When stock futures dominate price discovery

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Abstract

This paper revisits the role of leverage in price discovery, using one of the most liquid single stock futures markets in the world. Price discovery is analysed as a dynamic intra-day process. We find that the information share of the single stock futures is 55 percent during news arrivals. It increases to 61 percent, when the news is negative and the futures is preferred because of short-sales restrictions on the spot. A partial equilibrium analysis predicts that the trade-off between leverage and market liquidity will determine price discovery across securities. These predictions about the variations in price discovery are validated by empirical evidence.

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1 Introduction

When a security is traded in multiple markets, we expect that the market for derivatives will dominate price discovery for many reasons. The leverage in derivatives can be used to enhance returns while trading information, which will lead informed traders to prefer derivatives to the spot market (Black, 1975). Restrictions on short selling and problems with borrowing securities make it more costly to sell the spot when compared to the cost of selling derivatives (Miller, 1977). A new perspective is found in the more recent literature on funding constraints of financial market participants (Brunnermeier and Pedersen, 2009). It suggests that traders who face funding constraints can use derivatives as lower margin securities to improve the efficiency of their limited trading capital, compared to trading the spot.

For these reasons, traders are likely to prefer derivatives over the spot, and derivatives prices are likely to lead spot prices in price discovery. However, the empirical evidence on this question points overwhelmingly in the opposite direction. *Spot* prices dominate price discovery in both single stock options (Stephan and Whaley, 1990; Chakravarty *et al.*, 2004) and single stock futures (Shastri *et al.*, 2008; Fung and Tse, 2008; Kumar and Tse, 2009). For example, Chakravarty *et al.* (2004) report that, on average, prices of single stock options contribute 17 percent to price discovery, while Shastri *et al.* (2008) find that single stock futures contribute 24 percent. It is only with equity index futures that derivatives are found to dominate price discovery (Fleming *et al.*, 1996).

A closer examination suggests that a potential resolution of this puzzle may lie in noisy measurement and difficulties in estimation. For instance, when trading is fragmented across multiple exchanges with different microstructure in different time zones, the precisely synchronous data that is required to capture the true nature of price discovery is missing. Most empirical results are based on options markets, where the use of the 'implied price' for traded options introduces estimation risk. Finally, price discovery has traditionally been analysed as an average, though if derivatives are used to trade information, these are likely to dominate spot prices only during periods of high information (Chen and Gau, 2010; Brogaard *et al.*, 2012).

A few papers analyse the price discovery of single stock futures with findings that are consistent with the rest of the literature (Shastri *et al.*, 2008; Kumar and Tse, 2009). However, the liquidity of these contracts in most global exchanges is typically lower than that of single stock options or index derivatives. In this paper, we re-examine price discovery of single stock futures in a setting where the microstructure helps to eliminate the measurement problems listed earlier. These are the equity spot and single stock futures (SSFs) at the National Stock Exchange of India Ltd. (NSE), which are ranked among the most liquid exchanges in the world. The NSE has dominant market share in trading both equity spot and single stock futures in India, which minimises the measurement complexities that arise with fragmented trading. The spot and the SSF share a common trading platform at the NSE, giving us data that has minimal microstructure noise. Unlike most global exchanges, the SSF contracts on Indian equity are cash settled at maturity. Traders face constraints on short selling that cannot be mitigated through market mechanisms for borrowing securities which raises their costs of trading the spot, particularly during periods of negative information. For example, Suvanam and Jalan (2012) examine the securities lending and borrowing market (SLBM) in India, and conclude that regulatory constraints have inhibited the growth of the equity market, making it difficult for traders to borrow shares on the spot market. But this can be expected to emphasise the use of SSF.

In this setting, we analyse price discovery as a process with two sources of variation. The first source comes from cross-sectional variation across securities. We conjecture that the two factors that drive a trader's choice of a trading venue are liquidity and leverage on a security. We model the choice of a marginal trader who considers leverage and available liquidity of a security as endogenous, when deciding where to place a market order. Our partial equilibrium analysis predicts that the trader will choose the SSF when the gains from leverage are larger than the difference in market liquidity between the SSF and the spot markets. The second source of variation comes from temporal variation in information. We analyse price discovery of the SSF within the trading day by identifying periods of high information arrivals during which we expect derivatives to dominate price discovery. We differentiate the analysis when the news is negative, during which we expect that trader preferences would tend more strongly towards using derivatives because of short selling constraints on the spot.

The empirical analysis uses the Hasbrouck (1995) Information Share (IS) as the primary estimator of price discovery. Inference is augmented using the Yan and Zivot (2010) approach which combines both the IS and the Gonzalo and Granger (1995) Component Share (CS). 100 securities are examined at intervals of one-second for 104 days between March 2009 to August 2009. This is a dataset of over 200 million records, making this one of the most detailed examinations of the price discovery process between equity spot and the SSF.

The paper offers three findings. First, while the average IS of the SSF (IS_{ssf}) is 49 percent, it varies significantly across securities. Securities with higher liquidity on both the SSF and spot have a higher share of price discovery on the SSF, while the ones with lower liquidity on the SSF have a higher share on the spot market. Second, a firm fixed effects regression of IS_{ssf} on leverage and difference in the market liquidity of the SSF and the spot market finds that the leverage coefficient is significant and positive, while the coefficient on the liquidity difference is significant and negative. Third, during periods of high information flow, the share of IS_{ssf} increases to 55 percent, indicating the preference of SSF as the venue around such periods. We also find that the share of SSF rises even more when the news is negative.

These findings contribute to our understanding of price discovery as being a dynamic process, which is an outcome of the choices made by traders who continuously respond to shifts in information flows and microstructure variations across securities. The price discovery of the SSF is highest when information arrives, showing that traders prefer leverage while trading information. The asymmetric increase in price discovery during negative news provides new evidence that traders use derivatives to overcome microstructure constraints while trading information. The partial equilibrium framework, based on the preferences of a marginal trader, reveals that they choose to trade the SSF of securities with higher levels of leverage as well as when there is higher liquidity in the SSF market compared to the liquidity in the spot market. These findings stand in contrast to the earlier literature, where the SSF is shown to have little contribution to price discovery.

The paper is organised as follows: Section 2 describes the research setting within which we re-visit the question of which market, between single stock futures and equity spot, dominates price discovery. Section 3 presents the questions and testable propositions. Section 4 describes the data followed by a discussion on measurement of price discovery in Section 5. Section 6 presents the empirical analysis. Section 7 gives details of reproducible research. Section 8 concludes.

2 A clean microstructure setting

A principal advantage of studying price discovery on the equity markets of the NSE is the presence of very liquid single stock futures (SSF) markets. Even though derivatives trading at the NSE started with index futures in 1998, it was the SSF markets in 2001 that became the first liquid contracts,[1] and made the NSE one of the top five exchanges ranked in terms of number of contracts traded.

In addition to liquidity, the NSE has other advantages which makes it one of the cleanest measurement settings to understand price discovery between SSF and spot prices. Both equity spot and derivatives trade simultaneously[2] on anonymous, electronic limit order-book systems, where orders are matched on a price-time priority. Both trade during the same hours, between 9 am and 3:30 pm. The common platform ensures that the time-stamped trades and orders data for spot and SSF are precisely synchronised, eliminating measurement biases in the price discovery analysis. Out of the 1400 securities listed on the NSE, single stock futures and options traded on 223 of the most liquid securities during the period of the study. Further, unlike the U.S. markets, where fragmentation across multiple exchanges induces measurement errors in the price discovery analysis, equity trading in India is primarily concentrated on the NSE (NSE, 2009). In our sample, the NSE has a market share of 99 percent in equity derivatives, and a market share of 70 percent in equity spot.

[1] The SSF trading replaced a traditional market mechanism called *badla* which gave traders access to leverage through forward trading (Berkman and Eleswarapu, 1998). The familiarity of the brokers with the *badla* system facilitated an easy transition into trading the SSF.

[2] In India, exchanges are differentiated by asset classes (equity, fixed income, commodities) rather than spot and derivatives. This is unlike the better researched markets like those in the U.S., where the spot and the derivatives trade on different exchanges.

2.1 Settlement advantages of the SSF

Settlement issues also influence the trader's decision when choosing between alternative venues. Equity spot trades, at the NSE, are settled on a $T + 2$ basis. This is a shorter period than in most international markets, and imposes a greater pressure on the market participants to make timely delivery of funds or securities. Margin payments and mark-to-market profits and losses for the SSF transactions are done on a $T + 1$ basis, but are settled in cash.

Other features of the equity settlement process which affect the choice of traders are short-selling restrictions on the spot market. While all short positions on the spot must deliver the underlying equity on a $T + 2$ basis, the short positions on the SSF need only deliver funds. Since there is no well developed market or exchange mechanism for lending and borrowing shares, short-sellers tend to face higher funding constraints while selling the spot, which do not exist when selling the SSF.

2.2 Funding constraints of the trading community

Equity trading in India is dominated by relatively small financial firms, rather than the large institutions that dominate global markets such as banks, asset management, insurance and pension firms. 85 percent of the trades are from non-institutional sources which include retail, proprietary trades by brokerage firms, or hedge fund-like entities (NSE, Jun 2010). The low participation by institutions is partly the outcome of regulatory restrictions. Banks are constrained in how they can fund trading activity in the equity spot markets.[3] They are not permitted to fund activity in equity derivatives, particularly arbitrage.[4] Insurance firms[5] and pension funds[6] face similar restrictions on investments in both equity spot and derivatives. Capital controls mean that foreign institutional investors (FIIs) have regulatory and operational restrictions on how they can participate in the equity markets (Shah *et al.*, 2008). The unusually liquid SSF markets in India could thus be the outcome of choices of traders with funding constraints.

In the sample period analysed in this paper, there are no designated market makers for either the spot or the SSF, but there are no restrictions on traders to place limit orders on both sides of the markets simultaneously. The amount of capital that is deployed into trading activity is relatively small compared to the larger, developed economies. Data from the NSE shows

[3]From the Reserve Bank of India (RBI) Master Circular on Exposure Norms, DBOD No. Dir. BC. 7/13.03.00/2011-12 dated July 1, 2011 at `http://rbidocs.rbi.org.in/rdocs/notification/PDFs/68MC010712EF.pdf`

[4]From the RBI draft comprehensive guidelines on derivatives at `http://www.rbi.org.in/Scripts/bs_viewcontent.aspx?Id=457`

[5]From the website of the insurance sector regulator at `http://www.irdaindia.org/regulations.htm`

[6]From the website of the New Pension Systems regulator at `http://pfrda.org.in/writereaddata/linkimages/investment%20guidelines%2030_04_092418358081.pdf`

that the top 10 member firms account for 25 percent of the annual turnover.[7] Independent data from the balance sheets of listed securities firms shows that the top 10 firms had USD 160 million of equity capital. These are small numbers when compared against an annual turnover of USD 6.8 trillion on the NSE equity markets,[8] and suggests significant funding constraints for firms trading on the NSE.

SSF traded volumes on the NSE are consistently higher than the spot market volumes. Further, according to the data from the World Federation of Exchanges, NSE has consistently been amongst the top five exchanges in the world that trades SSF, based on the number of contracts traded. In contrast, there is very little trading on the SSO at the NSE. During the sample period of this paper, SSO traded volumes was only 7.56 percent of total volumes traded on all single stock derivatives. While we do not offer any analysis or explanation about why this is the case, this has two implications for the analysis in this paper: 1) there is insufficient data to analyse the price discovery of the SSO market, and 2) price discovery is narrowed to just two markets: spot and SSF.

3 Research questions

We use the setting described above to answer the following questions about the process of price discovery between SSF and spot:

1. Is there cross-sectional variation in price discovery? What drives this variation?
2. Is there temporal variation in price discovery? Is the share of SSF higher around periods of high information?

3.1 Cross-sectional variation in price discovery

Research that examines cross-sectional variation in price discovery attributes leverage as a motive for using derivatives, but does not explicitly account for it. Leverage is determined by the margin rules of the exchange clearing house (Kupiec, 1989, 1998). Margins are calculated based on the volatility of the security such that higher margins are charged for securities with higher volatility and vice-versa. Then, volatility of the security can be used as a proxy for leverage. This is consistent with Chakravarty *et al.* (2004) who show that price discovery of the SSO markets tends to be lower when volatility is higher.

Market liquidity can also affect the cross-sectional variation in price discovery. Shastri *et al.* (2008) find that price discovery on the U.S. SSF markets tends to be higher on days when

[7] From the NSE website at `http://www.nseindia.com/products/content/equities/equities/historical_topbrokersyearwise.htm`

[8] This is the sum of the annual turnover on the spot market and the futures and options contracts on equity, including both the index and the single stock products.

they are more liquid, even though the spot market continues to dominate. Chakravarty *et al.* (2004) also show that price discovery by the SSO varies by both the liquidity in the market as well as with product features such as the strike and the maturity. In addition, Easley *et al.* (1998), Pan and Poteshman (2006) and Anand and Chakravarty (2007) show that *traded volumes* on the SSO market predict spot prices. In limit order book markets, traders observe available liquidity *before* they place their orders. This *pre-trade liquidity* of the security (henceforth referred to as "liquidity") on alternative trading venues may influence where to trade.

A simple model will help understand how a trader chooses between alternative trading venues for a given security. We focus on the decision of a marginal trader for whom the liquidity and leverage are exogenously given, restricting ourselves to a partial equilibrium analysis. In this setup, a security has price P_0 at time $T = 0$, that can either move up to uP_0 with probability p, or down to dP_0 with probability $(1 - p)$ at $T = 1$. This security trades on both the spot and the SSF markets. When information arrives, the trader who faces a cost, r_f, of borrowing funds, has the choice of either placing a market order on the spot market or the SSF market. For the trader, an order of size $\$Q$ in the spot market requires the same capital as an order of value $\$\lambda Q$ in the SSF market, where λ is the leverage of the SSF.

As an example, if $\lambda = 5$, and the security has a price of \$100, the trader can either invest \$100 into the spot market ($Q_{\text{S}} = 100$) or take a position worth \$500 ($Q_{\text{SSF}} = \lambda \times Q_{\text{S}}$) in the SSF.

Both the SSF and the spot trade on an open electronic limit order book (OELOB) market. Since the limit order book is visible, the trader knows the transactions cost associated with the spot market $c_{\text{S}}(Q)$ and the futures market $c_{\text{SSF}}(Q)$ for all values of Q. For example, if the mid-quote price is \$100, and if a market buy order of value \$100,000 is executed at a buy price of \$101 per share, then $c_{\text{S}}(100,000) = 0.01$ or 1 percent of the value of the transaction.

We assume that no-arbitrage holds in the relationship between the spot and the SSF, and there are no dividend payments. This ensures that a simple cash-and-carry model holds. We represent the preferences of the trader by assuming that he maximises the ratio of expected return per unit risk of the transaction, $[E(r_M)/\sigma_M]$, where M is either "S" for the spot market or "SSF" for the single stock futures market.

The expected return and risk of a spot market position of Q is calculated as:

$$
\begin{aligned}
E(r_{\text{S}}(Q)) &= p[u - c_{\text{S}}(Q) - r_f] + (1-p)[d - c_{\text{S}}(Q) - r_f] \\
&= p[u - d] + d - c_{\text{S}}(Q) - r_f \\
&= E(r) - c_{\text{S}}(Q) - r_f
\end{aligned}
$$

$$
\begin{aligned}
\sigma^2_{\text{S}}(Q) &= E(r^2_{\text{S}}) - [E(r_{\text{S}})]^2 \\
&= p[u - c_{\text{S}}(Q) - r_f]^2 + (1-p)[d - c_{\text{S}}(Q) - r_f]^2 - [E(r_{\text{S}})]^2 \\
&= p(1-p)[u-d]^2 \\
&= \sigma^2
\end{aligned}
$$

Where $E(r)$ is the inherent return on the security in the spot market for a position of size Q, and σ^2 is the inherent risk on the security in the spot market.

For the same cost of funding, the trader can take a position of size λQ on the SSF market, which has a related trading cost of $c_{\text{SSF}}(\lambda Q)$. The expected return and risk of the SSF position is:

$$\begin{aligned}
E(r_{\text{SSF}}(\lambda Q)) &= p[\lambda u - c_{\text{SSF}}(\lambda Q) - r_f] + (1-p)[\lambda d - c_{\text{SSF}}(\lambda Q) - r_f] \\
&= \lambda(p[u-d]+d) - c_{\text{SSF}}(\lambda Q) - r_f \\
&= \lambda E(r) - c_{\text{SSF}}(\lambda Q) - r_f
\end{aligned}$$

$$\begin{aligned}
\sigma^2_{\text{SSF}}(\lambda Q) &= E(r^2_{\text{SSF}}) - [E(r_{\text{SSF}})]^2 \\
&= p[\lambda u - c_{\text{SSF}}(\lambda Q) - r_f]^2 + (1-p)[\lambda d - c_{\text{SSF}}(\lambda Q) - r_f]^2 - [E(r_{\text{SSF}})]^2 \\
&= p(1-p)[\lambda(u-d)]^2 \\
&= \lambda^2\sigma^2 \implies \\
\sigma^2_{\text{SSF}}(Q) &= \sigma^2 = \sigma^2_{\text{S}}(Q)
\end{aligned}$$

In the calculation of the risk of the two positions, we note that the payoff for both the spot and the SSF is linear but that the slope of the SSF market payoff is higher by the amount of the leverage, λ.[9] This makes the SSF a riskier proposition than the spot for speculators on the same base of capital deployed.

For a fair comparison in the problem of the trader's choice between the two markets, we assume that the trader will choose to place a market order of the same size on both markets. We set this to be λQ, for the sake of convenient exposition. The transactions costs for a position of λQ on the spot market will be $c_{\text{S}}(\lambda Q)$, and the funding cost will be λr_f. The transaction cost for the same order size on the SSF market will be $c_{\text{SSF}}(\lambda Q)$ and the funding cost will be r_f. The return to risk associated with the trader's choices are:

$$\begin{aligned}
\text{Spot:} \quad \frac{E(r_{\text{S}}(\lambda Q))}{\sigma_{\text{S}}(\lambda Q)} &= \left[\frac{\lambda E(r) - c_{\text{S}}(\lambda Q) - \lambda r_f}{\lambda\sigma_{\text{S}}}\right] \\
\text{SSF:} \quad \frac{E(r_{\text{SSF}}(\lambda Q))}{\sigma_{\text{SSF}}(\lambda Q)} &= \left[\frac{\lambda E(r) - c_{\text{SSF}}(\lambda Q) - r_f}{\lambda\sigma_{\text{S}}}\right]
\end{aligned}$$

The SSF market will be preferred if $E(r_{\text{SSF}}(\lambda Q))/\sigma_{\text{SSF}}(\lambda Q) > [E(r_{\text{S}}(\lambda Q))/\sigma_{\text{S}}(\lambda Q)]$. After removing the common terms, the condition under which the trader will prefer to trade on the SSF market rather than spot market is:

$$(\lambda - 1)r_f > [c_{\text{SSF}}(\lambda Q) - c_{\text{S}}(\lambda Q)] \tag{1}$$

[9] Since we assume there is sufficient arbitrage activity to eliminate basis risk in the current setting, it does not appear as a factor of risk.

The trade-off shows that a marginal trader will prefer the SSF as long as the gain from leverage is greater than the liquidity difference. This is similar to Easley *et al.* (1998) who find that if the leverage effect of options is large enough, or if the liquidity in the spot market is poor, then at least some traders will use the SSO. Equation 1 implies that neither the expected returns $\mathrm{E}(r_s)$ nor the risk of the security σ_{S} matters. It is only the microstructure that influences the choice of trading venue.

This analysis suggests two testable hypotheses for the cross-sectional variation in price discovery:

> H^1: Price discovery of the SSF is higher for securities where the liquidity difference $([c_{\mathrm{SSF}}(Q) - c_{\mathrm{S}}(Q)])$ is relatively more negative, *holding the leverage constant.*
>
> H^2: Price discovery of the SSF is higher for securities when leverage is relatively higher, *holding the liquidity difference constant.*

3.2 Temporal variation in price discovery

We identify two reasons for a trader to prefer leverage within the trading day: the arrival of information and funding constraints. Both make it more attractive for the trader to use the SSF which, in turn, is likely to affect price discovery in SSF.

A small recent literature has used high-frequency data to detect intra-day changes in price discovery in response to information. Muravyev *et al.* (2012) analyse the price discovery of options markets during high information periods, and find that these prices do not contain significant information about future stock prices. They estimate an average information share of 6.25 percent for the options market. Dong and Sinha (2012) analyse the price discovery surrounding news events using SSO prices data at five-minutes frequency. They find that the information share of the option markets rises significantly, from 10 percent during the non-information periods to 27 percent during the high information periods.

We identify time-series variation in price discovery in a manner similar to Muravyev *et al.* (2012). Price discovery is estimated over smaller time intervals within the trading day which are identified as periods of high information. However, unlike Muravyev *et al.* (2012) who identify such periods using violations of put-call parity in SSO prices, our identification approach uses periods of high information. One such period is during the start of the market, when traders respond to accumulated overnight news and information (Greene and Watts, 1996; Kalev *et al.*, 2004). Another such period is the time around corporate announcements (Cao *et al.*, 2005; Roll *et al.*, 2010). We use such periods in the data to test the following hypothesis about the price discovery process of SSF:

> H^3: Price discovery of the SSF is higher within a trading day, during periods of high information as compared to other periods.

H^3 tests whether the price discovery of the SSF rises during information arrivals, irrespective of the direction of the news. However, there are short-sales restrictions on the equity spot at the NSE. Such restrictions exacerbate the information asymmetry between the buy and the sell prices on the spot market, causing asymmetry in market outcomes such as market liquidity and price efficiency (Miller, 1977; Diamond and Verrecchia, 1987; Boehmer *et al.*, 2013). When prices take longer to adjust to information in one direction, it imposes a greater cost asymmetrically on the traders ability to take positions in the market. This is exacerbated for traders with funding constraints. In comparison, there are no such restrictions on the SSF, even at contract maturity because the SSF are cash-settled on the NSE. Thus, traders will have a significantly *stronger preference* for SSF during periods of negative news, which leads to the next hypothesis:

> H^4: Price discovery of the SSF is higher when news during high information periods is *negative* compared to when it is positive.

4 Data description and measures

We use high frequency limit order book data spanning from March 2009 to August 2009 for both the NSE equity spot and SSF market. The data are at one-second frequency and have information about the top twenty bid and ask quotes. This information allows us to estimate intra-day values of the price discovery measures, liquidity and leverage for all securities.

We focus on the 100 firms which constituted the S&P CNX-100[10] index during the study period. These securities account for approximately 82 percent of the total SSF market volumes and 51 percent of the total traded volumes on the spot market. Three out of the 100 securities did not trade in the SSF market during the sample period. Thus, the final sample comprises of 97 securities. Price discovery is measured using midquote prices of the near-month futures contracts and spot. Rollover to the next month futures contract prices is done two days prior to expiration. In total, we analyse 104 trading days for 97 securities. This adds upto 10,088 security days of data for both spot and the SSF markets. With 20,000 seconds per day, the data has over 200 million records.

4.1 Identification of high information periods

The analysis requires identification of high information periods. We use two sets of periods which have been previously identified in the literature as being high information periods in financial markets:

Market-wide information at the start of the trading day Intraday market volatility follows a U-shaped pattern, where the volatility peak at the start of the trading day is attributed to the inflow of overnight news into the market. Thomas (2010) tests for structural breaks

[10]CNX-100 is a 100 stock index covering 38 sectors in the economy, published by NSE.

in the intraday market volatility using the S&P CNX Nifty[11] index, and finds that the high volatility at the start of the trading day persists for half an hour on average. In this paper, we use the period from 09:55 am to 10:30 am for each day in the sample as a period of high information. We use the period between 12:00 pm to 1:00 pm as the low information period.

Security-specific information during corporate announcements Earnings announcements are regular events of high information that are specific to a security. For listed securities, such announcements are notified ex-ante by the exchange, and can arrive anytime within a trading day. The date and time-stamps of earnings announcements for the securities in our sample are hand-collected from archives at the NSE website, and cross-validated with information about the same firms from the Bombay Stock Exchange website.

Our sample period includes two seasons of earnings announcements for: a) The last quarter of the financial year (FY) 2009,[12] announced during the months of April and May 2009, and b) The first quarter of (FY) 2010, announced during July and August 2009. The first half hour immediately after the earnings announcements is used as the period of high security-specific information. There are 158 such instances in our sample.

4.2 Liquidity measures

Traditional measures of liquidity such as traded volumes and the bid-ask spread are readily observed from our data, but these measures are not useful to directly compare the liquidity across the two markets. This is because the minimum transaction size on the spot and SSF market are significantly different. For example, the average spot equity market trade on the NSE is USD 500 on average, while that on the SSF is USD 5000. The bid-ask on the SSF market is for quantities that are 10× larger than those on the spot market, on average. For this reason, we use an alternative, ex-ante measure of liquidity which can be used to directly compare liquidity costs across the two markets. This is the *impact cost*, which is the cost incurred for executing a market order of a transaction size Q. This is denoted as $\mathrm{C}(Q)$ and is defined as:

$$\mathrm{C}(Q) = 100 \times \frac{P_Q - P_{MQ}}{P_{MQ}} \tag{2}$$

where P_Q is the execution price on calculated for a market order of Q and P_{MQ} is the mid-quote price. For a liquid security, $\mathrm{C}(Q)$ will be small whether the transaction size Q is small or large. This implies that the execution price of a large order will be close to the mid-quote price. $\mathrm{C}(Q)$ can be calculated for all values of Q that are within the visible part of the LOB. For our analysis, we use Q = USD 5000, which is the average SSF transaction size. For each market, we compute $\mathrm{C}(Q)$ for both the buy and sell side at the frequency of one-second, and use the average of the two as the liquidity measure.

[11] This is the market index comprising the 50 largest firms in terms of market capitalisation and transactions costs traded on the NSE. It is calculated and published jointly by S&P in India and NSE (Shah and Thomas, 1998).

[12] The Indian financial year is from Apr 1 to Mar 31.

4.3 Leverage estimation

Leverage for security i on date t, $\lambda_{i,t}$, is estimated from the margins set by the exchange. The exchange determines the margin based on the volatility of the security, $\sigma_{s,i,t}$.[13] Leverage is inversely proportional to σ_{s}: when σ_{s} is high, margins go up and leverage goes down, and vice versa when σ_{s} is low.

The daily leverage values are not archived beyond a month by the NSE. We design an empirical strategy to estimate a time series of leverage for all the securities used for the analysis. For this, we first obtain a sample of one month of daily leverage values from the NSE. Next, we compute the daily average σ_{s} as the realised volatility of the security, which is computed as the sum of intraday squared returns at a frequency of five-minutes. Then, we estimate a linear relationship between the daily leverage and daily σ_{s} using the following fixed-effects regression:

$$\lambda_{i,t} = \gamma_{1,i} + \gamma_2 \sigma_{\mathrm{s},i,t-1} + \gamma_3 \sigma^2_{\mathrm{s},i,t-1} + \epsilon_{i,t} \tag{3}$$

where $\lambda_{i,t}$ denotes the leverage on security i at time t for the month of June, which was obtained through a request from the NSE. $\sigma_{\mathrm{s},i,t-1}$ is calculated as the realised volatility of security i on the spot market at $t-1$. The estimation provides us coefficient estimates for the intercept values of each security ($\hat{\gamma}_{1,i}$), $\hat{\gamma}_2 = -0.59$ and $\hat{\gamma}_3 = 0.15$. We then use these coefficient values and estimates of the daily values of $\sigma_{\mathrm{s},i}$ to obtain a time series of $\hat{\lambda}_i$ for each security for the entire period of our analysis.

Figure 1 illustrates the variation in the estimated leverage across the securities in the sample. The NSE sets a maximum level of leverage permitted for any security. There are very few observations at the maximum permitted value in our sample, which implies that it is not a binding constraint for our analysis. Table 1 provides descriptive statistics for the entire sample as well as for quartiles based on liquidity of the security. Liquidity quartiles are based on the average impact cost on the spot and the SSF markets.

5 Measuring price discovery: Methodology

There are typically two approaches in measuring price discovery across multiple markets. One is the Information Share (IS), proposed by Hasbrouck (1995), and the second is the Component Share (CS), which is based on the permanent and transitory decomposition proposed by Gonzalo and Granger (1995). There has been a significant debate on the correct interpretation of each measure. Lehmann (2002) points out that problems of interpretation

[13] The amount of leverage calculated at the NSE is the sum of the Value at Risk (VaR) and an Exposure Margin (EM). During the period of the study, the minimum VaR and EM imposed by the NSE was 7.5 percent and 5 percent, respectively. This implies that the minimum margin permitted at the exchange was 12.5 percent, and the maximum leverage permitted was 8×.

are inevitable when the measures are derived from a (reduced form) vector error correction model, but that the inference about the importance of any market for price discovery depends upon the parameters of the underlying structural model.

Yan and Zivot (2010) attempt to resolve the confusion by proposing a structural cointegration model for the price changes in multiple markets. They re-interpret the IS and the CS measures in terms of the underlying innovations: permanent, information-related innovations (η_t^P) due to the arrival of news and transitory, and non-information-related innovations (η_t^T) due to trading frictions. Both measures are shown to adjust for the relative avoidance of transitory shocks. However, only the IS captures the relative informativeness of a given market. They suggest that a combination of both measures can be used to separate the effects of information (η_t^P) and noise (η_t^T), so as to strengthen inference about the dominance of price discovery.

We build on this to compute the IS-CS ratio as:

$$\frac{|IS_1 \times CS_2|}{|IS_2 \times CS_1|} = \frac{|d^P_{0,1}|}{|d^P_{0,2}|}$$

where IS_1 is the information share for Market 1, CS_2 is the component share for Market 2. $d^P_{0,1}$ captures the contemporaneous response of Market 1 to a permanent shock, while $d^P_{0,2}$ captures the same for Market 2. The IS-CS ratio captures the contemporaneous response of each market to permanent shocks. A value that is greater than one implies that Market 1 reacts to permanent shocks more strongly than Market 2. Thus, the earlier literature would infer that "Market 1 leads Market 2" from the result that "$\text{IS}_1 > 0.5$". When the same result is used with the IS-CS ratio, it can support one of three possible interpretations:

1. Market 1 leads Market 2 if $\text{IS}_1 > 0.5$ *and* IS-CS ratio > 1.
2. Market 2 has a stronger response to transitory shocks due to which IS_1 is high, and it cannot be inferred that Market 1 leads Market 2, if $\text{IS}_1 > 0.5$ *and* IS-CS ratio < 1.
3. Market 2 leads Market 1 if $\text{IS}_1 < 0.5$ *and* IS-CS ratio < 1.

In our analysis, Market 1 represents the SSF market, and Market 2 represents the spot market. Here, a value of the IS-CS ratio greater than 1, along with an IS_{ssf} greater than 50%, will indicate that the SSF market reacts to permanent shocks more than the spot market. This helps to strengthen the interpretation that the estimated values of IS for a market represent a stronger response of the market price to information rather than to noise (Putnins, 2013).

6 Empirical analysis

We present our analysis of hypotheses, $H_1, \ldots, H_4$ in two ways. The first is a non-parametric approach of examining the average IS_{SSF} for the full sample, and for sub-samples based on liquidity quartiles. The second is a parametric approach based on estimations from fixed effects panel regressions.

6.1 Cross-sectional variation in price discovery

Table 2 shows the average IS_{SSF}[14] and IS-CS ratio estimates for the full sample as well as for sub-samples based on liquidity. For the entire sample, we find that the average IS_{SSF} is close to 50%. The average sample IS-CS ratio is 1.01, which implies that the SSF reacts as much to the permanent shocks as does the spot market.[15] This indicates that for the full sample, both the spot and the SSF have an equally dominant share in price discovery.

For the sub-samples, we find that the average IS_{SSF} is greater than 50 percent for liquid securities (Q1 and Q2). This validates H^1 that the SSF market dominates price discovery where there is greater liquidity. In contrast, the IS_{SSF} for the Q4 securities is less than 50 percent, showing that the spot dominates price discovery for those securities that have relatively lower liquidity on the SSF. These results are also consistent with Equation 1 which states that the lower are the transactions costs on the SSF market compared to the spot market (lower C(Q)), the more likely the trader is to use the SSF (higher IS_{SSF}). The IS results are consistent with IS-CS ratio estimates as described in Section 5, indicating correct inference.

We now proceed to the parametric approach which involves estimating a cross-sectional relationship between price discovery, leverage $\hat{\lambda}_{i,t}$, and liquidity difference between the SSF and the spot market $\text{C}_{(\text{SSF}-\text{S}),i,t}$ using a fixed effects panel regression of the form:

$$\text{IS}_{\text{SSF},i,t} = \alpha_i + \beta_2 \text{C}_{(\text{SSF}-\text{S}),i,t} + \beta_3 \hat{\lambda}_{i,t} + \epsilon_{i,t} \tag{4}$$

We test for the pair of nulls: $H_0^1 : \beta_2 = 0; H_A^1 : \beta_2 < 0$ and $H_0^2 : \beta_3 = 0; H_A^2 : \beta_3 > 0$ If the associated nulls are not rejected using a one-tailed test, we conclude that leverage and the liquidity difference explain cross-sectional variation in price discovery of the SSF. To eliminate the effect of outliers, we winsorise the data at the 99^{th} and 1^{st} percentiles.[16]

Table 3 presents the estimation results. The results validate the predictions from Equation 1 for how the trader chooses between the SSF and the spot market. $\hat{\beta}_2$ is negative and significant, which is consistent with the hypothesis that the more negative the liquidity difference between the SSF and the spot market, the higher will be the price discovery of the SSF. $\hat{\beta}_3$ is positive and significant, which is consistent with the prediction that the higher the

[14] Since $\text{IS}_{\text{S}} = 1 - \text{IS}_{\text{SSF}}$, we present only the IS_{SSF} estimates in the rest of the paper.

[15] The IS-CS ratio is based on the assumption of uncorrelated contemporaneous residuals. In the sample, the average correlation is 0.05, which is not significantly different from zero, and supports the assumption of uncorrelated residuals.

[16] An examination of Cook's Distance suggested the presence of influential observations.

leverage, the higher will be the price discovery role by the SSF. These results hold for price discovery at the level of individual securities, even when the SSF does not have a dominant role in price discovery for the market as a whole.

6.2 Temporal variation in price discovery

In order to examine the share of price discovery of the SSF and spot markets around high information periods (HI), we estimate the IS of the SSF ($\text{IS}_{\text{SSF},i,t,\text{HI}}$) for each security i in the sample, for each day t, during such periods.[17] We also estimate $\text{IS}_{\text{SSF},i,t,\text{LI}}$ during periods of low information (LI). Table 4 presents the estimates for high information and low information periods for the full sample as well as for liquidity sub-samples.

For the full sample, the table shows that during high information periods, the share of $\text{IS}_{\text{SSF},i,t}$ increases to 56%. This is significantly higher than the full sample average of the IS during low information periods (49%). The IS-CS ratio is also significantly higher than 1, indicating SSF reacts to permanent shocks more than the spot market during periods of high information. We see a similar shift in the $\text{IS}_{\text{SSF},i,t}$ across all liquidity sub-samples. The finding provides new evidence on the relative dominance of the SSF market in price discovery, especially around periods of high information.

We further test the response of price discovery during high information periods using the following regression:

$$\text{IS}_{\text{SSF},i,t,j} = \alpha_i + \beta_1 \text{HIGH-INF}_j + \epsilon_{i,t,j} \quad \forall j = \text{HI}, \text{LI} \tag{5}$$

where HIGH-INF_j is high information dummy variable, taking value 1 during periods of high information period, 0 otherwise. Using the regression estimates, we test the null: $H_0^3 : \beta_1 = 0; H_A^3 : \beta_1 > 0$. If H_0^1 is rejected, we conclude that price discovery of the SSF market increases during periods of high information.

Model 2 estimates in Table 5 presents the results. The results show that the value of $\hat{\beta}_1$ in Equation 5 is positive and significant. This indicates that the average price discovery of the SSF goes up by nearly 6 percent during periods of high information, validating H_A^3 that traders use the SSF market more during information arrival. This increase in IS_{SSF} is similar to Dong and Sinha (2012), who report that the information share of the SSO market increases around news events. However, their estimated average IS_{SSO} is much lower at 27 percent compared to our estimate of 56 percent for IS_{SSF}, a significantly higher number which may reflect the traders response to a combination of the arrival of information and high funding constraints.

[17] See Section 4.1 for details of how we identify high information periods.

We next test for asymmetry between positive and negative news using the regression:

$$\text{IS}_{\text{SSF},i,t,j} = \alpha_i + \beta_1^+ \text{HIGH-INF}_{t,j}^+ + \beta_1^- \text{HIGH-INF}_{t,j}^- + \epsilon_{i,t,j} \tag{6}$$

where

$$\text{HIGH-INF}_j^+ = \begin{cases} 1 & \text{if } \mathrm{r}_{m,t,j} > 0; \\ 0 & \text{otherwise} \end{cases}$$

$$\text{HIGH-INF}_j^- = \begin{cases} 1 & \text{if } \mathrm{r}_{m,t,j} < 0; \\ 0 & \text{otherwise} \end{cases}$$

where $\mathrm{r}_{m,t,j}$ denotes returns on the market index from the previous closing price to the price at the end of the high information period of the trading day. There are two high information dummy variables, HIGH-INF_j^+, HIGH-INF_j^-, instead of one to differentiate between positive and negative news during high information periods. The union of HIGH-INF_j^+ and HIGH-INF_j^- constitutes the HIGH-INF_j dummy specified in Equation 5. β_1^+ is the coefficient that captures the effect on the IS of the SSF during periods when information is high and positive, and β_1^- captures the effect when information is high and negative. We test the null:

$$H_0^4 : \beta_1^+ - \beta_1^- = 0; H_A^4 : \beta_1^+ - \beta_1^- < 0$$

If H_0^4 is rejected, we conclude that traders prefer the SSF even more when the news is negative compared to positive news.

Model 3 estimates in Table 5 presents the results. β_1^- is 6.9 percent while $\hat{\beta}_1^+$ is 5.5 percent, indicating that the increase in the share of the IS_{SSF} when the news is negative is higher than when the news is positive. A significance test of the difference between the values of β_1^+ and β_1^- indicates a rejection of the null hypothesis, H_0^4. This suggests that traders use the SSF even more when the information is negative, supporting the hypothesis that traders constraints play an important role in the high values of price discovery of the SSF in this market.

In the previous subsection, we saw that the trade-off between liquidity and leverage play an important role in determining the share of SSF in price discovery. We add these two variables as to our Equations 5 and 6, and test if our results in Table 5 are not driven by these missing variables from the regression. Thus, our new regression specifications are:

$$\text{IS}_{\text{SSF},i,t,j} = \alpha_i + \beta_1 \text{HIGH-INF}_j + \beta_2 \text{C}_{(\text{SSF}-\text{S}),i,t,j} + \beta_3 \hat{\lambda}_{i,t,j} + \epsilon_{i,t,j} \tag{7}$$

$$\text{IS}_{\text{SSF},i,t,j} = \alpha_i + \beta_1^+ \text{HIGH-INF}_{t,j}^+ + \beta_1^- \text{HIGH-INF}_{t,j}^- + \beta_2 \text{C}_{(\text{SSF}-\text{S}),i,t,j} + \beta_3 \hat{\lambda}_{i,t,j} + \epsilon_{i,t,j} \tag{8}$$

Table 6 presents the results. Both for Equations 7 and 8, the results hold for the high information dummy and liquidity differential variable. The coefficients with the high information dummies HIGH-INF_j (Model 4), HIGH-INF_j^+ and HIGH-INF_j^- (Model 5) continue to be positive and significant. Similarly, the sign of the coefficient with the liquidity differential variable ($C_{(\text{SSF}-\text{S}),i,t,j}$) also continues to be negative and significant. However, the coefficient on leverage, though positive, turns insignificant. These results suggest that the extent of cross-sectional variation is largely related to the intra-day variation in market liquidity and information flow and not so much on the leverage of the SSF.[18]

7 Reproducible research

An R package named `ifrogs` has been released into the public domain, with an open source implementation of the IS calculations used in this paper.[19]

8 Conclusion

Theory suggests that derivatives ought to matter a lot in price discovery, but this is not supported in the existing empirical literature. Using a high quality dataset from the liquid single stock futures market at the National Stock Exchange, this paper reverses the finding. The high frequency data is used in an analysis of price discovery as a *process* with cross-sectional and temporal variation.

We develop a partial equilibrium model of the choice of the marginal trader who trades based on differences in leverage and pre-trade liquidity. The empirical cross-section analysis validates the trade-off between leverage and pre-trade liquidity in the two markets: the higher the leverage and the higher the liquidity, the higher the price discovery in the futures. There is also evidence of significant temporal variation in price discovery. While the information share of the futures is 49 percent on average, it rises to 55 percent during high information periods. When the news is negative, it rises further to 61 percent because of the higher cost of borrowing securities to settle a short sale position in the spot market. Traders appear to efficiently use capital while responding to changes in information flows.

This research design does not permit causal claims about the impact of funding constraints of traders upon the role of the futures in price discovery. However, two reasons suggest

[18]We also examine if conditional on high information period, whether liquidity and leverage matter more in determining the share of SSF in price discovery. To investigate this, we interact the dummy variables in Equation 7 and 8 with the leverage and liquidity differential variables. None of the interaction terms turn out to be significant. This indicates that liquidity differential and leverage do not have any special role during periods of high information per se.

[19]Information about this package and a subset of the data is available on `http://ifrogs.org/releases/ThomasAggarwal2013_priceDiscovery.html`

that it is a contributory factor. The first is that the price discovery of the futures is high *on average* at the NSE. This cannot be attributed entirely to news, since this tends to be sporadic and less frequent for a single security. On the other hand, funding constraints are present at all times, and can influence the *average* price discovery. The second is that the SSF dominate the price discovery even more strongly during the arrival of bad news. Constraints on short-selling the spot implies that the trader has a stronger preference to use SSF during such times, and this appears as higher price discovery in the SSF.

This analysis opens up several questions for downstream research. If funding constraints influence trader's choices, then the next step can be to develop models that incorporate these constraints. The analytical framework developed in this paper takes liquidity as exogenous. While the empirical validation of the trade-off suggests that these simplications are useful, in equilibrium, market liquidity is endogenously determined by the decision of traders. This suggests a model where traders with varying degrees of funding constraints and access to information, jointly determine the liquidity in the limit order book. Such a model would help fully explain why the SSF of some securities have better liquidity and price discovery while others in the same microstructure do not. This work may be usefully carried forward in other exchanges worldwide, going beyond broad averages to a more fine grained view about the role of derivatives trading, which varies in the cross section and across time.

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Figure 1 Cross-sectional variation in the leverage for the sample

The graph shows the cross-sectional variation in the leverage for the securities in the sample vis-a-vis the annualized volatility. Leverage is estimated based on a sample of one month of daily leverage values obtained from the exchange. The details are described in Section 4.3. The estimated leverage values range from $2.5\times$ to $8\times$. There are very few securities with leverage at $8\times$ which is the maximum permitted leverage for the SSF at the NSE.

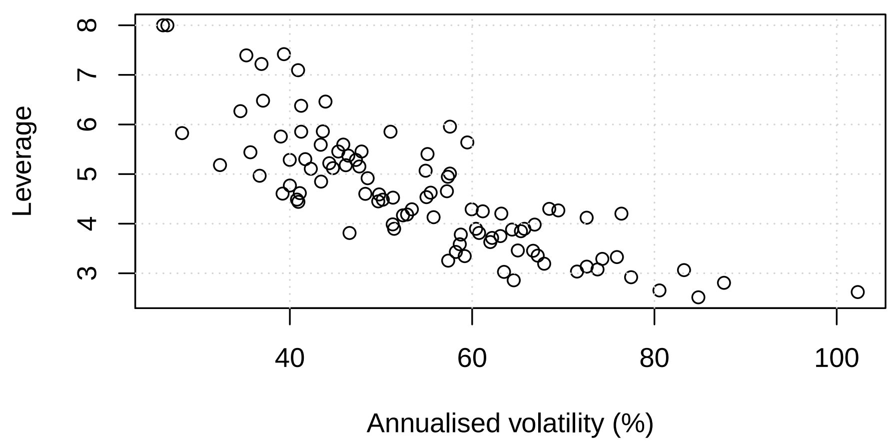

Table 1 Descriptive statistics of the sample

The table presents descriptive statistics of the sample for both the SSF and spot market. Each statistic is computed as the cross-sectional mean for the full sample as well as liquidity quartiles. Liquidity quartiles are based on the average impact cost on the SSF and spot market $(c_{\text{SSF},i} + c_{\text{S},i})/2$ for an order size $Q = 5000$. **Q1** is the quartile with the highest values of liquidity or leverage, while **Q4** is the quartile with the least. ** indicates that the difference between SSF and spot liquidity is significant at 5 percent.

	Market cap (Rs. Million)	Price (Rs.)	Liquidity (%) SSF	Liquidity (%) Spot	Leverage
All	299,317	523.66	0.24	0.13**	4.72
Q1 (Most)	779,074	818.78	0.04	0.04	4.44
Q2	215,908	497.88	0.06	0.07**	4.40
Q3	115,605	314.58	0.13	0.13	4.57
Q4 (Least)	70,184	458.60	0.29	0.74**	5.07

Table 2 Price discovery estimates for full and liquidity sub-samples

The table presents the IS_{SSF} liquidity quartiles, Q1...Q4, which are created based on the the average impact cost on the SSF and spot market $(c_{\text{SSF},i} + c_{\text{S},i})/2$ for an order size $Q = 5000$. C_{SSF} and C_{S} indicate the average liquidity costs on the SSF and the spot market respectively. Statistics for the IS estimates for each quartile is presented as the average upper bound (UB), the lower bound (LB), and the midpoint of the two (MID). **Q1** is the quartile with the highest liquidity, while **Q4** is the quartile with the least. The table also reports the value of IS-CS ratio to augment inference.
** on the MID variable indicates that IS_{SSF} is significantly different from 0.50 at 5 percent. ** on the IS-CS ratio indicates that the ratio is significantly different from 1 at 5 percent.

		Quartiles	IS_{SSF}			
C_{SSF}	C_{S}	by Liquidity	UB	MID	LB	IS-CS ratio
0.24	0.13	Full sample	0.53	0.49	0.47	1.01
0.04	0.04	Q1 (Most)	0.66	0.61**	0.55	1.14**
0.06	0.07	Q2	0.63	0.59**	0.55	1.13**
0.11	0.13	Q3	0.55	0.53	0.51	1.06
0.74	0.29	Q4 (Least)	0.25	0.24**	0.23	0.68**

Table 3 Fixed-effects panel regressions for changes in IS_{SSF} across securities

The table reports the estimates for Equation 4 specified as:

$$\text{IS}_{\text{SSF},i,t} = \alpha_i + \beta_2 \text{C}_{(\text{SSF}-\text{S}),i,t} + \beta_3 \hat{\lambda}_{i,t} + \epsilon_{i,t} \tag{9}$$

where $\text{C}_{(\text{SSF}-\text{S}),i,t}$ is the liquidity difference between the SSF and the spot markets, and $\hat{\lambda}_{i,t}$ is the estimated leverage in the SSF.
** indicates significance at 5 percent using a one tail test based on clustered standard errors.

	Model 1	
	Estimate	Std. Error
$\text{C}_{(\text{SSF}-\text{S}),i,t}$	-0.3093**	0.0853
$\hat{\lambda}_{i,t}$	0.0618**	0.0335
Total obs.	8,890	
Adjusted R^2	0.22	

Table 4 Price discovery estimates for high information and low information periods

The table shows estimated IS_{SSF} and IS_{S} for the full sample as well as liquidity sub samples during periods of high and low information. High information period is identified as the first half hour of trading and the first half hour after the corporate earnings announcement.
UB represents the upper bound of the IS estimate, and LB represents the lower bound. MID is the average of UB and LB. The table also reports the value of IS-CS ratio to help inferences on the IS estimate. Finally, the average impact cost (C) for a market order size of $ 5000 is calculated separately for these periods.
** indicates that the difference between SSF and spot values is significant at 5 percent level.

	IS_{SSF}			
	UB	MID	LB	IS-CS ratio
High Information				
Full sample	0.60	0.56**	0.53	1.15**
Q1 (Most)	0.72	0.66**	0.61	1.24**
Q2	0.71	0.67**	0.63	1.30**
Q3	0.62	0.60**	0.57	1.16**
Q4 (Least)	0.35	0.32	0.30	0.77
Low Information				
Full sample	0.52	0.49	0.45	1.00
Q1 (Most)	0.65	0.59**	0.54	1.14**
Q2	0.61	0.58**	0.54	1.13**
Q3	0.52	0.50	0.48	1.02
Q4 (Least)	0.28	0.27	0.26	0.69

Table 5 Fixed effects panel regressions estimates of changes in IS_{SSF} during high information periods

The table presents regression results for a fixed effects model (Model 2) for Equation 4 specified as:

$$\text{IS}_{\text{SSF},i,t,j} = \alpha_i + \beta_1 \text{HIGH-INF}_{t,j} + \epsilon_{i,t,j}$$

where $\text{HIGH-INF}_{t,j} = 1$ for $j = \text{HI}$ for high information periods during the trading day t and 0 for all other periods.
A second fixed effects model (Model 3) given by Equation 5 additionally tests for any effects of the benefits of short selling to explain the variation in IS_{SSF} during high information periods.

$$\text{IS}_{\text{SSF},i,t,j} = \alpha_i + \beta_1^{+} \text{HIGH-INF}^{+}_{t,j} + \beta_1^{-} \text{HIGH-INF}^{-}_{t,j} + \epsilon_{i,t,j}$$

where $\text{HIGH-INF}^{+}_{t,j} = 1$ for $j = \text{HI}$ when the index returns are positive during the high information periods on trading day t, zero otherwise. Similarly, $\text{HIGH-INF}^{-}_{t,j} = 1$ for $j = \text{HI}$ when the index returns are negative during the high information periods, zero otherwise. % OF OBS. indicates the percentage of observations when the dummy is 1.
** indicates significance at 5 percent based on clustered standard errors.

	Model 2			Model 3		
	Estimate	Std. Error	% OF OBS.	Estimate	Std. Error	% OF OBS
HIGH-INF	0.061**	0.005	50.86			
HIGH-INF^{+}				0.055**	0.006	23.36
HIGH-INF^{-}				0.069**	0.006	24.10
Total obs.			14,920			14,920
Adjusted R^2	0.20			0.20		
Test the null: $H_0^4 : \beta_1^{+} - \beta_1^{-} = 0; H_A^4 : \beta_1^{+} - \beta_1^{-} < 0$						
t-statistic = -1.74						

Table 6 Fixed effects panel estimates of changes in cross-sectional variation in $\mathrm{IS}_{\textsc{ssf}}$ during high information periods

The table presents regression results for a fixed effects model, (**Model 4**):

$$\mathrm{IS}_{\textsc{ssf},i,t,j} = \alpha_i + \beta_1 \mathrm{C}_{(\textsc{ssf}-\textsc{s}),i,t,j} + \beta_2 \hat{\lambda}_{i,t} + \beta_3 \textsc{high-inf}_j + \epsilon_{i,t,j}$$

where $\textsc{high-inf}_j = 1$ for high volatility periods of the trading day, when $j =$ information arrival during the trading day t and 0 for all other periods.
The second fixed effects model, (**Model 5**), additionally tests for asymmetric behaviour in the variation in $\mathrm{IS}_{\textsc{ssf}}$ depending upon the direction of the information:

$$\mathrm{IS}_{\textsc{ssf},i,t,j} = \alpha_i + \beta_1 \mathrm{C}_{(\textsc{ssf}-\textsc{s}),i,t,j} + \beta_2 \hat{\lambda}_{i,t} + \beta_3^{+} \textsc{high-inf}_j^{+} + \beta_3^{-} \textsc{high-inf}_j^{-} + \epsilon_{i,t,j}$$

where $\textsc{high-inf}_j^{+} = 1$ for high information periods with positive returns on Nifty and 0 otherwise. Similarly, $\textsc{high-inf}_j^{-} = 1$ for high information periods with negative returns on Nifty and 0 otherwise.
** indicates significance at 5 percent, based on clustered standard errors.

	Model 4		Model 5	
	Estimate	Std. Error	Estimate	Std. Error
$\mathrm{C}_{(\textsc{ssf}-\textsc{s}),i,t,j}$	-0.770**	0.076	-0.769**	0.075
$\hat{\lambda}_{i,t}$	0.024	0.033	0.027	0.033
$\textsc{high-inf}$	0.055**	0.005		
$\textsc{high-inf}^{+}$			0.049**	0.006
$\textsc{high-inf}^{-}$			0.061**	0.006
Total obs.	14,920		14,920	
Adjusted R^2	0.21		0.21	

Test the null: $H_0^4 : \beta_1^{+} - \beta_1^{-} = 0; H_A^4 : \beta_1^{+} - \beta_1^{-} < 0$
t-statistic = -1.72