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PREDICTABILITY AND PREDICTORS OF VOLATILITY SMIRK: A STUDY ON INDEX OPTIONS

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Abstract. The purpose of this study is to examine the presence of volatility smirk anomaly in index options and its predictability for future returns. The study tests the temporal properties of volatility smirk and further explores the factors determining the anomaly. The daily volatility smirk is computedfor the period 2004–2014 and the first lag of smirk is used in generalized least square (GLS) estimation framework, with set of control variables in two different specifications, to test the predictability as well as the determinants of volatility smirk. The study reports significant presence of volatility smirk in index options with an auto–regressive structure. Smirk predicts marginal returns and the predictability is robust to the control of major risk factors. It is also found that open interest of calls and puts, along with market risk premium and momentum premium, act as significant predictor of volatility smirk. The results are helpful in enhancing returns on investment in Index based funds and designing options strategies from the perspective of volatility risk. The study is first of its kind in the Indian market examining the reasons and consequences of existence of volatility smirk in index options.

Keywords: options, implied volatility, informed trading, moneyness, volatility smirk.

JEL Classification: G1.

Introduction

One of the major anomalies reported in the literature of derivatives is the presence of volatility smirk implicit in the prices of options (see Bates 2003, Xing et al. 2010). Volatility smirk refers to the difference of the implied volatilities of out–of–the–money (OTM) put options and at–the–money (ATM) call options for the same underlying. The presence of volatility smirk in the prices of index and stock options violates the Black and Scholes (1973) options pricing theory (B–S). The B–S theory suggests that every option should imply the same volatility for a given underlying. However, the presence of volatility smirk indicates that implied volatility, as a function of exercise/moneyness for a certain maturity, is a negatively skewed curve for most of the options (Foresi and Wu 2005).

Series of options prices provide insights into the climate of expectations of various market participants. For instance, a call option pays off only when it finishes in–the–money (ITM) implying that the underlying asset price is in excess of the exercise price. On the other hand, a put option pays off only when the reverse is true. Thus, the set of call and put options premium across all exercise prices provides a very direct indication of market participants' aggregate subjective distributions (Bates 1991, 2000). Therefore, an assessed downside risk in the market will lead "put options with exercise prices well below the current spot price"(OTM puts), being priced higher than "calls with exercise prices close to the spot price: (ATM calls). Large downward movements in the market make the "puts" more likely to finish ITM than the "calls"and results in steeper volatility smirk. Pan (2002) reports that investors tend to choose OTM puts to express their concerns about possible future negative jumps, thus making OTM puts more expensive.

The characteristics of volatility smirk and reasons thereof have been thoroughly analyzed for index options (Bates 1991, Pan 2002, Chen and Xu 2014) as well as stock

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options (Bollen and Whaley 2004, Xing et al. 2010). The recent studies on options suggest that the presence of volatility smirk could be attributed to the aversion of investors to future negative jumps in the prices of the underlying (see Bates 1991, Pan 2002, Kim and Zhang 2014). However, the empirical investigation on determinants of volatility smirk and the utility of smirk in enhancing the incentives of traders are sparse. Volatility smirk being a signal to negative price jump seeks attention as it can help market participants to mitigate their potential losses significantly, when they know the direction and magnitude of smirk–returns relationship. Conversely, it can also be helpful in enhancing their portfolio performance using short selling strategies. Moreover, such study would help the practitioner's in the field of finance understand the behaviour and implications related to complex trading variables such as volatility smirk.

This study empirically examines the predictors and predictability of volatility smirk using daily trading data of stock options traded on National Stock Exchange (NSE), India. Unlike previous studies (see Xing et al. 2010, Yan 2011), this paper, interestingly, finds that smirk displays positive causal relationship with marginal index returns. The results are consistent even after controlling for major risk factors. Moreover, it is observed that lag smirk along with calls and puts open interest help predicting next day's smirk. Market risk premium and returns of winners minus losers' portfolio (WML) of Carhart (1997) also turn out to be a significant predictor of smirk. Volatility being important factor for investment strategies and portfolio management activities, the results are helpful in enhancing returns on investment, particularly, in Index based funds and for designing options strategies based on volatility risk i.e. vega.

The remainder of this paper is organized as follows. Section 1, presents literature review and section 2 denotes objectives of the study. Section 3 describes the data and methodology whereas Section 4 presents the analysis and discusses the empirical results. Finally, the last section concludes the paper and highlights the limitations of the study and scope of further research.

1. Literature review

Xing et al. (2010), using individual stock options, document a positive volatility smirk with a median of around 5%. They further examine the predicting ability of volatility smirk for future stock returns and report that stocks with flatter smirks outperform those with steepest smirks, on a risk–adjusted basis. Yan (2011) examine the predicting ability of implied volatility smile for future stock returns using a sample of four thousand stocks during the period of 1996–2005. The author reports a negative relationship between the slope of implied volatility smile and stock returns.

Bianconi et al. (2015) use Black–Scholes options pricing model to compute implied volatility and implied risk free rate to re–price option contracts. They find volatility smile helpful in explaining the differences between market price and model based options price. However, there are evidences to the contrary where volatility smirk is not found to be a robust predictor of future returns (Heston 1993, Conrad et al. 2008). Heston (1993), for instance, develops an options pricing model with stochastic volatility assuming perfect information flow between the stock market and the options market. The volatility smirks generated using this model fails to predict underlying stock returns, which he attributes to the irrelevancy of expected returns for option pricing.

Moreover, an impressive range of researchers (see Manaster and Rendleman 1982, Chan et al. 2002, Mayhew and Stivers 2003, Chakravarty et al. 2004, Pan and Poteshman 2006, Ni et al. 2008, Taylor et al. 2010, Pathak et al. 2015) examine such inter–linkages across markets at firm level and provide mixed evidence of information content in prices and trading activity of the options market. However, our paper differs from existing studies on several grounds. Most of the studies examining informativeness of options market about future stock returns use prices or volume (Chan et al. 2002, Pan and Poteshman 2006) based variables; not many studies examine the information content of volatility smirk using options. In particular, no such study exists in the context of the Indian derivative market, which ranks second in the world in trading of stock index options. Thus, this study undertakes following objectives to be investigated.

2. Objectives

The first objective of our paper is to explore the existence of volatility smirk in index options and investigate whether this anomaly predicts future returns. Thus, it contributes to the literature by examining the inter–linkage of spot and options market and establish the causal relationship between returns and volatility smirk. Secondly, the paperintends to examine the potential predictors of volatility smirk. Investors can utilize the determinants of smirk, identified in this study, in extracting information about future stock returns and thereby enhance their incentives.

3. Methodology – data source, sample frame, empirical models

The sample period of our study is from January 01, 2003 to December 31, 2014. The end of the day data is collected for S&P CNX Nifty Index spot and options prices and other trading variable (i.e. number of contracts traded, open interest) data from National Stock Exchange (NSE) "daily bhav copy" of derivatives market available on exchange website (www.nseindia.com). The very motive of selecting Index options traded on NSE for our study is the preference of these options contracts by traders (among other derivatives). Although derivatives trading in India started only in year 2000 on two exchanges of India, i.e. NSE and Bombay Stock Exchange (BSE), NSE has found itself in global competition since its introduction of first derivative contract. Recently in 2010, as per report of World Federation of Exchanges (WFE), it has been ranked 2nd and 3rd in trading number of stock index options and number of single stock futures contracts respectively. It is also ranked 7th worldwide based on number of total derivatives contracts traded. The growth rate of derivatives trading in India has also been astounding with a CAGR of above 100% for turnover and contracts traded of index based derivatives.

The daily data for four factors given by Carhart (1997) is collected from the Indian market data library of Agarwalla et al. (2014). The authors compute factors for Indian market since 1995 using data from CMIE prowess database. We postulate that volatility smirk, computed using options on index, is the smirk on a portfolio. Since, volatility smirk and returns are found related in literature and Carhart four–factors are well established determinants of returns, therefore, we posit that the Carhart–factors can potentially determine smirk. We compute daily volatility smirk following Xing et al. (2010) where the smirk measure "$smirk_t$" on day t is the difference between implied volatilities of *OTM* puts and *ATM* calls denoted as $IVol_t^{OTMP}$ and $IVol_t^{ATMC}$. The daily implied volatilities ($IVol_t$) are computed by reverting Black and Scholes (1973) options pricing model for volatility for both *ATM* calls and *OTM* puts:

$$IVol_t = \left[\sum_{j=1}^{N} ISD_{jt}^2 * w_{jt}^2\right]^{1/2} \cdot \left[\sum_{j=1}^{N} w_{jt}\right]^{-1}, \qquad (1)$$

where $IVol_t$ is common implied volatility of Nifty index, ISD_{jt} s implied standard deviation of options j of a given moneyness catagory (*OTM* puts/*ATM* calls) on day t, w_{jt} is no of contracts traded on options j in *OTM* puts/*ATM* calls on day t and N is the number of options available on a given day:

$$smirk_t = IVol_t^{OTMP} - IVol_t^{ATMC}. \qquad (2)$$

A put option is classified as *OTM* if the strike price is between 80 to 95 percent of spot price. An *ATM* call options has the ratio of strike price to stock price between 0.95 to 1.05. NSE issues index options contracts for different trading cycles[1]. The 3 months trading cycle data – the near month (one–month), the next month (two–month) and the far month (three–month), contracts is employed in our study as other contracts experience negligible trading. However, in our analysis, all options in the 3 months cycle, which has non–zero volume on a given day, are considered to avoid missing on any important information. Since, there are multiple *OTM* and *ATM* options available on any given day; a volume–weighted approach is used to arrive at single smirk observation for each day. Number of contracts traded across options on a day are used as proxy for volume and is used as weights to compute weighted implied volatility on a given day t for both call and put options. Our final sample consists of 2888 daily–observations for the study period, which spans 12 years (2003–14).

The summary statistics of variables under consideration for this study, to illustrate their characteristics and behaviour, are presented in (Table 1). Unlike other variables, the average daily return on Nifty index is close to zero during our study period and has too little volatility. It ranges between +2.8% to –5% approx. with a median return close to zero. The distribution of daily returns is negatively skewed and leptokurtic which is consistent with literature. A significant average daily Smirk of 8% is observed and is found positively skewed with a median value of 5%. With a standard deviation of 13.8% the smirk has a wider range of +70% to –58% approximately. The average daily returns of Carhart four factors (*SMB*, *HML*, *WML* and $R_m - R_f$) are less than 1% but have very high volatilities. The trading activity variables volume and open interests of calls and puts are observed to be negatively skewed. The Augmented Dickey Fuller (*ADF*) test was conducted to check for the stationarity of the variables as a prerequisite to be used in a time series regression. The test rejected the null hypothesis of unit root at 1% critical value (–3.43) for all variables except for lncalloi where hypothesis is rejected at 5% critical value (–2.57).

The line plot, the Kernal density plot and Quantile–Quantile (*QQ*) plot of our prime variable "Volatility Smirk" are shown in (Fig. 1) and (Fig. 2) respectively, to depict its behaviour and distribution more clearly. The Epanechnikov Kernel function (Epanechnikov 1969) among others is used, as it is optimal in a mean square error sense. The plots clearly confirm the summary statistics that the distribution of smirk deviates from normality and has fat tails with high kurtosis.

Next, the ability of volatility smirk in predicting future returns is investigated. The volatility smirk reflects the investors' expectation of downward price jump (Xing et al. 2010). If informed traders prefer the options market to place their first trade and the spot market is sluggish to incorporate the implicit information in the options market, then the volatility smirk from options market should predict the future stock returns.

[1] *NSE* issues 3 months trading cycle – the near month (one), the next month (two) and the far month (three) as short term options contracts on index. The long term options contracts on index are issued in following manner – Three quarterly expiries (March, June, Sept & Dec cycle) and next 8–half yearly expiries (Jun, Dec cycle).

Table 1. Summary statistics

Stats	*Returns*	*smirk*	*Smb*	*Hml*	*Wml*	$r_m - r_f$	*lncallvol*	*lnputvol*	*lnputoi*	*Lncalloi*
Mean	0.000	0.080	0.021	0.069	0.069	0.082	11.973	10.984	15.362	16.588
SD	0.002	0.138	0.881	0.972	0.923	1.370	2.335	2.344	1.499	1.345
P50	0.000	0.050	0.055	0.030	0.129	0.163	13.014	11.716	15.901	17.167
Kurtosis	221.807	6.243	9.805	6.546	8.879	10.056	1.899	2.254	3.039	2.424
Max.	0.028	0.700	6.062	5.867	7.749	14.922	15.907	15.284	17.676	18.259
Min.	–0.049	–0.577	–9.603	–6.877	–7.008	–6.969	5.793	3.932	9.012	10.808
Skewness	–6.271	1.412	–0.646	0.168	–0.595	0.000	–0.529	–0.631	–0.949	–0.763
ADF test	–58.55	–28.30	–44.46	–40.67	–46.50	–40.15	–4.71	–6.51	–7.62	–3.02
N	2888	2888	2888	2888	2888	2888	2888	2888	2888	2888

Note: The table contains the descriptive statistics [Mean, Standard Deviation (SD), Median (P50), Kurtosis, Maximum (Max.) and Minimum (Min.), Skewness, Augmented Dickey–Fuller (ADF) test statistics for unit root, and number of observations (N)] of variables index returns (returns), Volatility smirk(smirk), Carhart four factors (smb, hml, wml, and $r_m - r_f$) and log trading activity variables volume (lncallvol, lnputvol) and open interest (lncalloi, lnputoi) for calls and puts respectively.

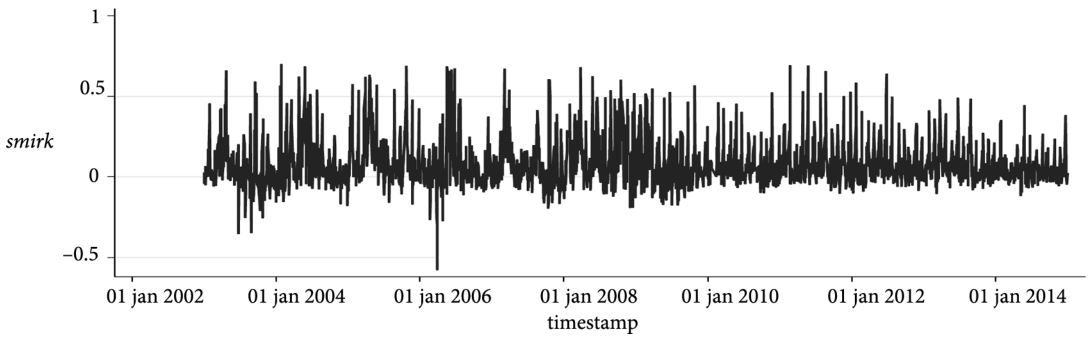
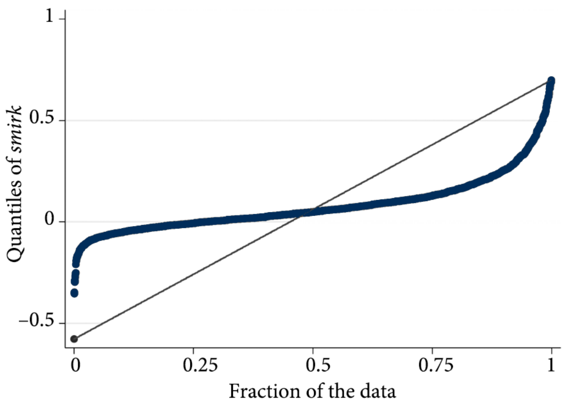
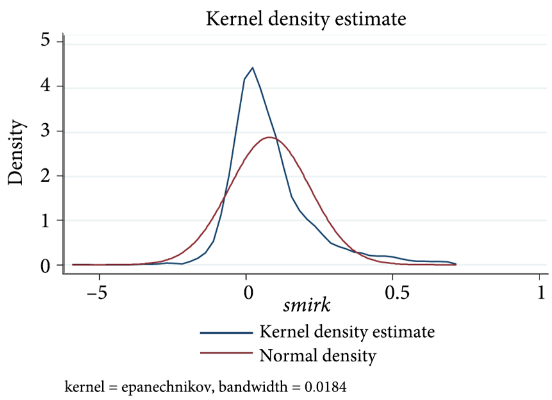


Fig. 1. Line plot of daily volatility smirk





A B

(Photo created by Pathak R. and Mitra A.)

Note: (Fig. 1) plots the distribution of daily volatility smirk. (Fig. 2) shows the Quantile (QQ) plot (A) and Kernal Density Plot (B) for Volatility Smirk, which depict the distributional characteristics of the variable.

Fig. 2. QQ Plot and Kernal Density Plot of volatility smirk

The generalized least square (GLS) estimation technique on the following model is used after controlling for potential trading variables to test whether the volatility smirk predicts the next day returns:

$$\Delta R_t = \beta_0 + \beta_1 smirk_{t-1} + \beta_{i,2} controls_{i,\,t} + \varepsilon_t, \quad (3)$$

ΔR_t, is the marginal return (change in returns: R_t–R_{t-1}) on day t, $smirk_{t-1}$ is the volatility smirk on day (t–1) and $controls_{i,t}$ is the set of control variables on day t. With above regression not only can we examine the significance of the predictability of smirk, but also control for numerous factors that potentially can affect returns at the same time. Establishing the predictability of volatility smirk for change in returns, the determinants of smirk is explored further. It is presumed that open interest variable of options is proxy for both liquidity and dispersion of investor's belief. Therefore, it can potentially determine the deviation in volatility estimates using *OTM* puts and *ATM* calls. The lag of open interests of both calls and puts is considered as potential predictors of smirk. Besides, it is also examined if previous day's index returns and four factors of Carhart (1997) can determine smirk. The first lag of smirk is included in our estimation model as we observe it exhibiting autoregressive structure. The following model is estimated using *GLS* procedure for the identification of predictors of *smirk*:

$$smirk_t = \beta_0 + \beta_1 smirk_{t-1} + \beta_{i,2}\ predictors_{i,\,t-1} + \beta_{i,3}\ factors_{i,\,t} + \varepsilon_t. \quad (4)$$

Here $smirk_t$ and $smirk_{t-1}$ are volatility smirks on day t and day (t – 1). $predictors_{i,\,t-1}$ represents predictor i at time (t – 1) whereas $factors_{i,\,t}$ represent other risk factor i on day t. The empirical results are presented in the next section.

4. Empirical results

Regression results of equations (3) and (4) are presented in (Table 2). First, we examine if smirk has information to predict next day's index returns after controlling for liquidity factors measured by open interests of calls and puts. We also include Carhart four factors in our estimation model, which have been found explaining returns across time and space in literature. We try two different specifications and report the relevant statistics thereof. Next, we report the results for predictor equation of volatility smirk. Here, we include auto–regressive term of smirk in our model along with trading activity variables i.e. open interests of calls and puts separately. As volatility smirk is computed from index options whose underlying itself is a portfolio, the four factors of Carhart are used in this model as potential predictor of smirk. The two specifications[2], which are differentiated by inclusion of lag returns term as predictor, are analysed.

As a test of multi–collinearity, the variance inflation factor (VIF) is estimated at both variables level and for the entire model. The average VIF value is observed to be lower than 3 in all cases, which indicate that, our results is not biased due to high correlations among predictors in the model.

The lag smirk significantly predicts marginal index returns in both specifications. This suggests that previous day volatility smirk contain information about next day's change in returns. Unlike Xing et al. (2010), a positive relationship between smirk and returns is observed implying that a high–implied volatility estimates from put options compared to that of calls, is indicative of positive returns

Table 2. Predictability and predictors of volatility smirk results

	Dependent Variables			
	ΔR_t		$Smirk_t$	
	Coefficients	Coefficients	Coefficients	Coefficients
lag_smirk	0.0009*** (2.73)	0.0009*** (2.70)	0.3708*** (27.99)	0.3715*** (28.07)
lag_returns	NA	NA	−1.21185 (−1.22)	NA
lag_calloi	NA	−1.5E-05 (−0.11)	−0.0307*** (−7.58)	−0.0309 *** (−7.62)
lag_putoi	NA	1.71E-05 (0.22)	0.0312*** (8.64)	0.0314*** (8.51)
smb__	−0.0001* (−1.82)	−0.0001* (−1.79)	−0.0017 (−0.64)	−0.0017 (−0.66)
hml__	−7.1E-05 (−1.18)	−6.9E-05 (−1.15)	0.0001 (0.06)	0.0001 (0.05)
wml__	5.96E-05 (1.01)	5.99E-05 (1.02)	−0.0084*** (−3.82)	−0.0085*** (−3.84)
rm_rf__	0.0001 (4.23)	0.0001 (4.25)	−0.0407*** (−24.53)	−0.0407*** (−24.53)
_cons	−8.7E-05 (−1.44)	−3.4E-05 (−0.02)	0.0832*** (3.25)	0.0833*** (3.26)
F	9.24	6.62	238.04	271.79
Adjusted R^2	0.0141	0.0135	0.3965	0.3964

Note: (Table 2) presents the empirical results of predictability and predictors of volatility smirk from equation 2 and 3 where dependent variables are change in daily returns of Nifty index (ΔR_t) and $Smirk_t$ respectively. The coefficients along with t–statistics in parenthesis are reported for both equations (two specifications). Here *lag_smirk* and *lag_returns* are first lag of volatility *smirk* and index *returns*. *lag_calloi* and *lag_putoi* represent the log of previous days open interests for call and put options respectively. *smb*, *hml*, *wml* and *rm_rf* are Carhart four factors and *_cons*. shows the intercept of the regression. The F–statistics and R–squared of the model is reported in last two rows.

*, ** and *** represent significance of statistics at 10%, 5% and 1% levels.

[2] Note that we arrive at the given specifications after a hit and trial procedure, which included testing for all possible set of combinations among the study variables.

on the next day. Moreover, among Carhart four factors only market risk premium affects the change in returns positively. Size premium (SMB or small minus big) is related with change in returns at 10% level of significance. Trading activity variables open interest for both calls and puts, which proxies for liquidity, do not determine returns. Hence, the study reports volatility smirk as an important predictor of future returns. The results also confirm the role of options market in disseminating information to the spot market.

Next, the predictors of smirk are examined that can help traders to estimate smirk and subsequently predict returns and maximize their trading incentive. It is observed that previous day's smirk largely determines smirk today. Besides, as expected, two factors from Carhart (1997) model i.e. market risk premium (*rm_rf*) and momentum premium (WML or winners minus losers) significantly predict smirk.

Previous day's open interests of both call and put options also predict smirk significantly but in opposite directions. A negative coefficient of call open interest for smirk prediction suggests that an increase in one–sided position in the call options indicates a decrease in the expected volatility of OTM put options traders below the volatility expectations of ATM call traders. The reverse is true in the case of put options open interest predictability of smirk. It is also observed that a very high percentage of variance explained (adjusted R^2 of around 40%) by predictor variables while predicting volatility smirk.

Conclusions

This study investigates the pattern of volatility smirk, its predictability and information content for the underlying asset's future returns. The volatility smirk is estimated as the difference between the implied volatilities of OTM puts and ATM calls. The study documents that the volatility smirk, thus computed, predicts the underlying asset's marginal returns even after adjustment to controls of relevant factors and trading variables. The results indicate that volatility smirk is a priced risk factor determining future returns. It is argued that the informational advantage of option traders might be the reason for the observed predictability. The study further examines the role of various factors such as market risk premium, size premium, value premium and momentum premium; along with other trading variables, in explaining the behaviour of smirk. It reports market risk premium and momentum premium along with open interest of calls and puts as significant predictor of volatility smirk. The findings signify the potential of profit making for traders and fund managers based on volatility smirk estimates provided by series of options trading on an underlying asset. The results are helpful in enhancing returns on investment in Index based funds and designing options strategies from the perspective of volatility risk.

This study highlights the importance of volatility smirk for investment in stocks on which options trade, and provides ways to estimate it. However, it has certain data limitations. The results of the study can be more insightful if conducted employing intra–day trading data. Besides, a comparative study of volatility smirk of stock options traded across different exchanges would strengthen the arguments of the study about volatility smirk.

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