Indian Equity Options: Smile, Risk premiums and Efficiency[1]

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Abstract

We study the pricing of equity options in India which is the world's second largest stock option market and third largest index options market. Several of our findings are supportive of market efficiency: a parsimonious smile adjusted Black Scholes model fits option prices quite well, and the implied volatility has incremental predictive power for future realized volatility. However the risk premium embedded in implied volatility for Single Stock Options is higher than in other markets, and appears to be in excess of what might be expected from theoretical considerations. This could be due to noise trading: Indian regulations and market structure allows greater participation of noise traders in option writing, possibly channels informed speculators into its highly liquid Single Stock Futures market, and perhaps gives greater scope for insider trading and market manipulation. The study suggests that even a very liquid market with substantial participation of global institutional investors can have structural features that lead to systematic departures from the behaviour of a fully rational market while being 'micro-efficient'.

Keywords: Volatility Smile, Risk premiums, Efficiency, Indian Equity Derivatives

[1]This paper is based on the dissertation of the first author. The authors are thankful to Prof. Ajay Pandey for his valauable advice and critical comments on an earlier version of the paper. Any errors remain the sole responsibility of the authors.

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Abstract

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1 Introduction

We examine the pricing of Indian Equity Options market, which in 2016 was the world's second largest[2] single stock options (SSO) market and the third largest[3] index option market. Indian equity derivatives market has many unique features that provide a good setting to investigate the pricing efficiency of the options market at both micro and macro levels. First, Indian regulations and market structure allows greater participation of noise traders in option-writing than in other countries.[4] Second, India has a very liquid Single Stock Futures (SSF) market along with a highly liquid equity options market. This may channel leverage-hungry informed speculators into its highly liquid SSF markets, unlike most developed markets like the US. Third, illiquid strike options are suspected to be used for tax hedging/ manipulation in India. All of the above factors could potentially make Indian equity options less efficient than in other countries. In contrast, the unfragmented Indian market is expected to result in more efficient pricing

[2]World Federation of Exchanges, Annual Statistics Guide, 2016

[3]The equity derivatives turnover on National Stock Exchange (NSE) was about INR 648 trillion in 2015-16 (SEBI Handbook of Statistics, 2016). The growth in the notional turnover of equity derivatives markets vis-à-vis the equity cash segment is one of the highest in the world at 15.54 in 2016 (Discussion Paper on Growth and Development of Equity Derivatives Market in India, SEBI, 2017)

[4]Discussion Paper on Growth and Development of Equity Derivatives Market in India, SEBI, 2017(Chart 2).

of derivatives. In India, all derivatives segments - Index Options, SSOs, Index Futures and SSFs - trade on the same exchange as the spot, potentially removing any noise arising from fragmented markets. The literature on Indian derivative market is scant, and this study is perhaps the first study that comprehensively examines the pricing efficiency of SSO and Index Option contracts at both micro- and macro-level.

We attempt to answer two questions on the efficiency of the Indian option market using a large dataset consisting of 66 unique SSOs and the Nifty[5] Index option during 2011-2015. First, we investigate whether the option prices are 'micro-efficient' by measuring the relative consistency in the prices across contracts with the same underlying. This is done by examining the conformity of observed option prices to a parsimonious smile-adjusted Black-Scholes model.

Second, we investigate the 'macro-efficiency' of the equity options market by verifying the relationship between the estimated smile-adjusted implied volatility (IV) and the realized volatility (RV). Empirical observations indicate that IV exceeds RV for all options. This difference has been attributed to mispricing and risk premium.[6] However, the magnitude of the difference between the IV and RV varies across underlying and markets. The difference has been found to be higher in index options than SSOs (Bollen and Whaley, 2004; Jackwerth and Rubinstein, 1996). Bakshi and Kapadia (2003a) argue that when the market is in stress, there is a rise in the market volatility. Investors are, therefore, willing to pay a higher price for the option contracts for insurance purpose. This implies a higher IV which has been observed by Aı et al. (2007); Bakshi and Kapadia (2003a); Bollerslev et al. (2011); Jones (2006); Carr and Wu (2008). The difference between IV and RV is higher for SSOs vis-à-vis Index options because the idiosyncratic volatility component of SSOs reduces the effect of market volatility. Theoretically, Girsanov's theorem states that under lognormality (GBM) assumptions, the risk-neutral and the physical volatility are the same, and only the drift is shifted. But under departures from GBM, this identity no longer obtains and IV exceeds RV. A risk premium can exist only if volatility risk is priced in equilibrium. This requires that the volatility risk is non-diversifiable and that volatility is correlated with the Stochastic Discount Factor (SDF). Both of these are true for index options but are much less true for SSOs. Lastly, we also investigate some empirical regularities between the IV and the RV.

Our main results are as follows. First, we find that the Indian equity

[5]Nifty 50 Index is India's market based stock-market Index, consisting of 50 highly liquid Indian stocks. Options on this Index are the Nifty Index Options.

[6]This risk premium is attributed to negative market volatility risk premium and to positive market-wide correlation shocks.

options market is micro-efficient. The median pricing errors in both the SSOs and the Nifty Index Option are very small at 0.3% and 0.8% respectively. Second, the difference between IV and RV is positive for both SSOs and Nifty Index Option. The mean difference between IV and the forward-looking (backward-looking) RV is about 3.11% (3.31%) for Nifty Index Option and 2.49% (3.55%) for SSOs. Further examination of determinants of SSO-IV suggests that the estimated SSO-IV is an optimal forecast of the risk-neutral volatility. Our results can be regarded as being supportive of rational markets except that SSO risk premiums appear to be too high relative to other economies. In line with global literature, we also find that (a) IV varies directly with RV; (b) stocks with lower RV also have lower IV; (c) IV has incremental predictive power for future volatility; and (d) the SSO smile contains a significant systematic component. The study suggests that even a very liquid market with substantial participation of global institutional investors can have structural features that lead to systematic departures from the behaviour of a fully rational market while being 'micro-efficient'.

The results of the study would be useful for arbitrageurs and traders. Various institutional investors like mutual funds, pensions funds, hedge funds, insurance funds, who use a lot of structured equity derivatives products (Francis et al., 2000) and operate arbitrage funds, would find our results useful. Booming global Alternative Investment Funds (AIF), especially category III, invest in listed and unlisted derivatives in India.[7] Our results would provide them useful insights for making informed decisions. Lastly, the results of the study may be helpful for hedgers. We find a systematic gap between IV and RV, which implies that a consistent strategy of a covered call may help enhance profits.

The structure of the document is as follows. Section 2 outlines the literature, Section 3 formulates the research questions, and Section 4 mentions data sources and sample formulation. Analysis of micro-efficiency and macro-efficiency are in Sections 5 and 6 respectively. Robustness tests are included in Section 7 while section 8 concludes.

2 Literature Review

2.1 Volatility Smile

Seminal work of Black and Scholes (1973) showed that option payoff can be replicated using a portfolio of the underlying stock and the bond, paving

[7] http://www.sebi.gov.in/media/press-releases/may-2012/sebi-notifies-sebi-alternative-investment-funds-regulations-2012_22799.html, http://www.sebi.gov.in/sebiweb/other/OtherAction.do?doRecognisedFpi=yes&intmId=16

the way for a theoretical option pricing formula. Black-Scholes made many assumptions to derive the formula including lognormally distributed instantaneous stock prices and friction-less markets. All parameters of the formula, except volatility, are observable from market data. Volatility was first estimated from historical stock prices. However, as option liquidity soared, investors used the market prices of options to back-calculate the volatility parameter, the Implied Volatility (IV), from the Black-Scholes formula. All else being equal, the theoretical price of an option should be a monotonically increasing function of its IV. Further, since only one volatility parameter (of the underlying) governs the option price, the plot of IV against strike price should be flat and constant through time. However, empirical findings greatly deviate from the expected flat and time-invariant relationship.

Rubinstein (1985) report a U-shaped 'smile'-like relationship between IV of individual stock options and their strike prices for a given maturity. The smile indicates that OTM options are severely overpriced in the market. Similar evidence was noted in Index options as well. Jackwerth (2000) analyzes monthly put trading strategies in S&P 500 Index options from 1988 to 1995 and finds that they deliver high (risk-adjusted) returns. Broadie et al. (2009) uses option prices from 1986 to 1996 and finds that a portfolio of long or short ATM or OTM options earned a significantly higher Sharpe Ratio. Jones (2006) reaches a similar conclusion with daily data. The smile could not be explained by market noise or bid-ask spreads. Such smiles are reported in various international markets as well. Mayhew (1995) surveys the literature on IV smile.

These smiles became skewed and downward-sloping ('volatility smirk'), particularly for Index Options, after the market crash of 1987 (Bates, 2000). A volatility smirk implied that OTM put options are priced higher in the market than OTM call options. Toft and Prucyk (1997) and Jackwerth and Rubinstein (1996) argue that investors became pessimistic after the crash causing the underlying distribution of Index returns to have a fatter left tail ('crashophobia'). Others have found volatility smirks in SSOs, although they are less steep than that in the Index (Bollen and Whaley, 2004).

A number of potential explanations for volatility smile/smirk have been given in the literature. Black (1976) and others suggested the leverage effect. A firm's debt-to-equity ratio increases when the price of the stock falls. Ceteris paribus, the impact of a shock on equity is larger after the fall in the asset value (than before) causing volatility to increase for low strike prices. However, Toft and Prucyk (1997) report that it is a minor effect and that it couldn't explain the volatility smile in the Index options. Information aggregation model was suggested by Grossman (1987) where trading allows investors to learn the true value of the asset and this learning then allows prices to adjust to the true value. However, such models predict that asset prices are equally likely to fall and rise, which is inconsistent with a downward-sloping smirk that implies that decreases are more likely than increases. Other explanations include increased risk aversion parameter during market stress (Franke et al., 1998) and higher buying pressure on put options for hedging purposes (Bollen and Whaley, 2004). However, these models only moderately explain the smile and do not explain the steep volatility smirk.

Another stream of literature relaxes the assumptions prevalent in Black-Scholes model to explain the smile. A smile arises if there is a departure from the lognormality of stock prices while retaining frictionless market assumptions. The model parameters like interest rate, volatility, etc. are allowed to vary deterministically or stochastically than being assumed constant. For example, deterministic volatility models allow the underlying stock volatility to evolve as a function of certain inputs (stock price and time as in Local Volatility Models) (Cox and Ross, 1976; Cox, 1996). However, even these models do not explain the volatility smirk completely.

These problems have motivated researchers to derive 'smile-consistent' volatility models. In this class of models, the market prices of standard European options are taken as given and an IV is computed by inverting those prices using the Black-Scholes formula. Thus, the computed IV is not only a no-arbitrage value, but it is endogenously determined from the options' market prices. The smile-consistent volatility models can be further classified as deterministic smile-consistent models and stochastic smile-consistent models. Deterministic smile-consistent models allow the smile to vary with given inputs (like strike price or option Delta). They are tractable and easily implemented through binomial/trinomial implied trees (Dupire, 1997; Jackwerth, 1997; Cox et al., 1979) or as an adhoc process (Malz, 1997).Skiadopoulos (2001) surveys smile-consistent volatility models. In this paper, we estimate a deterministic smile-consistent model for a large dataset of Indian equity options.

2.2 Variance Risk Premium

Realized Volatility, or RV, is defined as the volatility of the underlying stock over the life of an option, measured ex-post (forward-looking). It can also be computed as the volatility of underlying stock in the last 30 days (backward-looking). RV is a proxy for the true volatility of the underlying. Empirically, IV exceeds RV. Bakshi and Kapadia (2003b) find that the S&P 500 IV exceeds the RV by 3.3% during 1991 to 1995. French et al. (1987) showed that market returns and shocks to market volatility are negatively correlated. Bakshi and Kapadia (2003a) argue that this negative relationship implies that when the market is in stress (negative market returns), the market volatility increases. Holding options help hedge such market risk as the option Vega (sensitivity to underlying volatility) is positive. Hence investors are willing to pay a higher price for this insurance. This implies a negative volatility risk premium and a higher IV. Similar evidence is also noted by Aı et al. (2007), Bakshi and Kapadia (2003a), Bollerslev et al. (2011), Jones (2006), Carr and Wu (2008) and Broadie et al. (2009). Recently, Driessen et al. (2009) argue that Index options may have a correlation premium, which is insurance for reduced diversification during negative market movements.

However, IV and RV difference is smaller for SSOs. Bakshi and Kapadia (2003b) find a variance premium of 1.5% in their sample of 25 individual stock options from 1991 to 1995. Similar evidence is also noted by Bollen and Whaley (2004), Driessen et al. (2009) and Carr and Wu (2008). Bakshi and Kapadia (2003b) give two possible reasons for a smaller variance risk premia in SSOs than in Index Options. First, they argue that the idiosyncratic volatility component of SSOs' total volatility may reduce the effect of market volatility and hence the variance premium in SSOs. Second, market volatility may also affect the pricing of other risks (like jumps) in the index options making them more sensitive to market volatility than SSOs.

Theoretically, Girsanov's theorem states that under GBM (lognormality) assumptions, the risk-neutral volatility and the physical volatility are the same, and only the mean (drift) is shifted. But under stochastic volatility or jumps or other departures from GBM, this identity no longer obtains, and hence IV is greater than RV. This difference can be interpreted as evidence of mispricing or as negative volatility risk premium in Index options. A risk premium can exist only if volatility risk is priced in equilibrium. This requires that the volatility risk is non-diversifiable and that volatility is correlated with the Stochastic Discount Factor. Both of these are true for index options (volatility rises in bear markets). They are much less true for SSOs.

2.3 Options Mispricing in India

The bulk of empirical work in options markets in India deals with validating Black-Scholes model and noting the existence of a volatility smile in Nifty Index Option. Shaikh and Padhi (2014) study the volatility smile, term structure and implied volatility surfaces on Nifty Index Options from January 2012 to December 2012. They find a classical U-shaped volatility smile, and evidence of a volatility smirk. Narain et al. (2016) use Nifty Index Options prices from 2004 to 2014 and observes that IV of call options with lower strike prices was higher than IV of call options with the higher strike price. The results were reversed in the case of put options. Sehgal and Vijayakumar (2008) use daily Nifty Index option data of 2004 and 2005, and find the existence of an asymmetric volatility smile. Historical volatility and time to expiration seem to determine this smile asymmetry.

Varma (2002) shows evidence of severe mispricing in Indian Nifty Options during the period June 2001 to February 2002. The author uses Black's formula with Nifty Futures to calculate Implied Volatility of Index options. Volatility smiles are computed using a GARCH model on IV and found to be statistically different for put and call options, violating the put-call parity. Breeden-Litzenberger formula (Breeden and Litzenberger, 1978) is then used to compute the implied risk-neutral probability distributions for the terminal stock index price from the two smiles. As compared to normal or historical distribution, the implied probability distribution are more highly peaked and have thinner tails, implying volatility underpricing. Bi et al. (2014) use 10 SSOs closing prices from May 2012 to April 2013 to calculate their volatility under a GARCH (1,1) framework. The estimated volatility was fed into Black-Scholes option pricing formula, and the estimated prices were compared to market prices. The paper finds evidence of overpricing in the equity options markets.

The present literature, to the best of our knowledge, does not compare the pricing dynamics of Indian equity options market comprehensively. We use a recent and large dataset to observe both micro and macro-efficiency of 66 SSOs and Nifty Index Option. We further allow the volatility smile to vary with time by estimating a smile daily. We also compare IV with two measures of RV, and comment on the stylized empirical regularities between the IV and the RV.

3 Research Questions

Empirically examine mispricing in Indian Equity Options:

- Estimate 'volatility smile(s)' in Indian SSOs to observe any relative pricing inconsistency
- Identify any macro-pricing inefficiency and Risk Premia in Indian options market by measuring deviation between Implied Volatility and Realized Volatility

4 Data

The sample period for our study is January 2011 to December 2015. The sample period has been selected for two reasons. First, SSO contracts in

India switched from American to European type in January 2011. Thus, our sample consists of European options only. Second, Indian option market noticed an upward trend in volume after 2011, partly due to the shift to European options. We restrict our sample to Nifty Index option and to only those SSOs whose underlyings were components of the Nifty Index at any point between 2011 to 2015. These SSOs may be regarded as the most active contracts in India. Indian SSOs, especially illiquid contracts, are suspected to be used for tax manipulation purpose and therefore a liquidity filter was applied wherein all SSOs which traded less for less than (any) five minutes during the day have been excluded. As in Bakshi and Kapadia (2003b) and Driessen et al. (2009), only near-month SSOs with number of days to expiry between 7 and 30 (both included) calendar days are considered. All the scrips in the sample have atleast 100 valid trading days to remove newest entries.

The data on SSOs and Nifty Index Option is taken from National Stock Exchange (NSE) trade book.[8] As explained later, we use the Black's model instead of the Black-Scholes model to estimate the volatility smile. Black's model requires futures prices on the same underlying as the options. Since in India, the SSF market is more liquid than the SSO markets, we retrieve the last trading time (accuracy to the minute) of each unique option (characterized by scrip, expiry date, and strike price) and then match it to the futures price in that minute. Hence, all the SSFs and SSOs in our sample have prices within 59 seconds trading period.[9] This reduces any bias due to asynchronicity and stale prices. We follow the same pattern for Nifty Index Options. All options contracts whose market prices lies outside the Black model's arbitrage bounds have also been removed. Our sample of minute-matched futures and options would potentially reduce the number of options violating the arbitrage bounds due to pure asynchronicity. Finally, our sample consists of 66 unique SSOs and one (Nifty) index option.

Following Mixon (2009), we estimate smiles only for those SSO-days[10] where more than or equal to five unique options traded in a day. The specification avoids the problem of under- or perfect-fit of the quadratic smile.[11]

The riskfree rate is computed from the Implicit yield at Cut-off Price of 91-day Government Bonds (RBI).[12]

[8]Over 95% of equity derivatives in India trades on NSE (Discussion Paper on Growth and Development of Equity Derivatives Market in India, SEBI, 2017 (Pg. 7))

[9]The observations where futures price did not exist within the same minute were dropped (less than 1%).

[10]By SSO-Day we mean all option contracts of a particular underlying on a given day.

[11]The case of ≥ 3 unique options has been included as a robustness test.

[12]In the Black's formula, the riskfree rate appears as the discounting factor on the

5 Results: Micro-efficiency

This section addresses the first question, that is, it examines the extent of mispricing in the Indian equity options markets. We first outline the smile estimation method and then give the pricing errors.

5.1 Estimating Smile

We estimate a smile for each underlying-day[13] using a quadratic function, defined by $IV = a * Delta^2 + b * Delta + c$. The smile estimation method follows Malz (1997). Although some researchers have used a linear smile (Mixon, 2009), our choice of a quadratic function aims to capture the two most important departures from lognormality - fatter tails and skewness. A quadratic smile is, infact, a different parametrization of Vanna-Volga pricing. Any higher order smile may bring with it the problems of over-estimation. Our volatility smile is a call volatility smile. Following Varma (2002), we estimate the IV and delta simultaneously using Black's model rather than the Black-Scholes model. Black's model helps to circumvent the problems of cost-of-carry and dividend yields arising in Black-Scholes formula.

The smile delta range has been limited to [0,1], by converting the put option deltas to call deltas. To estimate the smile for each underlying-day, we minimize the sum of the squared pricing errors between the market prices of the options and the estimates of the prices using IV from the volatility smile recursively. We minimize the squared pricing error and not the IV error because the latter may be biased. For lower option prices, the IV can increase substantially while the option price itself may remain almost the same (Christoffersen et al., 2009).

The volatility smile is constrained to always lie above the X-axis within our domain of Delta [0,1] because negative IV (and hence prices) do not make sense. We do this by adjusting the smile parameter c to c_new. Note that simply adding back the minimum value of the function into c, i.e., $c\_new = c + b^2/4a$ and constraining $c >= 0$ does not work for two reasons - First, such unconditional addition may result in 'over-correction' if the location of the minima $(-b/2a)$ lies beyond our range of Delta [0,1]. Second, when a is close to 0, $b^2/4a$ may blow up. Thus, our adjustment requires that although we estimate a, b, c, the smile is characterized by a, b, c_new

difference of probability-weighted futures and strike prices, and has a very small effect on the price. Varma (2002) notes that even setting the riskfree rate to zero will make a difference of less than 1% for most option prices.

[13] each of 66 SSOs or Index Option

such that $c\_new = c + b^2/4a$ if $-b/2a \in [0,1]$ else $c\_new = c - min(0, a+b)$. Let us consider a simplified function $f = a * Delta^2 + b * Delta$ ($a >= 0$) (f and the smile function have the location of the minima at $-b/2a$, which is independent of c). The first part of the adjustment is adding the minimum value if the location of the minima ($-b/2a$) lies in Delta [0,1] domain. The second part derives from the fact that if $-b/2a$ does not lie in [0,1], then f would be monotonous between 0 and 1. In such a case, the location of minima would then occur at either 0 or 1, and the minimum would be $f(0) = 0$ or $f(1) = a + b$; whichever is lower we subtract from c. Any over-correction due to assuming the simplified function $a * Delta^2 + b * Delta$ rather than the actual function f will adjust in the next iteration as all these modifications occur within the estimation loop. The estimated smile is robust to sample size, size of error variances, and initial values supplied to it. Further, our sample of European options means that only the terminal asset price distribution matters and the stochastic process that carries the initial price to the terminal price is irrelevant.

Using the estimated smile for each underlying-day, we compute three parameters that perfectly describe the smile. The three parameters-level, scope and curvature, are measured as IV at Delta=0.5 (At-the-money or ATM IV), IV at Delta 0.25 - IV at Delta 0.75 (Risk-reversal or RR IV), and 0.5*(IV at Delta 0.25 + IV at Delta 0.75)-ATM (Butterfly or BF IV), respectively. Further, IV Skew is also computed as -RR/ATM. These are our IV variables used in all analysis. Unless explicitly mentioned, simply 'IV' refers to the ATM-IV.

5.2 Summary Statistics: Smiles

We have 41,565 smiles for 66 unique SSOs and 913 for Nifty Index option.[14] 41,378 (99.55%) SSO smiles have a non-zero quadratic coefficient, implying that a quadratic smile is a better fit than the linear for our sample.

The median (mean) number of smiles estimated for each SSOs is 693 (630). The estimated number of SSO smiles has risen each year from 5890 (2011) to 10,437 (2015) signifying the growing liquidity[15] in the Indian equity derivatives markets. For each smile for an SSO, the median number of points (unique options each day) are 12. The mean, minimum and maximum points are 13, 5 (by construction) and 72 respectively. The median (mean) for the

[14] For the purpose of our study, we have removed the outliers based on ATM SSO options (90th percentile or less than equal to 197%). This is following Driessen et al. (2009) whose sample excludes any extreme IVs. However, results with the full sample have been reported in the robustness section.

[15] A small part of the increase may be attributed to SSOs on underlying that were listed in the middle of the sample period.

Nifty Index Option is 47 (49).

5.3 Pricing Errors

This section addresses the first question, that is, it examines the extent of micro-mispricing present in the Indian equity options markets. We measure the pricing error of an option as the difference between the estimated price from the volatility smile and the market price of the option. Table 1 reports the pricing error in absolute (Rupees) and in percentage terms (Rupees divided by the closing spot price of the security that day). The mean pricing errors of both SSOs and Nifty Index options are very small, implying that the equity options market is relatively efficient.[16] The mean and median pricing errors are -0.3% (SSOs) and -0.8% (Nifty Index Option) of the closing spot prices.

[Insert Table 1 here]

However, the errors are negative, which implies that the estimated prices from the volatility smile are, in general, higher than the market prices. Further, Nifty Index Options seem to have less variation of mispricing across the various unique strikes and days (lower standard deviation at 0.05%). Across SSOs, the median (mean) of the median percentage pricing error for each SSO is -0.26% (-0.34%). Hence, there appear to be no outliers in the SSOs in terms of their pricing errors. One of the reasons for the lower pricing errors obtained could be attributed to the fact that our sample consists of the most liquid stocks in India.

To conclude, the Indian equity options market has low relative mispricing and is micro-efficient. Conformity to a quadratic smile is consistent with a rational market and the known stylized facts about return distributions in finance.

6 Results: Macro-efficiency

This section addresses the second research question about the macro-mispricing (or risk premium) present in the Indian equity options markets. We first outline estimation procedure of RV and then give our results.

[16] If the smile were calibrated using a linear OLS model, the mean pricing error would be zero. However, non-linear estimation means a small non-zero value can emerge.

6.1 Estimating RV

Following Bakshi and Kapadia (2003b), we compute the Realized Volatility as:

$$RV_{t,T} = \sqrt{\frac{N}{n}\sum_{i=t}^{T} R_{i-1,i}^2} \tag{1}$$

where R is the daily return, N is 252 and n is the number of trading days between t and T.[17]

For SSOs, R is calculated using dividend-adjusted returns obtained from the CMIE database. The Nifty returns are calculated as the difference of log closing prices, where the closing prices are collected from the NSE website. RV using SSF and Nifty Futures prices have been included as a robustness test later.

RV is calculated at two time-horizons as in Bakshi and Kapadia (2003b):

- From t-30 to t. All the trading days in the 30 calendar day period are taken to compute this RV. It is referred to as RV30 henceforth. Hence, this is a historical/ backward-looking measure of RV.
- From t to t+τ, where, τ = number of days to expiry. All trading days till option expiry are taken to compute this RV. It is referred to as RVexp henceforth. Hence, this is a forward-looking measure of RV.

6.2 Visual Evidence

The ATM (IV) and Realized Volatility (RV30 and RVexp) of SSOs and Nifty are plotted in Figures 1 and 2. The values represent the median values of ATM, RV30, and RVexp each month.

[Insert Figures 1 and 2 here]

The figures show that the median IV and RV follow a similar pattern. A simple visual inspection reveals that IV generally exceeds RV, suggesting some mispricing or risk premium in options. A wide range of risk premiums is consistent with rational markets. Further analysis provides evidence corroborated by these graphs and suggests the presence of macro-mispricing/ risk premium in the Indian equity options markets.

[17] Bakshi and Kapadia (2003b) note that subtracting the mean may introduce biases, and hence we calculate the RV without subtracting the mean.

6.3 Correlation between IV and RV

The correlations between ATM (IV) and RV30 and RVexp for SSOs and Nifty Index Options are given in Table 2. The correlations between IV and RV are around 0.58.[18]

[Insert Table 2 here]

6.4 Difference between IV and RV

We expect that IV (ATM) would exceed the RV for all options and the difference between IV and RV would be smaller for SSOs than Nifty Index Option. Table 3 give the various percentiles and mean of IV and the two measures of RV.

[Insert Table 3 here]

We observe that IV is higher than RV for SSOs as well as the Index Option. For SSOs, the difference between mean IV and mean RV30 is 2.49% (35.19% - 32.7%). For Nifty Index Options, the difference between mean IV and mean RV30 is 3.11% (19.14% - 16.03%). The difference in Nifty Index Option is higher than the corresponding difference in SSOs, in line with the literature (Bollen and Whaley, 2004; Jackwerth and Rubinstein, 1996; Bakshi and Kapadia, 2003b; Driessen et al., 2009).

However, the magnitude of the difference between IV and RV for SSOs is higher than found in other markets. In fact, when we take differences through RVexp or medians, SSOs appear to have a higher difference than the Index Option. The difference between the mean IV and mean RVexp of SSOs is 3.55%, while it is 3.31% for Nifty Index Options. The difference between median IV and median RV30 (RVexp) for SSOs is 2.41% (3.61%) and for Nifty Index Options is 1.95% (2.19%). Our values for IV-RV difference in SSOs are closer to that reported by Mixon (2009) at 6% than reported by Bakshi and Kapadia (2003b) at 1.5%.

The differences across firms in SSOs show a homogenous pattern. The mean difference between median IV and median RV30 (RVexp) is 2.29% (3.72%). For 7 (2) of 66 firms, the difference IV - RV30 (RVexp) is negative with an average of -1.62% (-1.42%).

[18] Although the correlation between IV and RV30 is higher than IV and RVexp, further examination in Section 6.5.3 shows that IV contains useful information about future volatility, and not just extrapolate the past.

Our results can be regarded as being supportive of rational markets except that SSO risk premiums appear to be too high relative to other economies. That being said, comparison with risk premiums in other economies is useful but not determinative. We explore the reasons behind this observation in section 6.5.4.

6.5 Regression Analysis

This section aims to analyse some cross-sectional and time-series dynamics of IV and RV.

6.5.1 Cross-section of IV and RV

First, we check if the cross-section of IV matches the cross-section of RV. As noted by Mixon (2009), this tests the relative mispricing in the options markets - higher volatility stocks should have higher prices. If the cross sections of IV and RV do not match, it could be argued that investors merely select "hot" stocks which may not have any bearing with the underlying's RV. It is essentially a restriction on the option pricing model. The regression equation is:

$$A\bar{T}M_i = \alpha + R\bar{V}_i + \epsilon_i \tag{2}$$

where $A\bar{T}M_i$ and $R\bar{V}_i$ are time-series averages of IV (ATM) and RV (RV30 or RVexp) of stock i.

The results are shown in Table 4. We see a coefficient of 0.93 (0.95) for RV30 (RVexp) which is close to unity and significant at 1%. This suggests that, in general, options on high volatility stocks are more expensive.[19]

[Insert Table 4 here]

6.5.2 IV and RV - Systematic relationship

The second question that we ask is whether ATM IV varies directly with RV. For this purpose, we run the pure-cross sectional regression,

$$ATM_{i,t} = \alpha + \beta RV_{i,t} + \epsilon_{i,t} \tag{3}$$

where RV is RV30 or RVexp, i is the firm, t is the trading day.

[Insert Tables 5 and 6 here]

[19]The regression results with volatility values in the natural log and RV computed from futures prices are reported in the robustness section 7.2.

We run the regression separately for Nifty Index Options (Table 5) and SSOs (Table 6). Our results are in line with Mixon (2009), who finds that if RV of a stock is less than RV of another stock, then the IV (ATM) of the former stock is also lesser than the latter's. Further, he observes that intuitively the slope should be positive, which our results support. The results are consistent with both definitions of RV.

We also control for time by including year-dummies. It aims to verify if the results of equation 3 are simply time series variation in the data. We find that the results remain unchanged when time-series effects are included. There is little change in slope for both Nifty Index Options and SSOs, implying the regression results are not due to aggregate movements in the data.

Additionally, we run a regression to control for firm fixed effects in SSO regression by including 65 dummy variables for 66 firms. This helps to examine any difference in IV levels across firms. The results in Table 6 show that there is a substantial increase in the explained variance when firm-level effects are controlled for. Further, we observe a decline in the slope coefficient of RV when firm effects are included similar to Mixon (2009). The decline could be interpreted that a transitory shock that increases RV also increases IV but to lesser extent.

Finally, we run a regression for SSOs including both the time and firm effects. The results are reported in Table 6. The results remain unchanged.[20] Hence, this section can be concluded with the observation that IV (ATM) are systematically related to the RV.

6.5.3 IV and future volatility

An equally interesting question we ask is whether IV contains new information above and beyond what can be extrapolated from the historical prices. Poon and Granger (2003) reviews literature on the predictive power of IV and reports empirical evidence on IV containing information about future volatility. The paper also states that the IV often beats the predictive power of many sophisticated volatility models that use historical data. Since RV30 is constructed using backward-looking prices, and RVexp is a constructed using forward-looking prices, the regression equation that is,

$$RVexp_{i,t} = RV30_{i,t} + ATM_{i,t} + \epsilon_{i,t} \tag{4}$$

where i is the stock and t is the trading day.

[20]The results with natural log of variables and RV computed with futures prices are included in Section 7.2

[Insert Table 7 here]

The results are shown in Table 7. For both SSOs and Nifty Index Option, IV is significant at 1% in the presence of RV30, demonstrating that the market is forecasting the future and not simply extrapolating the past. The results remain significant when controlled for firm and year effects. The R-square is high (37% and 39% for SSOs and Nifty Index Option, respectively) and in line with the global evidence. Poon and Granger (2003) lists that in equity options, the R-square is around 13-50% while the maximum reported R-square for Index Options is 50%. Hence, implied volatility of Indian equity options contains incremental predictive power for future realized volatility.

6.5.4 Determinants of SSO IV

Our results from Section 6.4 can be regarded as being supportive of rational markets except that SSO risk premiums appear to be too high relative to other economies. Therefore, a more detailed examination of the determinants of SSO IV (ATM) is called for. In an irrational market or one with a lot of frictions, IV will tend to reflect supply and demand: if a lot of investors want to buy options, the IV will rise far above the expected future volatility. In a market where dynamic hedging is unimpeded, writers will meet the demand by replication and IV will still reflect expected volatility over the life of the option. The first univariate regression we run is,

$$ATM_{SSO,i,t} = \alpha + \beta ATM_{Nifty,t} + \epsilon_{i,t} \tag{5}$$

where i is the stock and t is the trading date. We also control for firm and year dummies.

[Insert Table 8 here]

The results are reported in Table 8. The coefficient of ATM of Nifty Index Option Smile is positive and highly significant. In terms of R-square, over 38% of ATM of SSOs is explained by Nifty Index Option's ATM. Since ATM can be proxied for the level of the volatility smile, it seems that level of SSOs and Nifty Index Option seem to have a significant relationship.

Second, because of the non-linearity of option prices, we expect ATM of SSO to depend on the entire Index smile. Thus, we include all the Index smile parameters as dependent variables. The following multivariate regression equation is run,

$$ATM_{SSO,i,t} = \alpha + \beta_1 ATM_{Nifty,t} + \beta_2 RR_{Nifty,t} + \beta_3 BF_{Nifty,t} + \epsilon_{i,t} \tag{6}$$

where i is the stock and t is the trading date.

The results are presented in Table 8 (column 2). We observe that ATM, RR, and BF of Nifty Index Option have significant coefficients, but the explained variance is unchanged. Further, the coefficient of ATM of Nifty Index Option is the same in both univariate and multivariate cases. Since ATM, RR, and BF proxy for level, slope, and curvature of the Nifty Index Option smile respectively, we find that the level of the SSO smile is explained by the entire Nifty Index option smile in line with our expectation.

The third equation also includes RV and days to expiry as dependent variables. The results in Table 8 (column 3) indicate an increased R-square of 47%. Both RV and Days to expiry are highly significant, although the highest coefficients are from Nifty Smile (Nifty BF (1.63) and Nifty ATM (0.473)).

Finally, we include the lag of ATM IV for SSO as an independent variable, to account for the well-known clustering of volatility. The sample here includes SSO smiles of only those trading days for which a lag (consecutive or lag 1) smile is also available. The results are shown in Table 8 (column 4). The explained variance increases to 54% when the lagged variable is added. The coefficient of lagged ATM is also very high, indicating volatility clustering as is expected. Further, the previous variables also remain significant and of the same signs.

The results suggest that although the difference between the IV and RV of SSOs is higher in Indian equity options market, the market is nonetheless rational and the estimated IV is an optimal forecast of risk-neutral volatility.

6.5.5 Idiosyncratic Smile of SSOs

We now address how much of SSO smile characteristics are explained by the Nifty smile characteristics? The systematic component, or the explained variance, can be attributed to the average IV of stocks and the correlation between the stocks. The residuals, or the unexplained variance, can be attributed to the idiosyncratic/unsystematic volatility of the SSOs. The regression equation is,

$$IV_{SSO,i,t} = \alpha + \beta ATM_{Nifty,t} + \epsilon_{i,t} \tag{7}$$

where i is the stock and t is the trading date. Three measures from the SSO IV smile are considered separately- Risk-Reversal (RR), Butterfly (BF) and Volatility Skew (skew).

[Insert Table 9 here]

The results are reported in Table 9. All results are positive and significant. The table shows that 20%, 22%, and 4% of RR, BF and Skew of SSOs are explained by Nifty Index Option's RR, BF, and Skew respectively. The results of Skew are weaker as expected because SSOs generally do not have volatility skew while indices do (Volatility smile in SSOs vs. volatility smirk in Index). Higher R-square with firm-fixed effects indicates that SSO smile slope (RR) and curvature (BF) depend largely on firm characteristics which are to be expected on theoretical grounds.

Further, because of the non-linearity of option prices, we expect each of the SSO smile parameters to depend on the entire Index smile. Thus, we next include all the Index smile parameters in equation 7. The following multiple regression equation is run,

$$IV_{SSO,i,t} = \alpha + \beta_1 ATM_{Nifty,t} + \beta_2 RR_{Nifty,t} + \beta_3 BF_{Nifty,t} + \epsilon_{i,t} \qquad (8)$$

where i is the stock and t is the trading date.

The results are presented in Table 9. We observe that explained variance remains unchanged. The coefficients from univariate and multivariate regression also remain unchanged for RR and BF. However, all the additional coefficients are significant implying that SSO smile is explained by the entire Nifty Index Option smile. Overall, the results suggest the presence of a significant systematic component in the SSO smile.

7 Robustness Tests

7.1 Micro-efficiency

RV-F values are computed using near-month Single Stock futures prices for SSOs and near-month Nifty Index futures prices for Nifty Index Option. RV30-F is the backward-looking measure, and RVexp-F is the forward-looking measure (analogous to RV30 and RVexp). Table 10 give the various percentiles and mean of IV and the two measures of RV-F. The pattern is similar to that observed through RV computed from spot returns.

[Insert Table 10 here]

7.2 Macro-efficiency

We carry out the analysis using the natural log of variables or RV-F (as above) in this section. We find that these specifications do not alter the results. The regression results on time series average of IV regressed on RV are reported in Table 11. The results remain qualitatively same as that in the main section 6.5.1. Higher volatility options seem to have expensive options.

[Insert Table 11 here]

The regression results ov IV on RV are reported in Tables 12 and 13. The results remain qualitatively same as that in the main section.

[Insert Tables 12 and 13 here]

The results for RV regressed on IV for SSO and Nifty Index option are shown in Table 14. For both, ATM IV is significant in the presence of RV30 computed with futures prices as in the main section.

[Insert Table 14 here]

Results for samples including three unique options for smile estimation, including all SSO ATMs, and including near and next month options are qualitatively similar and are available on request.

8 Conclusion

India had the second highest notional turnover in SSOs and the third highest in Index Options in 2016. The structure of the Indian equity derivatives market is unique. First, Indian regulatory regime potentially leads to a greater proportion of noise traders among option writers than in other countries. Second, India has a very liquid Single Stock Futures (SSF) market along with a highly liquid equity options market. Third, illiquid strike options are suspected to be used for tax hedging/ manipulation. All of these could potentially make Indian SSOs less efficient than in other countries. We study mispricing in Indian equity options markets and answer two questions.

First, whether SSO prices in India consistent relative to one another? We estimate quadratic smiles using a large dataset and find that the median pricing errors in both the SSOs and the Nifty Index Option are very small at 0.3% and 0.8% respectively. The results suggest that Indian equity options market is micro-efficient and has low relative mispricing. Second, whether the 'volatility smile' reflects the true volatility. We find a positive difference between IV and RV for both Indian SSOs (2.49%) and Nifty Index Options (3.11%). The results can be regarded as being supportive of rational markets except that SSO risk premiums appear to be too high relative to other economies. Examining determinants of SSO IV suggests that the estimated IV is an optimal forecast of risk-neutral volatility. We further find that stocks with higher volatility have higher prices; and if RV of a stock is less than RV of another stock, then the IV of the former stock is also lesser than the latter's. We also observe that IV contains useful information about future volatility, above and beyond what is contained in past prices. Finally, our results suggest that the SSO smile has a significant systematic component.

Our results suggest that even a very liquid market with substantial participation of global institutional investors can have structural features that lead to systematic departures from the behaviour of a fully rational market while being 'micro-efficient'.

References

Ai, Y., Kimmel, R., et al. (2007). Maximum likelihood estimation of stochastic volatility models. *Journal of Financial Economics*, 83(2):413–452.

Bakshi, G. and Kapadia, N. (2003a). Delta-hedged gains and the negative market volatility risk premium. *Review of Financial Studies*, 16(2):527–566.

Bakshi, G. and Kapadia, N. (2003b). Volatility risk premiums embedded in individual equity options: Some new insights. *The Journal of Derivatives*, 11(1):45–54.

Bates, D. S. (2000). Post-'87 crash fears in the s&p 500 futures option market. *Journal of Econometrics*, 94(1):181–238.

Bi, Z., Yousuf, A., and Dash, M. (2014). A study on options pricing using garch and black-scholes-merton model. *Asian Journal of Finance & Accounting*, 6(1):423–439.

Black, F. (1976). Studies of stock price volatility changes. *Proceedings of the 1976 Meetings of the American Statistical Association*, pages 177–181.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of political economy*, 81(3):637–654.

Bollen, N. P. and Whaley, R. E. (2004). Does net buying pressure affect the shape of implied volatility functions? *The Journal of Finance*, 59(2):711–753.

Bollerslev, T., Gibson, M., and Zhou, H. (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of econometrics*, 160(1):235–245.

Breeden, D. T. and Litzenberger, R. H. (1978). Prices of state-contingent claims implicit in option prices. *Journal of business*, pages 621–651.

Broadie, M., Chernov, M., and Johannes, M. (2009). Understanding index option returns. *Review of Financial Studies*, 22(11):4493–4529.

Carr, P. and Wu, L. (2008). Variance risk premiums. *The Review of Financial Studies*, 22(3):1311–1341.

Christoffersen, P., Heston, S., and Jacobs, K. (2009). The shape and term structure of the index option smirk: Why multifactor stochastic volatility models work so well. *Management Science*, 55(12):1914–1932.

Cox, J. C. (1996). The constant elasticity of variance option pricing model. *The Journal of Portfolio Management*, 23(5):15–17.

Cox, J. C. and Ross, S. A. (1976). The valuation of options for alternative stochastic processes. *Journal of financial economics*, 3(1-2):145–166.

Cox, J. C., Ross, S. A., and Rubinstein, M. (1979). Option pricing: A simplified approach. *Journal of financial Economics*, 7(3):229–263.

Driessen, J., Maenhout, P. J., and Vilkov, G. (2009). The price of correlation risk: Evidence from equity options. *The Journal of Finance*, 64(3):1377–1406.

Dupire, B. (1997). *Pricing and hedging with smiles.* Mathematics of derivative securities. Dempster and Pliska eds., Cambridge Uni. Press.

Francis, J. C., Toy, W. W., and Whittaker, J. G. (2000). *The handbook of equity derivatives*, volume 14. John Wiley & Sons.

Franke, G., Stapleton, R. C., and Subrahmanyam, M. G. (1998). Who buys and who sells options: The role of options in an economy with background risk. *journal of economic theory*, 82(1):89–109.

French, K. R., Schwert, G. W., and Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of financial Economics*, 19(1):3–29.

Grossman, S. J. (1987). An analysis of the implications for stock and futures price volatility of program trading and dynamic hedging strategies.

Jackwerth, J. C. (1997). Generalized binomial trees. *The Journal of Derivatives*, 5(2):7–17.

Jackwerth, J. C. (2000). Recovering risk aversion from option prices and realized returns. *Review of Financial Studies*, 13(2):433–451.

Jackwerth, J. C. and Rubinstein, M. (1996). Recovering probability distributions from option prices. *The Journal of Finance*, 51(5):1611–1631.

Jones, C. S. (2006). A nonlinear factor analysis of s&p 500 index option returns. *The Journal of Finance*, 61(5):2325–2363.

Malz, A. M. (1997). Estimating the probability distribution of the future exchange rate from option prices. *The Journal of Derivatives*, 5(2):18–36.

Mayhew, S. (1995). Implied volatility. *Financial Analysts Journal*, pages 8–20.

Mixon, S. (2009). Option markets and implied volatility: Past versus present. *Journal of Financial Economics*, 94(2):171–191.

Narain, Nigam, N. K., Nigam, N. K., Pandey, P., and Pandey, P. (2016). Behaviour and determinants of implied volatility in indian market. *Journal of Advances in Management Research*, 13(3):271–291.

Poon, S.-H. and Granger, C. W. (2003). Forecasting volatility in financial markets: A review. *Journal of economic literature*, 41(2):478–539.

Rubinstein, M. (1985). Nonparametric tests of alternative option pricing models using all reported trades and quotes on the 30 most active cboe option classes from august 23, 1976 through august 31, 1978. *The Journal of Finance*, 40(2):455–480.

Sehgal, S. and Vijayakumar, N. (2008). Determinants of implied volatility function on the nifty index options market: Evidence from india. *Asian Academy of Management Journal of Accounting & Finance*, 4(1).

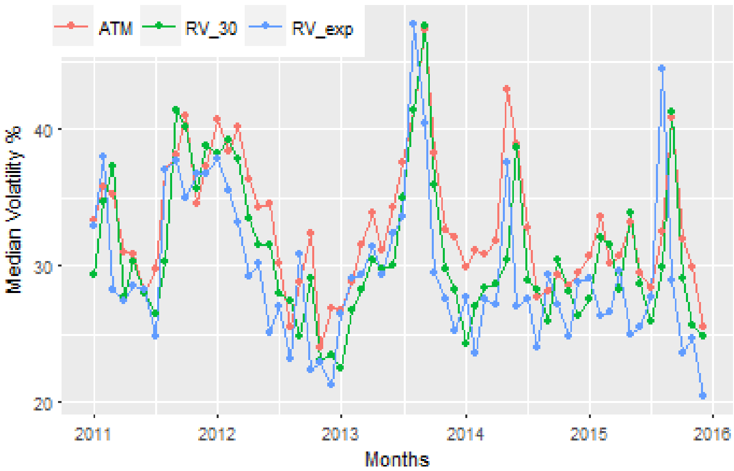
Shaikh, I. and Padhi, P. (2014). Stylized patterns of implied volatility in india: a case study of nse nifty options. *Journal of Indian Business Research*, 6(3):231–254.

Skiadopoulos, G. (2001). Volatility smile consistent option models: a survey. *International Journal of Theoretical and Applied Finance*, 4(03):403–437.

Toft, K. B. and Prucyk, B. (1997). Options on leveraged equity: Theory and empirical tests. *The Journal of Finance*, 52(3):1151–1180.

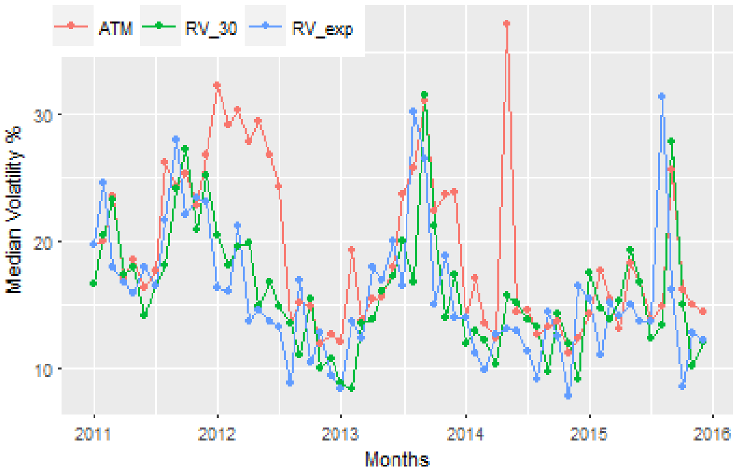
Varma, J. R. (2002). Mispricing of volatility in the indian index options market. *Working 0*.

Figure 1: SSOs - IV and RV



ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility. This graph computes month-wise median for the SSOs.

Figure 2: Nifty Index Option - IV and RV



ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility. This graph computes month-wise median for the SSOs.

Table 1: Average pricing errors

Statistic	Mean	St. Dev.	Min	Median	Max
Panel A: SSO					
Rs	−0.034	0.107	−4.360	−0.011	2.938
Rs/Spot Price	−0.009	0.073	−2.901	−0.003	0.067
Panel B: Nifty Index Option					
Rs	−0.585	0.286	−4.373	−0.533	0.067
Rs/Spot Price	−0.009	0.005	−0.090	−0.008	0.001

Note: Pricing Error is defined as the difference between the price of the option computed using Black's formula using volatility from the smile and the market price of the option. The errors are reported both in absolute (Rupees) and percentage (Rupees divided by the closing spot price of the security that day).

Table 2: Correlation between IV and RV

	ATM	RV30	RV_exp
Panel A: SSOs			
ATM	1		
RV30	0.578	1	
RV_exp	0.492	0.526	1
Panel B: Nifty Index Option			
ATM	1		
RV30	0.589	1	
RV_exp	0.410	0.480	1

Note: ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility.

Table 3: Summary Statistics IV and RV for SSOs

	Volatility	1%	10%	25%	50%	75%	90%	99%	Mean
SSOs									
1	ATM	17.37	22.77	26.57	32.23	40.13	50.17	84.15	35.19
2	RV30	13.61	19.41	23.89	29.82	38.15	49.01	79.23	32.7
3	RV_exp	10.21	17.19	22.09	28.62	37.6	49.26	82.97	31.64
Nifty Index Option									
1	ATM	10.45	12.27	14.12	17.13	23.55	29.26	37.82	19.14
2	RV30	7.46	10.35	12.91	15.18	18.34	23.22	30.84	16.03
3	RV_exp	7.19	9.3	12.28	14.94	18.21	23.51	32.88	15.83

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility .

Table 4: Time series average IV (ATM) regressed on time series average of RV -SSOs

	Dependent Variable	
	Avg. ATM	
	(1)	(2)
Avg. RV30	0.926***	
	(0.031)	
Avg. RVexp		0.947***
		(0.033)
Constant	0.050***	0.054***
	(0.010)	(0.011)
Observations	66	66
Adjusted R^2	0.934	0.927
Note:		*p<0.1; **p<0.05; ***p<0.01

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility . Standard Errors are in parenthesis.

Table 5: IV (ATM) regressed on RV - Nifty Index Options

	Dependent Variable			
	ATM			
	(1)	(2)	(3)	(4)
RV30	0.793***		0.802***	
	(0.036)		(0.038)	
RVexp		0.487***		0.462***
		(0.036)		(0.039)
Constant	0.064***	0.114***	0.055***	0.122***
	(0.006)	(0.006)	(0.009)	(0.009)
Year Controls	No	No	Yes	Yes
Observations	913	913	913	913
Adjusted R^2	0.347	0.167	0.439	0.282

Note: *p<0.1; **p<0.05; ***p<0.01

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility . Standard Errors are in parenthesis.

Table 6: IV (ATM) regressed on RV - SSOs

	Dependent Variable							
	ATM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RV30	0.618***		0.612***		0.428***		0.421***	
	(0.004)		(0.004)		(0.005)		(0.005)	
RVexp		0.484***		0.479***		0.281***		0.274***
		(0.004)		(0.004)		(0.005)		(0.005)
Constant	0.150***	0.199***	0.172***	0.223***	0.181***	0.227***	0.207***	0.253***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
Year Controls	No	No	Yes	Yes	No	No	Yes	Yes
Firm Controls	No	No	No	No	Yes	Yes	Yes	Yes
Observations	41,565	41,565	41,565	41,565	41,565	41,565	41,565	41,565
Adjusted R^2	0.334	0.242	0.338	0.246	0.403	0.359	0.407	0.363

Note: *p<0.1; **p<0.05; ***p<0.01

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility . Standard Errors are in parenthesis.

Table 7: RVexp regressed on RV30 and IV(ATM)

	Dependent Variable: RVexp			
	Nifty		SSO	
	(1)	(2)	(3)	(4)
RV30-Nifty	0.415***	0.174***		
	(0.040)	(0.042)		
ATM-Nifty	0.164***	0.223***		
	(0.030)	(0.030)		
RV30-SSO			0.395***	0.245***
			(0.005)	(0.006)
ATM-SSO			0.287***	0.201***
			(0.005)	(0.005)
Constant	0.061***	0.122***	0.086***	0.133***
	(0.006)	(0.008)	(0.002)	(0.006)
Year Controls	No	Yes	No	Yes
Firm Controls	No	NA	No	Yes
Observations	913	913	41,565	41,565
Adjusted R^2	0.254	0.369	0.330	0.390

Note: *p<0.1; **p<0.05; ***p<0.01

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility . Standard Errors are in parenthesis.

Table 8: Determinants of SSO ATM IV

	Dependent Variable: SSOs ATM			
	ATM-SSO			
	(1)	(2)	(3)	(4)
LAG ATM-SSO				0.365***
				(0.006)
RV30-SSO			0.291***	0.185***
			(0.005)	(0.006)
RVexp-SSO			0.153***	0.112***
			(0.004)	(0.005)
ATM-Nifty	0.682***	0.631***	0.473***	0.309***
	(0.010)	(0.013)	(0.012)	(0.015)
RR-Nifty		−0.432***	−0.218***	−0.192***
		(0.055)	(0.054)	(0.062)
BF-Nifty		3.417***	1.630***	0.573**
		(0.204)	(0.203)	(0.225)
Days			−0.001***	−0.001***
			(0.0001)	(0.0001)
Constant	0.180***	0.152***	0.100***	0.067***
	(0.006)	(0.006)	(0.006)	(0.008)
Year Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Observations	41,565	41,565	41,565	26,690
Adjusted R^2	0.384	0.392	0.466	0.541

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

ATM is the IV of the 50 Delta option, read off from the estimated Volatility smile. RR is defined as the difference of IV of 25 Delta option and IV od 75 Delta option, both read from the volatility smile. BF is defined as the difference between the average of IV of 25 Delta option and IV of 75 Delta option and the ATM. Skew is defined as negative RR divided by ATM. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility. Standard Errors are reported in parenthesis.

Table 9: SSO IV measures regressed on Nifty Index Option IV measures

	Dependent Variable: SSOs IV					
	RR	BF	Skew	RR	BF	Skew
	(1)	(2)	(3)	(4)	(5)	(6)
ATM-Nifty				-0.034^{***}	0.045^{***}	0.039^{*}
				(0.004)	(0.002)	(0.023)
RR-Nifty	0.593^{***}			0.521^{***}	0.137^{***}	-1.331^{***}
	(0.011)			(0.016)	(0.007)	(0.103)
BF-Nifty		0.509^{***}		0.175^{***}	0.770^{***}	-0.174
		(0.023)		(0.060)	(0.026)	(0.349)
Skew-Nifty			0.019^{***}			-0.016^{***}
			(0.005)			(0.006)
Constant	-0.007^{***}	0.015^{***}	0.081^{***}	-0.004^{*}	0.008^{***}	0.032^{***}
	(0.002)	(0.001)	(0.010)	(0.002)	(0.001)	(0.011)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,565	41,565	41,565	41,565	41,565	41,565
Adjusted R^2	0.195	0.218	0.036	0.198	0.232	0.045

Note: *p<0.1; **p<0.05; ***p<0.01

RR is defined as the difference of IV of 25 Delta option and IV od 75 Delta option, both read from the volatility smile. BF is defined as the difference between the average of IV of 25 Delta option and IV of 75 Delta option and the ATM. Skew is defined as negative RR divided by ATM. RV30 is the t-30 to t backward-looking realized volatility. RVexp is the t to t+ Number of days to expiry for the option forward-looking realized volatility. Standard Errors are reported in parenthesis.

Table 10: Summary Statistics IV and RV-F

	Volatility	1%	10%	25%	50%	75%	90%	99%	Mean
Panel A: SSOs									
1	ATM	17.37	22.77	26.57	32.23	40.13	50.17	84.15	35.19
2	RV30_F	13.65	19.28	23.73	29.88	38.55	49.96	93.42	35.17
3	RV_exp_F	10.22	16.88	21.83	28.49	37.71	50.12	94.17	33.85
Panel B: Nifty Index Option									
1	ATM	10.45	12.27	14.12	17.13	23.55	29.26	37.82	19.14
2	RV30_F	8.34	10.72	13.21	15.73	18.98	23.79	31.26	16.58
3	RV_exp_F	6.94	9.59	12.52	15.39	18.6	24.24	34.14	16.24

Notes: ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30-F is the t-30 to t backward-looking realized volatilit y. RVexp-F is the t to t+ Number of days to expiry for the option forward-looking realized volatility. RV-F are computed using near month futures prices.

Table 11: Time series average IV (ATM) regressed on time series average of RV-F -SSOs

	Dependent Variable			
	Avg. ATM		Avg. ATM	
	(1)	(2)	(3)	(4)
Avg. RV30-F	0.736***			
	(0.054)			
Avg. RVexp-F		0.677***		
		(0.054)		
Avg. LN-RV30			0.866***	
			(0.034)	
Avg. LN-RVexp				0.847***
				(0.036)
Constant	0.095***	0.125***	0.542***	0.643***
	(0.020)	(0.019)	(0.116)	(0.123)
Year Controls	No	No	No	No
Firm Controls	No	No	No	No
Observations	66	66	66	66
Adjusted R^2	0.741	0.706	0.911	0.896

Note: *p<0.1; **p<0.05; ***p<0.01
ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30-F is the t-30 to t backward-looking realized volatility. RVex -F is the t to t+Number of days to expiry for the option forward-looking realized volatility. RV-F are computed using near-month futures prices. LN refers to the natural log of the variable. Standard Errors are reported in parenthesis.

Table 12: IV (ATM) regressed on RV-F for Nifty Index Options

	Dependent Variable			
	ATM		ATM	
	(1)	(2)	(3)	(4)
RV30-F	0.773^{***}			
	(0.035)			
RVexp-F		0.489^{***}		
		(0.034)		
LN-RV30			0.681^{***}	
			(0.029)	
LN-RVexp				0.454^{***}
				(0.029)
Constant	0.063^{***}	0.112^{***}	-0.432^{***}	-0.846^{***}
	(0.006)	(0.006)	(0.055)	(0.055)
Year Controls	No	No	No	No
Firm Controls	No	No	No	No
Observations	913	913	913	913
Adjusted R^2	0.344	0.180	0.376	0.216

Note: *p<0.1; **p<0.05; ***p<0.01

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30-F is the t-30 to t backward-looking realized volatility. RVex -F is the t to t+Number of days to expiry for the option forward-looking realized volatility. RV-F are computed using near-month futures prices. LN refers to the natural log of the variable. Standard Errors are reported in parenthesis.

Table 13: IV (ATM) regressed on RV-F -SSOs

	Dependent Variable			
	ATM		ATM	
	(1)	(2)	(3)	(4)
RV30-F	0.086***			
	(0.002)			
RVexp-F		0.057***		
		(0.002)		
LN-RV30			0.603***	
			(0.004)	
LN-RVexp				0.435***
				(0.003)
Constant	0.321***	0.333***	−0.392***	−0.567***
	(0.001)	(0.001)	(0.005)	(0.005)
Year Controls	No	No	No	No
Firm Controls	No	No	No	No
Observations	41,565	41,565	41,565	41,565
Adjusted R^2	0.048	0.027	0.391	0.271

Note: *p<0.1; **p<0.05; ***p<0.01

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30-F is the t-30 to t backward-looking realized volatility. RVex -F is the t to t+Number of days to expiry for the option forward-looking realized volatility. RV-F are computed using near-month futures prices. LN refers to the natural log of the variable. Standard Errors are reported in parenthesis.

Table 14: RVexp regressed on RV30-F and IV(ATM)

	Dependent Variable: RVexp-F			
	Nifty		SSO	
	(1)	(2)	(3)	(4)
RV30-F-Nifty	0.408***	0.157***		
	(0.040)	(0.042)		
ATM-Nifty	0.188***	0.236***		
	(0.031)	(0.030)		
RV30-F-SSO			0.110***	0.078***
			(0.006)	(0.006)
ATM-SSO			0.418***	0.205***
			(0.014)	(0.017)
Constant	0.059***	0.128***	0.153***	0.163***
	(0.006)	(0.008)	(0.005)	(0.022)
Year Controls	No	Yes	No	Yes
Firm Controls	No	N/A	No	Yes
Observations	913	913	41,565	41,565
Adjusted R^2	0.263	0.385	0.036	0.063

Note: *p<0.1; **p<0.05; ***p<0.01

ATM is IV of the 50 Delta option from the estimated Volatility smile. RV30-F is the t-30 to t backward-looking realized volatility. RVex -F is the t to t+Number of days to expiry for the option forward-looking realized volatility. RV-F are computed using near-month futures prices. Standard Errors are reported in parenthesis.