towards close (Kyle (1985), MRR (1997), Easley and O'Hara (1992)). We should expect that informed rational traders can conceal their information more effectively if they trade when Rahu occurs close to market open, than when Rahu falls towards close. Comparison of trades per interval, and intensity of trading across the two panels of Table 4 shows that trading is subdued when Rahu occurs in the afternoon. On average, there are only 4.48 trades during Rahu when Rahu falls in the afternoon compared to 10.12 trades when Rahu falls in the morning. It is not surprising then that the trading process is noisier when Rahu falls in the afternoon; the Amihud measure during Rahu is higher in Panel B than Panel A. Statistical significance of differences across the two panels are reported at the bottom of Panel B.

4.2 Effect of index inclusion

We examine the effect of index inclusion on trading during Rahu. We sort the sample on the basis of whether a stock belongs to the Nifty 50 stock index. The Nifty 50 is a 50-company, float-adjusted market-cap weighted stock index that represents about 66% of the free float market capitalization of the stocks listed on the NSE. It is used to benchmark fund portfolios, and for derivatives trading. For a stock to quality for inclusion in the Nifty 50, its market impact is required to be below 0.50%.² Foreign money managers are much more likely to trade stocks included in the index. These investors are expected to be immune to the Rahu superstition, so we expect the Rahu effect to be muted among stocks in the Nifty 50. The results are in Table 5. As expected, the number of trades, the size of a trade and the intensity of trading are about four times larger for the stocks in the index, than for stocks not in the index. The Rahu effect is much more muted for the index stocks. The number of trades per minute does fall to 40.01 during Rahu compared to 54.38 and 49.27 for pre- and post-Rahu periods, but the size of trade is higher at 82.42 during Rahu for the index stocks compared to 78.61 in the pre-Rahu period for these same stocks. But even among the indexed stocks, the intensity of trading falls in the Rahu period, coupled with a higher Amihud measure. The strongest case for a lack of a Rahu bias among indexed stocks comes from the signal-to-noise ratio which in magnitude is higher during the Rahu than during the other two periods, but is not significantly so. The non-indexed stocks are characterized by a signal-to-noise ratio well below 1.0 (0.70) and an Amihud measure of 0.20 INR per 1000 shares, both of which are significantly different from their corresponding values in the pre- and post-Rahu periods.

² Source: NSE website

4.3 Effect of underlying stock liquidity

It is difficult to parse whether the results on index inclusion can be attributed to foreign money managers who are presumably immune to the Rahu superstition or due to higher liquidity in indexed stocks. In this section, we separate the effect of liquidity by sorting the sample into twenty portfolios. Total volume of trading during the entire sample period is computed for each ticker in the sample. Stocks are separated into twenty portfolios on the basis of total volume into one of these twenty portfolios. Cross-sectional regressions are estimated with the portfolio ventiles. The dependent variables are the Amihud illiquidity measure, the signal-to-noise ratio, and the intensity of trading.

Table 6 has the results from an estimation of the cross-sectional regressions. As expected, the size of trade, and the intensity of trading are positively related to the volume ventile. The coefficients are statistically significant. The positive coefficients are consistent with greater liquidity being associated with larger volume of trading. The signal-to-noise ratio is positively related to the volume ventile in the pre-Rahu and Rahu periods, and is marginally related to the volume ventile in the post-Rahu period. The Amihud illiquidity measure is negatively related to the volume ventile, which is consistent with lower values of the Amihud measure indicating a lower price impact. We estimate two additional sets of regressions: in the first set, we calculate the difference of the independent variables between the pre-Rahu and Rahu periods. In the second set, we calculate the difference between the post-Rahu and Rahu periods. We regress the differences in each of the two sets on the volume ventile. The noteworthy results are the coefficients on the volume ventile for the Amihud measure and the signal-to-noise ratio. The coefficient on the Amihud measure is positive, which indicates that the difference between the pre-Rahu and Rahu measure is shrinking at higher volume ventile. The coefficient on the signal-tonoise ratio is negatively related to the volume ventile, indicating that the difference in the signalto-noise ratio between the pre-Rahu and Rahu periods shrinks for higher volume ventile. Both these results are consistent with the Rahu bias declining for the more liquid stocks. The same results hold when considering the difference in the Amihud measure and the signal-to-noise ratios between the post-Rahu and Rahu periods.

5. Conclusions

The results here are tentative evidence that irrational traders can compromise trading efficiency. Trading efficiency improves even in the presence of irrational traders when there is greater liquidity in the underlying stock. There are numerous studies which show that liquidity risk is a priced risk factor. The evidence in this paper suggests another channel through which liquidity reduces risk: greater liquidity reduces the vulnerability of a stock to irrational trading. Additional tests involve estimation of the GMM model to obtain critical parameters such as market resilience, and, autocorrelation of order flow.

REFERENCES

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets*, 5, 31-56.

Baker, M. and J. Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *The Journal of Finance*, 61(4), 1645-1680.

Barclay, M. J., and T. Hendershott, 2003, Price Discovery and Trading After Hours, *The Review* of *Financial Studies*, 16(4), 1041-1073.

Biais, B., Hillion, P., and C. Spatt, 1999, Price discovery and learning during the preopening period in the Paris Bourse, *Journal of Political Economy*, 107(6), 1218-1248.

Chordia, T., Roll, R., and A. Subrahmanyam, 2000, Commonality in Liquidity, *Journal of Financial Economics*, 56, lead article.

Chordia, T., Roll, R., and A. Subrahmanyam, 2008, Liquidity and Market Efficiency, *Journal of Financial Economics*, 87, lead article.

Chordia, T., Roll, R., and A. Subrahmanyam, 2002, Order imbalance, liquidity, and market returns, *Journal of Financial Economics*, 65, 111-130.

Easley, D., and M. O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance*, 47(2), 576-605.

Foucault, T., Kadan, O., and Kandel, E., 2005, Limit Order Book as a Market for Liquidity, *Review* of *Financial Studies*, 18(4), 1171-1217.

Glosten, L., and P. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed agents, *Journal of Financial Economics*, 14, 71-100.

Goyenko, R. Y., C. W. Holden, and C. A. Trzcinka, 2009, Do liquidity measures measure liquidity?, *Journal of Financial Economics*, 92, 153–181.

Hasbrouck, J., and D. J. Seppi, 2001, Common factors in prices, order flows, and liquidity, *Journal of Financial Economics*, 59(3), 383-411.

Hasbrouck, J., 2009, "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data," *The Journal of Finance*, 64, 1445–1477.

Kyle, A. S., 1985, Continuous Auctions and Insider Trading, Econometrica, 53(6), 1315-1336.

Madhavan, A., Richardson, M., and M. Roomans, 1997, Why Do Security Prices Change?, *Review of Financial Studies*, 10, 1035-64.

Rossu, I., 2008, A Dynamic Model of the Limit Order Book, *Review of Financial Studies*, 22(11), 4601-4641.

Shleifer, A., and R. Vishny, 1997, The Limits of Arbitrage, Journal of Finance, 52(1), 35-55.

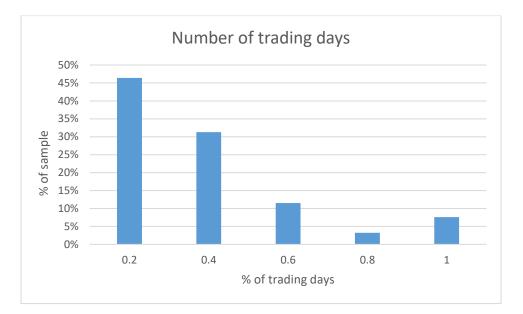
Table 1 The Rahu period

Average length of Rahu (in minutes)	91.067
Median length of Rahu	91.000
Maximum length of Rahu in the sample period	100
Minimum length of Rahu	82
Standard deviation of length of Rahu	5.976
When Rahu falls at market open	12.93%
When Rahu falls at market close	27.14%
When Rahu falls during morning trading (before noon)	57.15%
When Rahu falls during evening trading (after noon)	42.85%

Table 2Sample description

Total # of tickers	1786	# of tickers with starting before 1	•••
Total tickers in sample with more	1304	Exactly 0%	260
than 30 trading days in a year			
# of tickers with 1 year of data	183	0-1%	167
# of tickers with 2 years of data	225	1-5%	645
# of tickers with 3 years of data	277	5-10%	108
# of tickers with 4 years of data	188	>10%	124
# of tickers with 5 years of data	145		
# of tickers with > 5 years of data	286		

Figure 2 Trading frequency



	Before	During	After	F-test for equality of means across the three periods
Length of period t	199.10	76.67	136.80	0.001
	216.15	81.83	134.84	
# of trades in period t	1572.73	498.09	1090.22	0.001
	1483.10	464.65	933.02	
Trades per interval= # of trades in period	8.78	7.13	8.12	0.001
t/length of period t	7.85	5.76	7.26	
Size of trade =volume in period t/# of	184.58	190.85	195.02	0.514
trades in period t	168.62	179.36	181.03	
Intensity of trading = volume in period t	1099.54	1021.67	1026.27	0.066
/length of period t	915.79	740.38	907.93	
Amihud Illiquidity= absolute(return in	0.00009	0.00019	0.00013	0.001
period t)/volume in period t	0.00004	0.00009	0.00005	
Signal to noise ratio: The beta coefficient in the OLS regression: r = alpha_t + beta_i*r_t + epsilon_t, where r_t is the return from the close of after-hours	0.968	0.716	0.901	0.001
trading on the previous day to the end of period t on the current day, and r is the daily return from previous close to current close	0.992	0.813	0.984	

Table 3Trading activity around Rahu

Table 4Trading activity around Rahu sorted by time of day of Rahu

Panel A: Rahu occurs during AM trading session	l
--	---

	Before	During	After	F-test of equality
Length of period t	65.91	69.21	166.22	0.001
	61.82	79.32	170.34	
# of trades in period t	972.95	606.60	1327.63	0.001
	878.35	613.06	1289.83	
Trades per interval= # of trades in period	13.17	10.12	8.51	0.001
t/length of period t	12.33	8.41	7.69	
Size of trade =volume in period t/# of trades	188.61	181.43	189.04	0.840
in period t	162.04	163.65	173.33	
Intensity of trading = volume in period t	1686.13	1470.93	1019.17	0.001
/length of period t	1463.81	960.97	898.94	
Amihud Illiquidity= absolute(return in	0.00012	0.00018	0.00012	0.001
period t)/volume in period t	0.00006	0.00009	0.00005	

Panel B: Rahu occurs during PM trading session

	Before	During	After	F-test of equality
Length of period t	242.11	83.29	47.93	0.001
	242.49	83.72	54.28	
# of trades in period t	1766.40	401.57	373.17	0.001
	1779.17	403.01	389.39	
Trades per interval= # of trades in period	7.37	4.48	6.90	0.001
t/length of period t	6.77	4.39	6.22	
Size of trade =volume in period t/# of trades	183.28	199.22	213.09	0.020
in period t	169.37	189.10	199.70	
Intensity of trading = volume in period t	910.11	622.04	1047.95	0.001
/length of period t	785.41	592.10	948.07	
Amihud Illiquidity= absolute(return in	0.00008	0.00020	0.00016	0.001
period t)/volume in period t	0.00004	0.00010	0.00007	

Table 4 (continued)

Panel C: F-test for significance of difference between Rahu in the morning or in the afternoon

	F-test for equality of means
Length of period t	0.001
# of trades in period t	0.001
Trades per interval= # of trades in period t/length of period t	0.001
Size of trade =volume in period t/# of trades in period t	0.07
Intensity of trading = volume in period t /length of period t	0.001
Amihud Illiquidity= absolute (return in period t)/volume in	0.001
period t	

Table 5Sort on inclusion in Nifty 50 index

Panel	A:	Trading	measures
-------	----	---------	----------

	Pre-H	Rahu	Ra	lhu	Post-Rahu		
	Non-	Index	Non-	Index	Non-	Index	
	index		index		index		
Length of period t	198.61	211.74	76.40	83.36	136.38	148.03	
# of trades in period t	1248.33	9845.23	389.21	3155.95	860.85	6939.98	
Trades per interval	6.97	54.38	5.70	40.01	6.38	49.27	
Size of trade	188.72	78.61	196.41	82.42	200.30	85.19	
Intensity of trading	966.57	4362.64	922.54	3288.46	904.49	3931.46	
Amihud Illiquidity	0.00009	0.00000	0.00020	0.00001	0.00014	0.00000	
Signal to noise ratio:	0.967	1.01	0.70	1.21	0.90	1.01	

Panel B: F-tests for significance of means across periods and index inclusion

	F-test for equality	F-test for equality	F-test that
	across the three	of means across	index=non-index
	periods for non-	the three periods	
	index	for index	
Length of period t	n/a		N/A
# of trades in period t	0.001	0.001	0.001
Trades per interval	0.001	0.001	0.001
Size of trade	0.50	0.02	0.001
Intensity of trading	0.26	0.001	0.001
Amihud Illiquidity	0.001	0.001	0.001
Signal to noise ratio:	0.001	0.43	0.007

Table 6
Cross-sectional regressions

	soft=1			soft=2 soft=3				soft=1-2				soft3-2			
	intercept	Volume ventile	Adj Rsq	intercept	Volume ventile	Adj Rsq	mercept	Volume ventile		mercept	Volume ventile	Adj Rsq	intercept	Volume ventile	Adj Rsq
Size of trade	57.77	8.82	83.58	40.29	9.79	77.44	55.42	9.62	55.9	17.48	-0.97	-0.67	15.13	-0.17	-5.5
	5.41	9.89		2.79	8.14		2.41	5.01		1.4	-0.93		0.75	-0.1	
Intensity of trading	-847.03	130.79	24.88	-626.38	102.14	28.66	-675.66	110.8	25.68	-220.66	28.64	13.94	-49.28	8.65	4.4
	-1.46	2.7		-1.5	2.94		-1.4	2.75		-1.3	2.02		-0.65	1.37	
Amihud Illiquidity	0.001	-0.00006	49.88	0.002	-0.0001	54.99	0.001	-0.00005	50.77	-0.0008	0.00005	19.88	-0.0009	0.00005	45.38
	6.1	-4.46		7.06	-4.92		6.63	-4.54		-3.65	2.39		-5.77	4.1	
Signal to noise ratio	0.97	0.001	24.29	0.33	0.039	58.62	0.92	0.004	10.21	0.63	-0.037	55.56	0.61	-0.037	52.43
	144.74	2.6		3.61	5.15		31.84	1.78		6.69	-4.85		6.18	-4.56	