

Limits to arbitrage: The case of single stock futures and spot prices

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March 2015

Abstract

Market frictions such as transactions costs, funding constraints and short selling constraints limit arbitrage, but these frictions affect different stocks differently. Using intraday data on a liquid single stock futures and spot market, we examine the effect of these frictions on arbitrage efficiency of the two markets. We find evidence of significant cross-sectional variation in the size and asymmetry of no-arbitrage bands. To the extent that market frictions affect all stocks similarly, commonality in the size of no-arbitrage bands is expected. We find that 17% of variation in the size of no-arbitrage bands is explained by the first principal component. Changes in funding liquidity is a key factor that determines variation in the common component.

Keywords: Limits to arbitrage, Mispricing, No-arbitrage bands, Short-selling constraints, Transactions costs, Funding constraints

JEL Classification: G13, G14

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1 Introduction

“It is good for a scientific enterprise, as well as for a society, to have well-established laws. Physics has excellent laws, such as the law of gravity. What does economics have? The first law of economics is clearly the law of supply and demand, and a fine law it is. We would nominate as the second law “the law of one price,” hereafter simply the Law.”

– Lamont and Thaler (2003)

The law of one price is the basic building block of finance theory. It states that identical goods should trade at identical prices. If not, arbitrage opportunities emerge which bring back the prices to the same level. Theoretically, arbitrage requires no capital, involves no transactions costs and is riskfree. However, in reality, *limits* to arbitrage in the form of market frictions such as explicit (taxes, turnover charges) and implicit costs (liquidity costs), funding constraints, regulatory restrictions like short selling constraints exist (Shleifer and Vishny, 1997; Gromb and Vayanos, 2002). These factors collectively make arbitrage difficult and result in persistent deviations in the prices of similar goods. This results in no-arbitrage bands around the prices of the securities within which arbitrage is not profitable. Arbitrageurs enter the market only when the deviations are large enough to compensate them for the costs, that is, when the deviations are outside the no-arbitrage bands.

Substantial market microstructure literature has focused on identifying these market frictions and its impact on the arbitrage efficiency in the capital markets. The pair of securities examined include index futures and spot,¹ stock options and spot (Ofek *et al.*, 2004; Creemers and Weinbaum, 2010), and very recently, internationally cross-listed securities such as American depository receipts (ADRs), and their home-market security prices (Gagnon and Karolyi, 2010). Though perfect substitutes by themselves, these set of pairs suffer from various issues. For example, index futures and spot arbitrage suffers from stale price issues, difficulties in trading the entire basket of securities with appropriate weights at the same time (Miller *et al.*, 1994). Similarly, studies on cross-listed pairs face challenges related to asynchronous trading due to non-overlapping trading hours, complexities related to determining the full extent of transactions costs, regulatory restrictions on foreign ownership (Gagnon and Karolyi, 2010).

In contrast, single stock futures (SSF) and spot offer a clean setting to analyse arbitrage efficiency and eliminate issues related to index trading, estimation risk in options and cross-listed pairs of securities. Yet, not much empirical evidence exists regarding the arbitrage efficiency of these markets. A probable reason for this could be the illiquidity of the SSF

¹See (Cornell and French, 1983; Modest and Sundaresan, 1983; Figlewski, 1984; Mackinlay and Ramaswamy, 1988; Yadav and Pope, 1990; Klemkosky and Lee, 1991; Chung, 1991; Gay and Jung, 1999; Yadav *et al.*, 1994; Dwyer *et al.*, 1996; Martens *et al.*, 1998; Forbes *et al.*, 1999; Ackert and Tian, 2001; Tse, 2001; McMillan and Speight, 2006; Kim *et al.*, 2010).

markets world over. We fill this missing gap by analysing the arbitrage efficiency in a market with high liquidity on both the spot as well as the SSF market. Using intraday data over the period between March 2013 to August 2013 on 141 pairs of single stock futures and spot prices at the National Stock Exchange, India, we examine how market frictions shape-up the no-arbitrage bands on the spot and SSF prices, and how these bands vary with varying liquidity across stocks. Higher liquidity facilitates arbitrage by reducing costs (Roll *et al.*, 2007). Thus, the width of no-arbitrage bands for stocks with higher liquidity is expected to be smaller than that of the stocks with lower liquidity.

In addition, the presence of short selling constraints on the spot market adversely affect arbitrage on the negative side. Studies including Yadav *et al.* (1994), Dwyer *et al.* (1996), Brooks and Garrett (2002), Fung and Draper (1999), McMillan and Speight (2006) analyse index spot and futures prices and find that short selling constraints widen the no-arbitrage bands on the negative side due to higher costs involved in entering the spot position. Using data on options prices, Ofek *et al.* (2004) find that violations of put-call parity are asymmetric in the direction of short sales constraints, and their magnitudes are strongly related to the cost and difficulty of short selling. The recent research focusing on the 2008-09 short sales ban in the US market also finds an adverse impact of short selling on the equity markets. McMillan and Philip (2012) perform a cross-country analysis of the impact of short sales ban during 2008-09 on the index spot-futures efficiency. They find that the ban caused the basis to be lower than in the normal periods, with the speed of adjustment coming down. For single stocks, we expect short selling constraints to affect different stocks differently, depending on the ease with which the stocks can be borrowed.² Thus, we examine if the no-arbitrage bands exhibit an asymmetric behavior, and if there is cross-sectional variation in the asymmetry. Since it is relatively easier to borrow liquid stocks than the illiquid ones, we expect larger asymmetry in the bands for the illiquid stocks.

Using non-linear threshold autoregressive models, we find evidence of no-arbitrage bands around spot and SSF prices. When mispricing is positive, we find that the average upper threshold across all stocks is 3 basis points. This implies that when the SSF prices are overpriced than the spot prices to the extent of 3 basis points, arbitrageurs are unlikely to enter the market. On the negative side, that is, when spot is overpriced and SSF is underpriced, the threshold limit is much higher, at 15 basis points. This asymmetry in the upper and lower threshold can be explained by the short selling constraints that exist on the spot market. We also find significant cross-sectional variation in the size of the bands across stocks. The size of the no-arbitrage bands and asymmetry increases with decreasing liquidity of the stocks.

We next examine the commonality in the no-arbitrage bands across stocks. The evidence so far with regard to commonality relates to returns, trading activity, order flow, liquidity.³ We

²Factors determining the ease with which stocks can be borrowed include the percentage of stock available in the market as floating stock, stock liquidity (Nagel, 2005).

³See Fama and French (1995), Chordia *et al.* (2000), Huberman and Halka (2001), Lee *et al.* (2012), Karolyi *et al.* (2012).

hypothesise that frictions related to arbitrage activity is composed of two major components: frictions arising out of market factors such as taxes, market liquidity, market volatility, funding liquidity, and idiosyncratic factors related to the stock specific liquidity, returns volatility. To the extent that market frictions affect all stocks similarly, we expect a common factor in the no-arbitrage bands that can be attributed to the systematic component of trading frictions.

We further investigate the factors that drive the commonality, or the variation in the systematic factor. Changes in explicit trading costs, funding costs, microstructural variables such as liquidity, liquidity risk, stock volatility are the factors that are likely to drive the commonality. We examine the determinants of commonality using regression analysis.

Using principal component analysis, we find evidence of significant commonality in the size of the no-arbitrage bands across stocks. We find that about 34% of the variation in the size of no-arbitrage bands across stocks can be explained by the first three principal components, with the first factor explaining about 17% variation. We refer to the first factor as the systematic component. This finding links with the commonality literature which has so far focused on commonality in returns, liquidity, order flow, trading activity, and very recently, market efficiency (Rosch *et al.*, 2014).

The period of the analysis covers an interesting phase of tightening of funding liquidity in mid-July 2013. Due to an intense pressure on the exchange rate, the central bank of India, intervened in the money markets by raising the interest rates. This sudden and significant increment raised the funding costs for the traders and affected the arbitrage efficiency adversely. We find evidence that the day when the interest rates were raised, the systematic factor of the no-arbitrage bands went up significantly, indicating the worsening of arbitrage efficiency in the equity markets. Our regression results provide further evidence of how funding constraints are the most important factor in determining the arbitrage efficiency even for SSF and spot prices.

The regression results indicate that explicit factors such as taxes, microstructural factors like market liquidity and volatility play a significant role in explaining the variation in commonality of the size of no-arbitrage bands. We find that the factor that affects the commonality most significantly is funding constraints. More than 18% of variation in the systematic component of the no-arbitrage bands can be explained by funding constraints. This evidence is consistent with the recent literature that asserts that funding liquidity is a key factor in determining market liquidity and thus market efficiency (Brunnermeier and Pedersen, 2009; Gagnon and Karolyi, 2010; Rosch *et al.*, 2014).

The rest of the paper is organised as follows: Section 2 describes the market structure at NSE, Section 3 explains data and variables used in the analysis. Section 4 documents evidence on the presence of no-arbitrage bands and cross-sectional variation in bandsize and asymmetry. Section 5 discusses the results of principal component analysis providing evidence of commonality in the size of no-arbitrage bands. Section 6 examines the factors that determine the variation in commonality. Section 7 concludes.

2 Market structure

This paper focuses on the equity spot and the futures market of the National Stock Exchange, India (NSE). In contrast to the global markets, NSE has a unique setting where both, the spot and the futures market trade at the same platform. Thus, there are no issues related to time asynchronicity. Unlike the single stock futures market around the world, these contracts are actively traded on the NSE platform, making it one of the top five exchanges in the world that trades single stock futures.⁴ Some of the unique market features at NSE are described below:

Trading Trading on both the spot and the futures market is done through a fully automated electronic limit order book time with orders executed on a price-time priority basis. In addition to NSE, Bombay Stock Exchange is another major stock exchange that offers equity spot and futures trading. However, majority of volumes on both the markets are concentrated on the NSE.

The current trading hours are between 9:00 am to 3:30 pm. Trading begins through a call auction market which starts at 9:00 am and continues until 9:15 am. From 9:15 am onwards, the markets enter the continuous trading system.

Out of about 1500 securities that are listed and traded on the NSE equity spot segment, only about 141 securities are traded on the derivatives market during the period of study. The selection of the securities to be traded on derivatives segment is made on the basis of liquidity of the contract. The futures contracts are one-month, two-month and three-month contracts. As in other global markets, most of the trading is concentrated in the near-month contracts. The tick size on both the spot and the SSF market is 5 paise (5%).

Short selling constraints and the SLB scheme Short selling is not permitted on the equity spot market. To enable traders to lend and borrow securities, Security Lending and Borrowing Scheme (SLBS) was introduced by the NSE in April 2008.⁵ Just as the spot and futures market, this platform enables lending and borrowing of stocks through an anonymous automated screen based mechanism with order matching done on price time priority. However, the activity on the SLB scheme has remained relatively low.⁶

Trading costs Trading involves explicit costs that the traders are charged upfront, such as brokerage, transaction charges, securities transaction tax (STT), and implicit costs that the trader faces as liquidity costs of trading.

Table 1 gives a summary of the explicit transaction costs that a trader faces while trading on equity markets in India. In addition to the costs mentioned in the table, the trader is charged a brokerage fee which varies as per the turnover. Service tax of 12.36% is charged on the brokerage and transaction charges.

Clearing and Settlement Settlement on the spot market is conducted on a $T + 2$ basis and on a $T + 1$ basis for the SSF market. The SSF are cash settled instead of physically settled.

⁴<http://www.world-exchanges.org>

⁵See www.nseindia.com/products/content/equities/slbs/slbs_trades_archives.htm

⁶See Suvanam and Jalan (2012), Grover (2014).

Table 1 Summary of explicit costs of trading

Summary of explicit transaction charges a trader faces on trading in the Indian equity markets in 2013. All charges are charged as a percentage of total turnover.

Charges	Equity Delivery	Equity Intra-day	Futures
Securities Transactions Tax (STT)	0.100 %	0.025% only on sell-side trade	0.017% (upto May 31, 2013) 0.010 % (w.e.f Jun 1, 2013) only on sell-side trade
NSE Transactions Charges	0.0035%	0.0035%	0.002%
SEBI Turnover Charges	NIL	NIL	0.0002%
Stamp Duty	0.01%	0.002%	0.002%

Unlike most other global markets, traders pay daily margins on both the spot as well as the SSF positions.

3 Data and market variables

3.1 Data details

The analysis uses intraday limit order book data from March 1, 2013 to August 31, 2013 (120 trading days) for all the 141 stocks traded on the derivatives segment of the NSE. The data are obtained from the exchange and comprise of price and quantity information up to twenty best bid and ask quotes. We use near month SSF data, and rollover to the next contract two days prior expiration. One-month Mumbai Inter-Bank Offer Rate (MIBOR) is used as a proxy to capture the interest rate borne by the traders to borrow from the market. MIBOR is a benchmark reference rate for the deals in the money market. It is disseminated jointly by the Fixed Income Money Market and Derivatives Association of India (FIMMDA) and NSE. In order to derive it, market participants are polled regarding their expectations of the interest rates, and an average is taken after segregating the noise.

The period of study covers an interesting phase of tightness in funding liquidity. In mid-2013, the Indian Rupee experienced significant volatility as a result of expectations of a tapering of quantitative easing by the Federal Reserve Bank, US. The Indian currency depreciated by about 17% in the period between May 15, 2013 to August 20, 2013. As a result, the central bank of India undertook several measures to counter the significant currency depreciation.⁷ On July 15, 2013, the central bank indirectly intervened in the money markets by increasing

⁷See Shah (2013).

the interest rates and constraining the funds available under the liquidity adjustment facility.⁸ These actions had a sharp impact on the short term interest rates, with MIBOR increasing from 7.88% on July 15, 2013 to 9.23% on July 16, 2013. This tightening in the interest rates provides an interesting event to analyse how changes in funding liquidity impacts traders and thus the arbitrage efficiency of the markets.

In addition, the period also saw a microstructural change, in terms of a relaxation in the securities transactions tax (STT) paid by the traders on the futures market. Beginning July 1, 2013, the STT was reduced from 1.7 bps⁹ to 1 bps.

Table 2 provides descriptive statistics of the sample used in the analysis. Average statistics for the entire sample as well sub-samples based on liquidity costs are indicated. We use the sum of the roundtrip bid-ask spreads on the spot and the SSF segment as a proxy to capture liquidity costs for arbitrage.

Table 2 Sample characteristics

The table provides average daily descriptive statistics of the sample of stocks analysed in the study. The statistics are presented for the full sample as well as sub-samples based on liquidity quartiles. The daily values of each variable is first averaged across all days for a stock, then an average across all stocks in a set is taken. Number of trades are reported only for the spot market. Q1 indicates the set of most liquid stocks, while Q4 indicates the set of least liquid stocks.

Liquidity quartiles	Market Cap	Price	# of trades	Traded value	
	(Rs.)	(Rs.)		Spot (Rs. Million)	SSF
All	330,121	579.74	27,116	573	1,022
Q1 (Most)	837,658	828.13	55,879	1,491	2,635
Q2	295,613	614.79	25,793	422	770
Q3	81,306	226.89	16,436	208	392
Q4 (Least)	76,066	625.57	8,853	117	196

We next discuss the measurement of variables used in the analysis.

3.2 Market variables

Basis (z_t) : We measure basis as the deviation of the observed futures price from the theoretical futures price as derived from the simple cost of carry model. It is computed as:

$$z_{i,t} = \frac{F_{i,t} - S_{i,t} \times \exp(r_t - d_t)(T - t)}{S_{i,t}}$$

⁸See: RBI Press Release, July 15, 2013 http://www.rbi.org.in/scripts/BS_PressReleaseDisplay.aspx?prid=29086.

⁹'bps' stands for basis points. 100 bps = 1%.

where $F_{i,t}$ is the midquote¹⁰ price of futures for stock i at time t , $S_{i,t}$ is the spot midquote price for stock i at time t , r_t is the risk-free rate for lending and borrowing over the remaining life of the contract $(T - t)$, and d_t is the dividend yield over the contract lifetime. We use MIBOR as the risk-free rate.¹¹

Basis risk (σ_z) : Basis risk captures the variability in the basis. Higher basis risk induces greater risk in the arbitrage position. We capture basis risk as the standard deviation of basis in a five minutes interval.

Liquidity costs (LiqCosts) : Beyond the explicit costs, an arbitrageur faces liquidity costs in the form of price impact. In a cash-and-carry arbitrage (when z_t is positive), the arbitrageur incurs liquidity costs in buying spot and selling futures, and then reversing both the positions whether before expiry or at expiry. Similarly for the reverse-cash-and-carry arbitrage (when z_t is negative). We use the sum of quoted bid-ask spread on the spot and the SSF market as a proxy to capture the round-trip liquidity costs incurred in undertaking an arbitrage position.

Liquidity risk (σ_{liq}) : Just as basis risk, to capture variation in liquidity, we compute the standard deviation of quoted spread within every five minutes interval. This is done separately for the spot and the SSF market.

Stock volatility (σ_r) : We capture intraday volatility of the stock as the standard deviation of returns within a five minutes interval for the spot as well as the SSF market.

Barring the basis, higher values of each measure described above make arbitrage risky and costly, which deter the arbitrageur from undertaking an arbitrage position. This results in the basis (or the mispricing error) to be persistent for longer periods of time. Each measure is computed at a 1-second frequency for each stock each day. The median value within the day is used as the value for the day.¹²

Table 3 reports the summary statistics of market variables described above for the sample as well as sub-samples based on liquidity costs. The table shows that for all stocks in the sample, as well as across all liquidity quartiles, the median value of basis is *negative*. The negative value is indicative of the effect of the short sales constraints that are prevalent on the spot market. A positive basis can be corrected by selling SSF and buying spot. However, a negative basis requires selling of spot and buying futures, which requires an active securities lending market. The absence of an active securities lending and borrowing market in India makes it difficult for arbitrageurs to borrow shares on the spot, and correct the mispricing (Suvanam and Jalan, 2012; Grover, 2014).

The table also indicates the variability in the basis, captured by basis risk. Higher is the basis risk, higher is the risk associated in undertaking an arbitrage position. As we move

¹⁰Midquote price is the average of the bid and the ask price.

¹¹We do not account for dividend yield in the computation of basis. Miller *et al.* (1994) argue that since stocks go ex-dividend overnight, if overnight price changes are excluded, the effect of dividend is completely removed. In the analysis, we use intraday values of the basis at one second frequency.

¹²All risk measures ($\sigma_z, \sigma_{liq}, \sigma_r$) are annualised by multiplying the daily value by $\sqrt{252}$.

Table 3 Sample summary statistics of market variables

The table reports summary statistics of market variables for full sample as well as sub-sample of stocks based on liquidity costs quartiles. For each stock each day, we compute these values at one second level, and then take the median value for the day. We average these values across all days for a stock, and then average across all stocks. Liquidity costs (LiqCosts) are the roundtrip costs incurred on the SSF and spot market proxied by quoted spread. Basis (z_t) and liquidity costs (LiqCosts) are indicated as % of midquote price. All risk measures captured by $\sigma_r, \sigma_z, \sigma_{liq}$ are annualised values.

Liquidity quartiles	# of stocks	z_t	σ_z	LiqCosts	<i>All values in %</i>			
					σ_{liq}		σ_r	
					Spot	SSF	Spot	SSF
All	141	-0.06	1.43	0.18	0.48	0.32	34.6	44.9
Q1 (Most)	37	-0.07	0.95	0.09	0.32	0.16	29.3	36.4
Q2	34	-0.07	1.27	0.16	0.48	0.32	33.7	40.7
Q3	34	-0.04	1.59	0.24	0.64	0.48	38.8	51.1
Q4 (Least)	36	-0.03	1.90	0.33	1.11	0.69	39.0	53.1

away from the most liquid to the less liquid securities, basis risk increases, raising the risk in the arbitrage position, thus, reducing the incentive for arbitrageurs to correct the mispricing.

The next column in the table indicates the roundtrip liquidity costs incurred by the arbitrageur to undertake two positions. There is significant variation in the liquidity costs across sub samples as proxied by roundtrip bid-ask spread. For the most liquid stocks, liquidity costs are at an average 9 bps, while that for the least liquid is 33 bps. Also, it turns out that liquidity risk is higher on the spot market than on the SSF market. The last two column indicate the returns volatility on the spot and the SSF market. As expected, returns volatility is higher for illiquid stocks than the liquid stocks. We also observe significant difference in the variance of returns on the spot and the SSF market for stocks in the least liquid quartile.

4 Market frictions and the no-arbitrage bands

In perfect markets with no market frictions, the value of z_t is expected to be zero. However, in reality, market frictions exist, and cause z_t to be a non-zero value. These frictions include: transactions costs, short selling constraints and funding constraints.

Transactions costs include explicit and implicit costs that are incurred when positions are opened or closed (Modest and Sundaresan, 1983; Yadav and Pope, 1990; Brenner *et al.*, 1990). Explicit costs include brokerage fees, commissions, and taxes that are levied upfront. Implicit costs are liquidity costs captured by bid-ask spread, market impact and vary dynamically. Though the explicit costs are common across all stocks, the implicit costs can differ depending upon the stock (il)liquidity. Higher are these costs, higher is the deviation which may not

get corrected by arbitrageur.

Short selling constraints are regulatory constraints which prohibit the arbitrageur from naked shorting of the stock on the spot market. These constraints require the arbitrageur to borrow the stock from the market which imposes search costs on him. If the stock is limited in supply, or lending is limited, the cost of borrowing it increases (DAvolio, 2002; Ofek *et al.*, 2004). Besides, there is also a risk of early re-call of the stock by the lender.

While the transactions costs have a symmetric impact on the positive as well as negative deviations, short selling constraints have impact only on the negative deviations, by making reverse-cash-and-carry arbitrage difficult.

In addition to the transactions costs and short selling constraints, there are funding constraints. Unlike in the perfect world, taking arbitrage positions requires capital. If access to capital becomes difficult in the form of higher fund raising costs, arbitrageurs may not be able to enter the market and correct the mispricing (Shleifer and Vishny, 1997; Gromb and Vayanos, 2002). Thus, higher funding constraints increase the size of deviation which may persist for longer periods of time.

The market frictions described above collectively make arbitrage risky¹³ and costly. Opportunities for arbitrage arise only when z_t is large enough to compensate for costs arising out of these frictions. That is, when

$$|z_t| \geq C$$

where C represents the costs beyond which expected returns from an arbitrage position is higher than the expected costs. Thus, C constitutes an imaginary no-arbitrage bands that get created around the theoretical futures price within which arbitrage is not profitable. C can be asymmetric due to market frictions such as short selling constraints. Our first focus is to determine the no-arbitrage bands for the sample of stocks analysed in this study.

While some of the market frictions noted above can be observed directly (e.g explicit costs such as taxes), others such as the implicit costs, effect of short selling constraints cannot be observed directly. This motivates the need for an econometric approach to estimate the upper and the lower thresholds within which arbitrage is not profitable. We follow Yadav *et al.* (1994) and use a three-regime threshold autoregressive (TAR) model to estimate these bands. Several subsequent studies including Dwyer *et al.* (1996), Martens *et al.* (1998), Kim *et al.* (2010) use the same approach. Even though these models allow for multiple regime TAR models, we constrain this exercise to a three-regime model. Multiple regimes in no-arbitrage bands can be expected because different arbitrageurs may face different costs, especially in the case of constrained arbitrage capital. Forbes *et al.* (1999) however argue that arbitrage is undertaken by large sophisticated financial institutions, and it is less likely that these institutions will leave opportunities for less equipped arbitrageurs. Besides, the upper and the lower thresholds immediately outside the no-arbitrage bands indicate the minimum level of costs faced by the arbitrageurs.

¹³High variation in stock liquidity and high stock volatility increase the riskiness of the arbitrage position

The three regime TAR model on the basis is given as:

$$\begin{aligned} z_t &= \phi_0^{(1)} + \sum_{i=1}^p \phi_i^{(1)} z_{t-i} + \epsilon_t^{(1)} & z_{t-d} \leq C_1 \\ z_t &= \phi_0^{(2)} + \sum_{i=1}^p \phi_i^{(2)} z_{t-i} + \epsilon_t^{(2)} & C_1 \leq z_{t-d} \leq C_2 \\ z_t &= \phi_0^{(3)} + \sum_{i=1}^p \phi_i^{(3)} z_{t-i} + \epsilon_t^{(3)} & z_{t-d} > C_2 \end{aligned}$$

where, i indicates the lag structure to be imposed on z_t , C_1 is the lower threshold when z_t is negative, while C_2 is the upper threshold when z_t is positive. Arbitrage opportunities emerge only when z_t exceeds either C_1 or C_2 . ‘d’ is the delay parameter. It determines the lag with which arbitrageurs enter the market. ϵ_t^j is i.i.d $(0, \sigma^{(j)2})$, j indicates the upper ($z_{t-d} \leq C_1$), middle ($C_1 \leq z_{t-d} \leq C_2$) or the lower regime ($z_{t-d} > C_2$).

If arbitrageurs enter the market, the next observations of z_t will move rapidly towards zero. However, when the absolute value of z_t is small, arbitrage will not be profitable and z_t may not change much (Martens *et al.* (1998)). Thus, in the upper and the lower regime, z_t is expected to follow a stationary process, while in the middle regime, it may follow a non-stationary process.¹⁴

We estimate the model on each stock each day using 1-second frequency data. We use Akaike Information Criterion (AIC) to determine the lag length. We also need to select the set of delay parameters, S , to be used in the model estimation. Since different stocks have different liquidity costs, the delay parameter is expected to differ across stocks. We use a variety of values for delay parameters, $S = 1, 5, 15, 20, 30, 45, 60, 75, 100, 120, 140, 160, 180, 240, 300$ and then pick the model which meets the stationarity condition as well as has the minimum AIC value.¹⁵ Since a minimum percentage of observations are expected to be in the no-arbitrage regime, we constrain a minimum percentage of such observations to 40%.¹⁶ The difference between the estimated upper and the lower threshold constitutes the size of the no-arbitrage band, or the *bandwidth* (bw).

Table 4 presents the estimates of the upper and lower thresholds obtained from the estimation of the TAR model for the full sample as well as sub-samples based on liquidity costs quartiles. The reported values are the mean and median values of the lower and upper threshold across stocks (obtained after an averaging on all the dates for each stock). The table shows that on an average, the lower threshold is 15 bps away from the midquote price when the basis is negative, and upper threshold is 3 bps higher than the midquote price. The size of the no arbitrage band (or the bandwidth), thus, on an average is 18 bps. The *asymmetry* in the estimated upper and lower threshold reflects the effect of the short selling constraints in the

¹⁴For z_t to be stationary, the sum of the coefficients (ϕ_i^j) in the upper and the lower regime should strictly be less than 1.

¹⁵In some cases, we find that the basis is negative (positive) for the entire day. In that case, the model estimates both the thresholds as negative (positive) values. In such cases, we constrain the upper (lower) threshold as zero, and use the regime from zero to the upper (lower) threshold obtained from model estimation as the no-arbitrage zone.

¹⁶We repeat the exercise by changing this to 30%, 50%, but it does not have any impact on the results

Table 4 Estimated no-arbitrage bands from TAR model

The table presents the estimated values of the upper and the lower thresholds obtained from the estimation of a three-regime TAR model for all stocks in the sample. Quartiles are based on liquidity costs as defined in Section 3.2. For each stock, we first estimate the threshold values for each day, and then take an average across all days.

Liquidity quartiles	Lower threshold				Upper threshold			
	Mean	SD	Median	MAD	Mean	SD	Median	MAD
All	-0.15	0.16	-0.12	0.04	0.03	0.04	0.02	0.04
Q1 (Most)	-0.13	0.09	-0.11	0.04	0.01	0.01	0.00	0.00
Q2	-0.14	0.09	-0.12	0.06	0.02	0.02	0.01	0.01
Q3	-0.18	0.27	-0.12	0.03	0.04	0.03	0.04	0.03
Q4 (Least)	-0.15	0.11	-0.13	0.04	0.07	0.06	0.04	0.05

market. These constraints increase the costs for the arbitrageur resulting in the deviation persisting for longer periods of time when spot is overpriced and futures is underpriced.

Across liquidity quartiles, the table indicates a significant cross-sectional variation in the upper as well as the lower threshold. The size of the bandwidth increases as we move from the most liquid to the least liquid stocks, consistent with the hypothesis that higher liquidity costs raise the transactions costs of arbitrageurs. For the most liquid stocks, the upper threshold is zero, indicating not much obstruction due to liquidity and explicit costs. The lower threshold is negative and significantly different from zero, once again indicating the impact of short selling constraints. For the least liquid quartile, we see that both the upper and the lower thresholds are large, but continue to be asymmetric in nature. The average value of the lower threshold is 15 bps away from the midquote price (when the basis is negative), while the upper threshold is 7 bps when basis is positive.

We compare the size of the no-arbitrage bands with the proxy for liquidity costs: the sum of the roundtrip bid ask spread on the spot and the SSF market shown in Table 3. We observe that only for Q1 and Q2, the estimated bands completely capture the liquidity costs, not so much for Q3 and Q4. We, however, do not put much emphasis on this mismatch since each of these measures are averages of averages, and these costs fluctuate significantly on an intra-day basis.

5 Commonality in no-arbitrage bands

In the previous section, we estimated the no-arbitrage bands constituted by the costs (C) due to market frictions. Market frictions are however likely to impact different stocks differently (Nagel, 2005). For example, stocks with higher liquidity are expected to have lower width of no-arbitrage bands, in comparison to stocks with lower liquidity. Similarly, higher levels

of liquidity risk on a stock make arbitrage risky, and reduce the incentive for arbitrageurs to enter the market. These stock-specific factors cause significant cross-sectional variation in the size of no-arbitrage bands.

However, to the extent that these factors affect all stocks similarly, some commonality in no-arbitrage bands is expected. Just as common factors such as market volatility, market return and market liquidity affect the systematic liquidity and systematic risk of firm's returns (Kamara *et al.*, 2008),¹⁷ these factors also result in a commonality in the no-arbitrage bands. This commonality is the systematic component in the size of bands which is non-diversifiable. Thus, we conjecture that the size of the no-arbitrage bands is determined by C , which in turn can be decomposed as

$$C = C_s + C_i$$

where C_s represents the systematic component, while C_i represents the idiosyncratic component.

In this section, we examine if such commonality (or the systematic component) exists in no-arbitrage bands on the SSF and the spot market. We investigate the commonality by using principal component analysis (PCA) as proposed by Hasbrouck and Seppi (2001).¹⁸ The technique uses linear combinations of the original variables (example, cross-sectional data of no-arbitrage bands in our case) to explain the variance-covariance structure of the underlying data. The linear combinations are chosen to maximise the explanatory power, with the first linear combination having the maximum explanatory power.

Let $x_{i,t}$ be a variable observed for security i at time t . In our case, $x_{i,t}$ represents the no-arbitrage band. For N securities and T periods, let X_1, X_2, \dots, X_N be vectors of length T such that $X_i^T = [x_{i,1}, x_{i,2}, \dots, x_{i,N}]$, let X be the matrix $[X_1, X_2, \dots, X_N]$, and let Σ be the covariance matrix of X . A combination such as:

$$Y_j = \gamma_j^T X = \gamma_{1,j}X_1 + \gamma_{2,j}X_2 + \dots + \gamma_{N,j}X_N$$

represents one of the linear combinations that could represent one common factor Y_j . The variance of Y_j is defined as $\gamma_j^T \Sigma \gamma_j$.

If γ_j maximises the variance of Y_j , then Y_j is referred as the first principal component. The second component is the linear combination that maximises the variance of Y_j subject to the condition that it is uncorrelated with the first principal component. There can be as many as N principal components extracted in this manner, conditional on each being uncorrelated with all previously extracted principal components (Corwin and Lipson, 2011).

¹⁷Kamara *et al.* (2008) argue that the common factors capture the market conditions that affect the supply of liquidity of market makers and produce correlated trading by investors.

¹⁸Subsequent studies including Corwin and Lipson (2011), Lee *et al.* (2012) also followed this technique to extract common components from microstructural variables such as order flow, trading volumes.

In terms of eigenvalues and eigenvectors, the variance of the first principal component, $\lambda_1 = \text{Var}(Y_1)$, equals the first eigenvalue of Σ and the coefficient vector, γ_1 , equals the first eigenvector. Similar notation can be used for each of the N principal components. Eigenvalues are used to determine the strength of the commonality, and individual security loadings of the eigenvector are used as a means of interpreting the common component.

Hasbrouck and Seppi (2001) suggest standardizing all the variables of the underlying data to unit variances while performing principal component analysis. In our analysis, this is not a concern since, the elements of $X_{i,t}$ only represent the no-arbitrage bands for different stocks, and are therefore consistent in units. We still standardize all the values for each stock to zero mean and unit variance.¹⁹

After standardization, total variation in X equals the number of original variables (the number of stocks in our context). Thus, the proportion of total variation explained by the j^{th} principal component equals:

$$\frac{\lambda_j}{\lambda_1 + \lambda_2 + \dots + \lambda_N} = \frac{\lambda_j}{N}$$

Conditional on the first component explaining a significant variation in the underlying data, we propose to use the first component as the systematic component of the no-arbitrage bands.

We perform PCA on the no-arbitrage bands estimated for all the 141 stocks. We find that the first three components explain about 37% of total variation in the no-arbitrage bands across stocks, with the first component explaining 17% variation. The second and third components explain 11% and 8% variation respectively. This provides evidence of commonality in the size of the no-arbitrage bands.

Economic interpretation of the first component of bandwidth

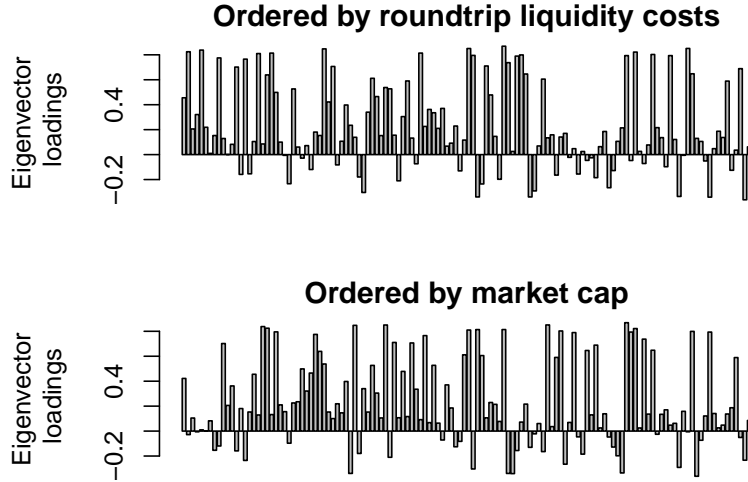
We examine the loadings allocated to different stocks in the first principal component to draw inferences on economic interpretation of this factor. Figure 1 plots the loadings of the first component. The two plots show the loadings on stocks sorted by liquidity costs (in ascending order) and market capitalisation (in descending order). While we see that for most of the stocks the loadings are positive, there does not emerge any clear pattern in weights allocation in terms of market capitalisation or liquidity costs.

We use the first component as the component reflecting the systematic factor in the no-arbitrage bands. We derive it by multiplying the matrix of stock-wise bandwidth with the vector of the loadings attached to each stock. Figure 2 plots the time-series of the first component. The higher values of the measure indicates a worsening of the arbitrage efficiency in the market, reflected by wider size of the bands. We observe a significant surge in the size

¹⁹We do not find any difference in the results without standardization.

Figure 1 Eigenvector of the first component from PCA on bandwidth

The figure plots the eigenvector loading on stocks from the first principal component for no-arbitrage bands. The first plot shows the loadings on stocks sorted by increasing liquidity costs, while the second plot shows the loadings on stocks sorted by decreasing market capitalisation.



of bands in mid-July when the Reserve Bank of India intervened in the money markets by raising interest rates to contain the exchange rate volatility.²⁰

6 Determinants of variation in the systematic component

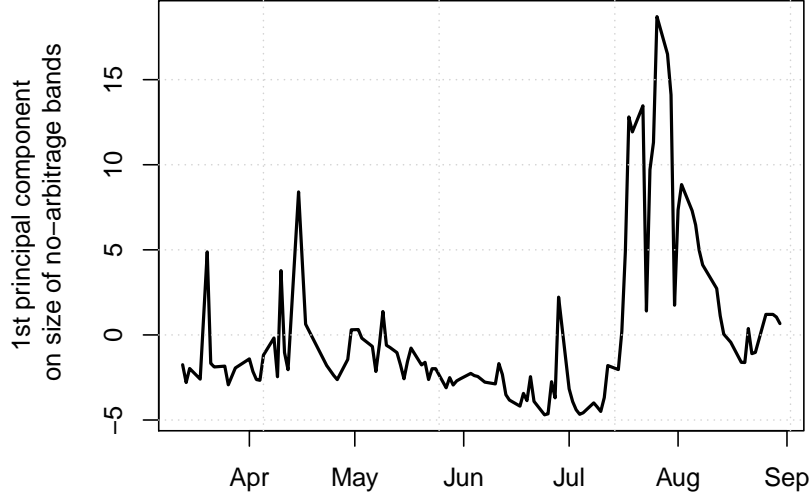
Given the evidence of commonality in no-arbitrage bands, we now turn to examining its sources. We describe the factors that may affect the systematic component below:

1. Funding liquidity: Brunnermeier and Pedersen (2009) argue that the ease with which an asset is traded depends on the ease with which traders can obtain funding. Higher fund raising costs affect traders adversely by increasing the inventory carrying costs for market makers, and cost of capital for arbitrageurs (Shleifer and Vishny, 1997; Gagnon and Karolyi, 2010; Rosch *et al.*, 2014). Tightness in funding liquidity not only affects the market liquidity (Rosch and Kaserer, 2013; Hu *et al.*, 2013), but also the arbitrage activity in the market. Thus, fluctuations in the cost of accessing capital is likely to have an impact on the systematic component of the size of the no-arbitrage bands. As described earlier, we use MIBOR to capture tightness in funding liquidity.

²⁰See Section 3.1 for more details on the intervention.

Figure 2 Systematic factor for no-arbitrage bands

The figure plots the daily time series of the systematic factor for no-arbitrage bands derived from principal component analysis on all stocks for the period between March 1, 2013 to Aug 31, 2013.



2. Market variables: The systematic component of no-arbitrage bands is also expected to be affected by aggregate market variables such as market liquidity (Liq_m), market liquidity risk ($LiqRisk_m$), and market volatility (Vol_m). Higher market volatility increases the risk of maintaining inventory which puts an upward pressure on spreads that market makers charge (Chordia *et al.*, 2000). The commonality in these market variables constitute the non-diversifiable risk making arbitrage risky. We use the aggregate market values of each of these variables as possible sources of variation in the systematic component.

To derive the aggregate market component of each of these market variables, we follow two approaches: One, we use equally weighted average of each of these variables across all stocks (as followed in Chordia *et al.* (2000) as measure of market liquidity). As a second approach, we conduct a PCA on the standardized values of each of these measures and use their first component as the market component.

3. Explicit costs such as change in taxes: To the extent that the values of explicit costs (see Table 1) are constant during the period, the explicit costs get accounted by the mean of the systematic component. However, the period under study also saw a reduction in the STT on the derivatives market. We account for that by including a dummy in our regression framework.

We use these variables in a regression setup to determine the extent to which they affect the systematic component.

6.1 Univariate analysis

We estimate the following regression using each factor conjectured as a possible source of variation in the bands:

$$P_t^{BW} = \alpha + \beta_0 \times Factor_t + \beta_1 \times Dummy_t + \epsilon_t \quad (1)$$

where P_t^{BW} denotes the first principal component (or the systematic factor) on the size of the no-arbitrage bands (or the bandwidth) on day 't'; $Factor_t \in (\text{MIBOR}, \text{Liq}_m, \text{Vol}_m, \text{LiqRisk}_m)$; $Dummy_t$ accounts for STT reduction during the period of analysis. It takes value 1 for days after May 31, 2013, 0 otherwise.

Table 5 presents regression estimates of Equation 1 with each factor in one model. Panel A shows regression results with equally weighted average market variables such as liquidity, liquidity risk and volatility as market outcomes.²¹ We find a positive and significant association of liquidity, liquidity risk and stock volatility with the systematic component. A one standard deviation increase in market (il)liquidity brings about 23.5 standard deviation increase in the size of the bands. Similarly, higher levels of liquidity risk and price risk have an adverse impact on market efficiency by widening the size of the systematic component of the bands. The dummy variable turns out to be negative and significant, indicating that a decline in STT in June 2013 improved market efficiency by bringing down the size of the bands. However, it should be noted that a regression with only the dummy variable by itself had a negligible explanatory power.

Panel B reports the regression results with market values computed using the first principal component of each of the market variables.²² The findings based on the first component are similar to the findings from the equally weighted average of each market variable measure. The R^2 using each of these market variable related measures range between 4-10%.

The last panel of Table 5 indicates the regression results with MIBOR as the explanatory variable. We find a positive and significant relation between MIBOR and the systematic component of no-arbitrage bands. A 1 standard deviation increase in MIBOR results in 1.22 standard deviation increase in the size of the systematic component of the bands. The R^2 also turns out to be 18% indicating MIBOR has a significant explanatory power in determining the size of the bands.

²¹We derive the market-based value of these measures by taking an equally weighted average of each of these measures across all stocks.

²²Appendix A describes the principal component analysis results on each variable in detail.

Table 5 Regression results on systematic component of bandwidth

The table reports regression estimates for the equation:

$$P_t^{BW} = \alpha + \beta_0 \times Factor_t + \beta_1 \times Dummy_t + \epsilon_t$$

where P_t^{BW} denotes the first principal component (or the systematic factor) on the size of the no-arbitrage bands (or the bandwidth) on day ‘t’; $Factor_t \in (MIBOR, Liq_m, Vol_m, LiqRisk_m)$; $Dummy_t$ accounts for STT reduction during the period of analysis. It takes value 1 for days after May 31, 2013, 0 otherwise. Panel A indicates the results based on equally weighted average of each market variable across all stocks. Panel B indicates the regression results based on the first principal component of each market variable. Panel C reports the regression results with funding constraints as the explanatory variable in the regression. The regression estimates are robust to the outliers in the data. The values in parenthesis indicate the t-statistic of the estimated coefficient.

<i>Factor</i>	β_0	β_1	R^2	# of obs.
Panel A				
<i>Liq_m</i>	22.28 (2.27)	-0.91 (-1.87)	0.04	113
<i>LiqRisk_m</i>	97.34 (1.89)	-0.63 (-1.27)	0.04	113
<i>Vol_m</i>	0.10 (3.33)	-1.29 (-2.96)	0.09	113
Panel B				
<i>Liq_{pc1,m}</i>	0.13 (3.66)	-1.25 (-3.21)	0.09	113
<i>LiqRisk_{pc1,m}</i>	0.08 (2.43)	-0.81 (-1.89)	0.06	113
<i>Vol_{pc1,m}</i>	0.13 (3.47)	-1.30 (-2.96)	0.10	113
Panel C				
MIBOR	1.06 (6.56)	-0.90 (-2.74)	0.18	113

6.2 Multivariate analysis

Each of the factor used in the regression in Table 5 is likely to be correlated to the other factor. For example, funding costs determine the capital available to traders to trade in the market, which affects the market variables: liquidity, liquidity risk as well as volatility. In addition, each of these three variables exhibit significant correlation between each other.²³ Thus, a regression with all these variables in one equation will result in issues related to multicollinearity.

We eliminate the correlation between these variables by performing a principal component

²³These three variables amongst themselves have a correlation coefficient greater than 0.75.

analysis on the average market values of each of these variables.²⁴ We use the first principal component from the PCA on these market variables and re-estimate the regression specified in Equation 1.

The first principal component (P_{MF}) extracted from a PCA on Liq_m , $LiqRisk_m$ and Vol_m explains 76% variation in these factors collectively, indicating a significant correlation across the three variables. Further, since all these market variables are also affected by changes in funding liquidity, we cannot include MIBOR in the same regression. The correlation coefficient between MIBOR and P_{MF} turns out to be 0.77. To eliminate multicollinearity, we repeat the principal component analysis exercise by adding MIBOR as the fourth factor along with the market values of the three market variables (Liq_m , $LiqRisk_m$ and Vol_m). The first component from these four variables ($P_{MF,MIBOR}$) explains 76% of the variation.

Figure 3 plots the time-series of the systematic component of no-arbitrage bands along with the first component based on the three market variables (P_{MF}) and with the first component based on all the four variables including MIBOR ($P_{MF,MIBOR}$). We also add MIBOR to the plot to indicate changes in the costs of funding during the period under study. The dashed line in the graph indicates the date of intervention by the central bank of India, when the interest rates in the money market were increased to contain exchange rate volatility. The graph shows an increase in the systematic component with the date of increase in the interest rates, indicating how sudden tightness in the funding liquidity affected the arbitrage trades. The increase in the systematic component of the market variables continues until a few days after the increase in MIBOR.

The above observations are reflected in our regression results as well. Table 6 reports the estimates results using P_{MF} as a factor, along with the STT dummy (See **M1**). As we observed in the univariate results, there is a positive and significant association between the systematic component of the size of no-arbitrage bands and market variables. A deterioration in the market variables causes an increase in the systematic component of the size of the bands. Model 2 (**M2**) in Table 6 shows the regression results by using ($P_{MF,MIBOR}$) as the explanatory variable along with the STT dummy. We find similar results as in **M1**, with the explanatory power of the model improving from 7% to 10%. The results suggest that funding constraints have a key role in determining arbitrage efficiency in the markets. The results are similar to the findings by Rosch *et al.* (2014) who also find that funding liquidity plays a significant role in determining aggregate market efficiency.

7 Conclusion

Several papers in the past have explored the effect of limits to arbitrage in the context of index futures and spot, but none on the stock futures and spot data. This study attempts

²⁴We use our first approach, that is, equally weighted average across stocks in the principal component analysis.

Figure 3 Time series of the systematic factor with other factors

The figure plots the systematic factor along with the first component extracted from a principal component analysis on only the three market variables: market liquidity, market liquidity risk and market volatility; and from the three market variables and MIBOR. The figure also plots MIBOR. The dashed line indicates the date of intervention by the Reserve Bank of India to contain exchange rate volatility.

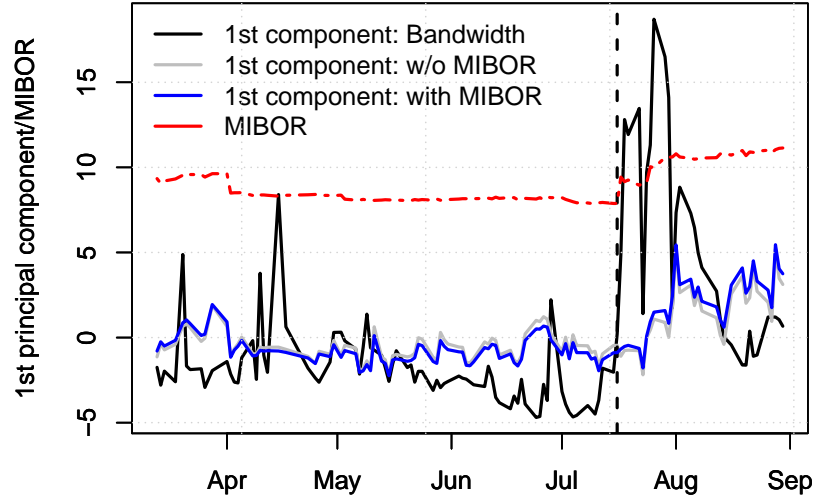


Table 6 Multivariate regression results

The table presents results of the regression estimated for the equation:

$$P_t^{BW} = \alpha_0 + \beta_0 \times P_{MF,t} + \beta_1 \times Dummy_t + \epsilon_t$$

where P_t^{BW} denotes the first principal component (or the systematic factor) on the size of the no-arbitrage bands (or the bandwidth) on day 't'; $P_{MF,t}$ is the first component on the market variables ($Liq_m, Vol_m, LiqRisk_m$), with and without MIBOR. $Dummy_t$ accounts for STT reduction, taking value 1 for days after May 31, 2013, 0 otherwise. The regression estimates are robust to the outliers in the data. The values in parenthesis indicate the t-statistic of the estimated coefficient.

	M1	M2
Dummy	-1.03 (-2.94)	-1.08 (-2.69)
P_{MF}	0.54 (2.94)	
$P_{MF,MIBOR}$		0.55 (3.64)
R ²	0.07	0.10
# of obs.	113	113

to fill this gap by investigating the effect of market frictions on arbitrage in (efficiency) in a much more cleaner setting of stock futures and spot prices. Market frictions result in no-arbitrage bands around the theoretical prices of futures. We find that on an average, when there is negative deviation, the mispricing persists at least until it is less than equal to 15 bps away from the midquote price. On the positive side, this limit is smaller, to the extent of 3 bps. Consistent with the prior literature, this asymmetry in the upper and the lower limit, reflects the effect of the short selling constraints on the spot market (Ofek *et al.*, 2004). Evidence of significant cross-sectional variation in the size of the bands is also found, which can be explained by the differences in the liquidity of the stock.

We also explore the possibility of commonality in the size of no-arbitrage bands. We conjecture that a part of these bands can be explained by market-related factors common to all stocks (the systematic factor) and the rest to the stock-specific factor (the idiosyncratic factor). We find evidence of such commonality. 17% of the variation in the size of no-arbitrage bands can be explained by the first principal component, which we refer as the systematic component. This finding links with the commonality literature which has so far focused on the returns (Fama and French, 1995), liquidity (Chordia *et al.*, 2000), and very recently, market efficiency (Rosch *et al.*, 2014).

We delve into the factors that can be attributed to the variation in the systematic component. We find that explicit factors like taxes, market factors like liquidity and volatility have a significant explanatory power in explaining the variation. The factor that has maximum explanatory power turns out to be funding constraints captured by MIBOR. This evidence is consistent with the recent literature which asserts that funding liquidity is a key factor in determining market liquidity. We find that tightening of the interest rates in the money market by the central bank worsened the arbitrage efficiency of the equity markets, an unintended consequence of an action by the regulator.

A Principal component analysis results on market variables

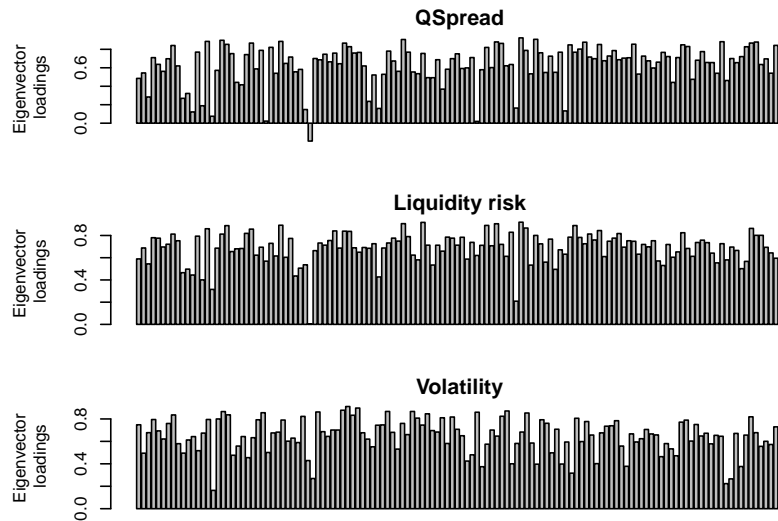
Table 7 presents the results of principal component analysis on each of the market variable: Liquidity, liquidity risk and stock volatility. The eigenvalues of the first component on these variables range between 44-50%, indicating a significant level of commonality. The first component on liquidity variable explains about 45% of the total variation in liquidity across all stocks. Similarly on liquidity risk and stock volatility, the first component explains about 49% and 44% of total variation. The second and the third component share for each of these variables is less than 10%.

Table 7 Eigenvalues obtained from PCA on market outcomes

	Mean	Median	SD	Eigenvalues			Cumulative explained variance (%)
				1	2	3	
Liquidity	0.21	0.18	0.13	45.09	7.40	3.68	56.17
<i>LiqRisk</i>	0.03	0.02	0.02	49.52	7.41	5.97	62.90
<i>Volatility</i>	39.42	34.66	19.97	44.75	4.68	3.86	53.29

Figure 4 also plots the weights assigned to each stock in the first component computation. We see that for all the three variables, the weights are generally positive and similar, indicating that this component captures the systematic component of each of these variables.

Figure 4 Loadings on the first component from PCA on market outcomes



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