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Exploring Volatility Risk Premia in USD/INR Currency Options: Insights from the Indian Market

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This paper explores the relationship between the implied volatility from USD/INR currency options and realized volatility of the underlying currency market, and examines whether the implied volatility is an unbiased predictor of the realised volatility in the Indian context. Using data across various tenors from one month to one year, the study finds that implied volatility is a significant predictor of the realised volatility for shorter tenors, but its predictive power diminishes with an increase in tenor. The results also suggest that while the implied volatility is significant, it is not an unbiased predictor of realised volatility. The paper therefore investigates the existence of a volatility risk premium, defined as the difference between realised and implied volatility, and examines its influencing factors such the spot rates returns, forward premia, and the impact of market events like the global financial crisis and the Fed taper tantrum.

JEL Classification: G13, G14, G15, F31

Keywords: Market Efficiency, Volatility Risk Premia, Currency Options, Implied Volatility

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1. Introduction

Volatility is a fundamental concept in finance, representing the degree of fluctuation in the price of a financial instrument over time. It serves as a critical measure of uncertainty, with higher volatility generally indicating higher risk. While this higher risk might create uncertainty for some investors, a deeper understanding of volatility can also offer opportunities for market participants to better navigate and adapt to changing market conditions. By understanding volatility, investors can make more informed decisions about asset allocation, hedging strategies, and overall risk management.

Implied volatility, specifically in the context of currency options, is a key metric that reflects market expectations regarding future currency movements and helps gauge market sentiment. Unlike realized volatility, which measures past price fluctuations, implied volatility represents the market's forecast of future volatility, as inferred from currency option prices. Implied volatility plays a vital role in options pricing, with higher implied volatility typically leading to higher option premiums, all else being constant.

Given its role as a forward-looking indicator, it is important to examine how accurately implied volatility forecasts the realized volatility over the life of a currency option contract. In efficient markets, implied volatility should act as an unbiased predictor of future volatility, incorporating all available market information. However, if implied volatility proves to be a biased estimate of realized volatility (i.e., it overestimates or underestimates actual volatility), it suggests that realized volatility is influenced not only by expected volatility (proxied by implied volatility) but also by a volatility risk premium. The volatility risk premium can thus be defined as the difference between realized volatility and implied volatility.

The literature has identified the existence of the volatility risk premium across various asset classes, including currencies. However, most of the existing research has focused on developed economies, with limited studies exploring emerging market currencies, particularly in India. If the volatility risk premium is found to be present in currency markets, it creates opportunities for market participants to trade this difference, through the use of derivative products such as variance swaps, that offer a mechanism to better manage the gap between the two more effectively.

Considering these prospects, the structure of the paper is organized as follows: *Section 2* provides a brief overview of the trading patterns in the Indian currency options market. *Section 3* reviews the existing literature, highlighting relevant studies on efficiency in currency markets and volatility risk premia. The gap in the literature, which this paper aims to address, along with the research objectives, is presented in *Section 4*. *Section 5* outlines the data sources and the methodology used in the analysis. Empirical analysis and results are provided in *Section 6*. Finally, the concluding remarks are offered in *Section 7*.

2. Trading Pattern in the Indian Currency Options Market

In India, the currency options market operates through both exchange-traded platforms and over-the-counter (OTC), with each exhibiting distinct market characteristics. Exchange-traded currency options market for the USD/INR pair was introduced on October 29, 2010, providing a formal platform for trading options on the Indian Rupee against the US Dollar. Trading was subsequently expanded with the introduction of other major currency pairs, including EUR/INR, GBP/INR, and JPY/INR, on February 27, 2018. At present, the majority of exchange-traded currency options are executed on the National Stock Exchange (NSE), with the USD/INR pair being the most actively traded among the available currency pairs. The market participants in the currency options market consist of both proprietary and as well as client trades, ranging from entities such as corporations, domestic institutional investors (e.g., banks, insurance companies, mutual funds, and non-banking financial companies), and individual investors, among others.

Over the last decade and a half, transparency in the OTC market improved with robust regulations, as the Reserve Bank of India (RBI) mandated that all inter-bank OTC foreign exchange derivative transactions be reported to the Trade Repository platform developed by the Clearing Corporation of India Limited (CCIL). Reporting to CCIL Trade repository, which became operational on July 9, 2012, and was implemented in phases. With respect to currency options, the first phase involved reporting of all outstanding inter-bank FCY/INR options By July 31, 2012. The subsequent phase, which required the reporting of inter-bank FCY/FCY options trades (i.e., trades not involving the INR as one of the currencies), came into effect on November 5, 2012. Reporting of OTC foreign exchange derivative transactions between Authorized Dealers and their clients, covering both FCY/INR and FCY/FCY options, commenced on April 2, 2013.

	Exchange Traded		OTC Traded (Interbank)	
Year	Daily Average Value	Total Yearly Value	Daily Average Value	Total Yearly Value
2010	14	608	-	-
2011	92	22187	-	-
2012	97	23427	-	-
2013	96	23321	-	-
2014	41	9620	-	-
2015	88	21187 (43%)	160	28072 (57%)
2016	146	35085 (50%)	148	35682 (50%)
2017	158	38159 (49%)	165	40049 (51%)
2018	200	48117 (49%)	205	49214 (51%)
2019	266	64418 (56%)	213	51643 (44%)
2020	320	78468 (72%)	124	30420 (28%)
2021	605	145879 (81%)	138	33177 (19%)
2022	1213	294656 (86%)	199	48330 (14%)
2023	683	165330 (74%)	245	59204 (26%)
2024	406	81624 (61%)	234	51169 (39%)

Source: Exchange traded data is sourced from NSE,BSE and USE. OTC Interbank data is obtained from CCIL Trade Repository,
Notes: In Case of Exchange Traded Options, the trading Value from Nov-2010 has been considered. In case of OTC Traded Currency Options, trading value from April 2015 have been considered, following the public dissemination of trade-by-trade data . For the Year 2024, values up to October 2024 have been considered for both segments. Figures in the parenthesis indicates percentage share of total yearly traded value.

Currency options in India have experienced significant growth in both exchange-traded and OTC markets (*Table 1*). However to curb speculative trading, on May 3, 2024, the RBI mandated that forex derivative contracts involving the rupee on stock exchanges be used solely for hedging contracted exposure. Market participants were required to demonstrate valid foreign exchange exposure to engage in currency derivatives trading. This move aligned with the Foreign Exchange Management Act (1999), which limits currency derivatives to hedging purposes. As a result, the average daily traded value in exchange-traded currency options declined in the year 2024. The OTC market for currency options, on the other hand, has seen a steady growth trajectory.

A closer look at the tenor-wise analysis of trading activity (*Table 2*), reveals that over 99% of the traded value on the exchange is concentrated in tenor buckets of <= 1 week, 1 week to 1 month, and 1 month to 2 months. In contrast, in the OTC market, 57% of trading volumes occur in tenor buckets upto 3 months (wherein the >1 week and <=1 month tenor bucket recorded the highest share), and the remaining trading activity spread across tenor buckets beyond 3 months.

Table 2: Tenor wise Percentage Share of Trading Activity in Currency Options

Tenor Interval	Exchange Traded	OTC (Interbank)
<=1W	66.59%	7.95%
>1W-1M	29.15%	29.83%
>1M-2M	3.91%	13.85%
>2M-3M	0.33%	6.09%
>3M-4M	0.01%	8.47%
>4M-5M	0.00%	0.98%
>5M-6M	0.00%	1.91%
>6M-7M	0.00%	7.75%
>7M-8M	0.00%	0.19%
>8M-9M	0.00%	0.25%
>9M-10M	0.00%	2.48%
>10M-11M	0.00%	0.14%
>11M-12M	0.00%	1.62%
>1Y-3Y	0.00%	14.97%
>3Y-5Y	0.00%	2.55%
>5Y	0.00%	0.99%

Source: Exchange traded data is sourced from NSE. OTC Interbank data is obtained from CCIL Trade Repository,
Notes: Tenor wise analysis derived from day wise trading details for the period August 2022 to October 2024.

In the case of exchange-traded options, a breakdown of trading activity by option type (*Table 3)* across various tenor buckets shows that for the more liquid tenor buckets (up to 2 months), the traded value is almost equally split between call and put options. However, for the less liquid tenor buckets traded on the exchange, there was no particular pattern in the choice between calls and puts. In contrast, for over-the-counter (OTC) traded options, the trading activity is nearly evenly divided between call and put options across all the tenor buckets considered.

Table 3: Tenor wise Percentage Share of Trading Activity in Currency Options

Tenor Bucket	Exchange Traded		OTC Traded	
	CALL	PUT	CALL	PUT
<=1W	51.49%	48.51%	48.66%	51.34%
>1W-1M	51.69%	48.31%	50.15%	49.85%
>1M-2M	53.66%	46.34%	49.16%	50.84%
>2M-3M	67.63%	32.37%	52.93%	47.07%
>3M-4M	75.95%	24.05%	51.33%	48.67%
>4M-5M	69.80%	30.20%	55.08%	44.92%
>5M-6M	59.03%	40.97%	59.78%	40.22%

>6M-7M	74.24%	25.76%	51.13%	48.87%
>7M-8M	54.59%	45.41%	42.75%	57.25%
>8M-9M	0.32%	99.68%	49.80%	50.20%
>9M-10M	1.61%	98.39%	51.29%	48.71%
>10M-11M	0.01%	99.99%	41.55%	58.45%
>11M-12M	0.00%	100.00%	54.25%	45.75%
>1Y-3Y	0%	0%	49.90%	50.10%
>3Y-5Y	0%	0%	54.82%	45.18%
>5Y	0%	0%	50.89%	49.11%

Source: Exchange traded data is sourced from NSE. OTC Interbank data is obtained from CCIL Trade Repository,
Notes: Tenor wise analysis derived from day wise trading details for the period August 2022 to October 2024.

The distribution of strike prices (*Table 4*) shows a concentration around the At-the-Money Forward (ATMF) levels, although it is pertinent to note that trades with strike prices exactly at the ATMF are relatively limited. Furthermore, trading activity tends to diminish as strike prices move further away from the ATMF levels.

Table 4: Tenor-wise Distribution of Trading Activity Across Strike Prices

Tenor Bucket	<78	78-79	79-80	80-81	81-82	82-83	83-84	84-85	85-86	86-87	>87
Exchange Traded											
<=1W	0%	1%	8%	5%	12%	34%	40%	0%	0%	0%	0%
>1W-1M	0%	1%	5%	5%	9%	30%	46%	3%	0%	0%	0%
>1M-2M	0%	1%	2%	5%	8%	27%	41%	14%	2%	0%	0%
>2M-3M	0%	0%	0%	0%	1%	14%	50%	31%	4%	0%	0%
>3M-12M	0%	0%	0%	0%	1%	5%	61%	29%	4%	0%	0%
>1Y	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
OTC Traded											
<=1W	0%	0%	3%	0%	11%	23%	58%	5%	0%	0%	0%
>1W-1M	0%	0%	1%	1%	8%	27%	53%	10%	0%	0%	0%
>1M-2M	0%	0%	1%	3%	6%	26%	49%	15%	1%	0%	0%
>2M-3M	0%	0%	0%	2%	6%	17%	49%	20%	1%	5%	0%
>3M-12M	0%	1%	0%	2%	9%	12%	39%	23%	6%	5%	4%
>1Y	0%	0%	0%	1%	1%	6%	6%	12%	5%	3%	66%

Source: Exchange traded data is sourced from NSE. OTC Interbank data is obtained from CCIL Trade Repository,
Notes: Tenor wise analysis derived from day wise trading details for the period August 2022 to October 2024.

Table 5: Tenor-wise analysis of the Percentage of Total Trading Days

Tenor Bucket	Exchange Traded	OTC Market
<=1W	81%	45%
>1W-1M	95%	84%
>1M-2M	92%	51%
>2M-3M	70%	28%
>3M-4M	23%	40%
>4M-5M	23%	10%
>5M-6M	19%	13%
>6M-7M	12%	33%
>7M-8M	10%	2%
>8M-9M	10%	2%
>9M-10M	8%	15%
>10M-11M	6%	2%
>11M-12M	2%	4%
>1Y-3Y	0%	51%
>3Y-5Y	0%	13%
>5Y	0%	7%

Source: Exchange traded data is sourced from NSE. OTC Interbank data is obtained from CCIL Trade Repository,
Notes: Tenor wise analysis derived from day wise trading details for the period August 2022 to October 2024.

Table 5 indicates that Exchange-traded options were traded on more than 70% of trading days in tenor buckets up to 3 months, with the most liquid tenor bucket (i.e. tenors ranging from over 1 week to 1 month) recording activity on 95% of the trading days. In contrast, the most liquid tenor bucket in case of OTC options, observed trading activity on 84% of the trading days.

3. Literature Review

The first section of this literature review delves into the predictive power of implied volatility, particularly in the context of currency market, and explores its ability to forecast future volatility. It expands to include studies that examine the role of implied volatility derived from stock options in predicting realized volatility in equity markets and associated indices. Additionally, the review addresses the biases and inefficiencies present in implied volatility as a forecasting tool. In the second section, the review broadens its scope to investigate the concept of volatility risk premia, analysing its existence and implications across different asset classes, including currencies and equities.

3.1. The Predictive Power of Implied Volatility

Chang and Tabak (2007) examined the relationship between U.S. Dollar–Brazilian Real exchange rate volatility implied in option prices and subsequent realized volatility. They investigated whether implied volatilities provide information about future volatility that is not captured by past returns. Using generalized method of moments estimation, their findings suggested that implied volatilities offered superior forecasts of realized volatility compared to GARCH models and moving average predictors.

The predictive power of implied volatility from foreign exchange options in forecasting future exchange rate return volatility was also examined by *Galati and Tsatsaronis (2014)*. Using daily implied volatility data for four exchange rates (Japanese yen, Deutsche Mark, pound sterling, and French franc) against the U.S. dollar (in certain cases the Deutsche Mark), and considering three contract maturities (one, three, and twelve months), they found that implied volatility from one-month options provided information content about future realized volatility, outperforming historical volatility measures. This result held across all four exchange rates. However, as the contract maturity increased, the predictive accuracy of implied volatility diminished. Although implied volatility from three-month and twelve-month options generally continued to outperform historical volatility, this outperformance was not always statistically significant.

Challenging the common practice of using one-month options, *Plíhal and Lyócsa (2021)* investigated the use of implied volatility from short-maturity options (one-day and one-week) to predict realized volatility for the EUR/USD exchange rate. Their findings show that short-term implied was found to be more effective in forecasting future volatility, particularly for the next day and week, compared to past realised volatility data. The study highlighted that implied volatility from short-lived options was a stronger predictor of realised than traditional volatility models.

The information content of the Japanese Yen Implied Volatility Index (JYVIX) in forecasting the future volatility of USD/JPY exchange rates was tested by *Qing et al. (2021)*. Their findings revealed that JYVIX contained significant information about future volatility and offered incremental predictive power over traditional GARCH-type models. The study suggested that JYVIX, as a forward-looking index, provided better forecasts for conditional volatility than for realized volatility.

Turning to equity markets, the use of implied volatility as a predictor of future realized volatility has been widely explored. One of the foundational studies in this area is the work of Christensen and Prabhala (1998) which examined whether implied volatility from S&P 100 index option prices predicts ex-post realized volatility. Their study employed a different research design, using lower-frequency, nonoverlapping data over a longer period, with each implied and realized volatility estimate corresponding to a distinct time period. They found that implied volatility effectively predicted future realized volatility, both independently and alongside past volatility. Notably, implied volatility subsumed the information from past volatility in some cases. The study also highlighted a structural change in index option pricing after the October 1987 stock market crash, with implied volatility becoming a significantly better predictor of future volatility post-crash.

Investigating the relationship between implied volatility and realized volatility using monthly data from the stock markets of BRIC countries *Bentes (2017)* employed both autoregressive distributed lag and error correction models, comparing the results with those from ordinary lease squares regression. The findings revealed varying results regarding the informational content of implied volatility depending on the methodology used. However, both methods indicated that implied volatility was an unbiased estimate of realised volatility for India, though it was not found to be efficient in any of the BRIC countries. Additionally, the error correction results highlighted the presence of both short- and long-run effects for India, while Russia exhibited only short-run adjustments.

Chen and Li (2023) examine the information content of stock option-implied volatility, focusing on its relationship with news events. They analyse the arrival intensities and magnitudes of both scheduled and unscheduled news, distinguishing between fundamental and non-fundamental news. Their study finds that these news measures are strongly correlated with contemporaneous stock return volatility, and many can be predicted by implied volatility. Approximately one third of the predictive power of implied volatility on future realized volatility is attributed to its ability to forecast these news events, with the majority of this predictive power stemming from its capacity to predict the arrival intensities of both scheduled and unscheduled news.

Neely (2004) examined the bias and inefficiency of implied volatility as a forecast of realized volatility in foreign exchange futures. The study found that none of the usual explanations for implied volatility’s bias were effective in this context. High-frequency volatility measures did not reduce the bias, and horizon-by-horizon estimation did not eliminate it. Autocorrelation in implied volatility was identified as a plausible explanation for the bias, but no evidence of sample selection bias was found. The research also showed that out-of-sample forecasts from econometric models, could improve predictions of realized volatility when combined with implied volatility.

3.2. Volatility Risk Premia Across Asset Classes

Exploring how volatility risk premium derived from currency options is priced in returns and its implications for market participants, *Ornelas (2019)* provided empirical evidence supporting a positive relationship between currency volatility risk premia and currency returns in the future, suggesting that a higher volatility risk premia leads to currency appreciation. The author argued that when risk aversion increases, the market discounts the currency, and this discount is later reversed, resulting in positive returns over time. The study found that using the global currency volatility risk premia, which is an average across all currencies, provided more robust results than regional or specific volatility risk premia, particularly for emerging markets.

Londono and Zhou (2012) added to the literature on the forward premium puzzle by relating exchange rate returns to the stock and currency variance premiums, measured as the option-implied variance minus the realized variance of stock and currency returns respectively. The paper provided empirical evidence indicating that currency variance risk was priced in currency markets, with the currency variance risk premium significantly predicting currency depreciation against the U.S. dollar over a 6-month horizon.

Corte, Ramadorai, and Sarno (2014) identified a new currency strategy with strong return and diversification properties, based on the predictive ability of currency volatility risk premia for forecasting currency returns. They explained that the volatility risk premium reflects the cost of insuring against currency volatility fluctuations. The strategy involved selling currencies with high insurance costs and buying those with low insurance costs. The returns were primarily driven by movements in spot exchange rates, rather than interest rate differentials, and the strategy played a significant role in a minimum-variance portfolio of common currency strategies.

Eraker Bjorn (2008), Carr and Wu (2009), Drechsler and Yaron (2010), and *Han and Zhou (2010),* all investigated the volatility risk premium as an indicator of market uncertainty and explored its connection with equity returns. A commonality of the findings across the studies was that the volatility risk premium was a significant predictor of returns.

Mueller, Vedolin, and Yen (2012) examine the behaviour of bond variance risk premia, finding that these premia exhibit significant spikes during periods of economic crises. They demonstrate that variance risk premia reflect a broad range of macroeconomic uncertainties, with increases in uncertainty regarding both the nominal and real aspects of the economy leading to higher variance risk premia. However, uncertainty surrounding monetary policy has a notably negative effect on these premia. The study further highlights that bond variance risk premia have predictive power for excess returns across various asset classes, including Treasuries, stocks, corporate bonds, and mortgage-backed securities, both in-sample and out-of-sample.

4. Objective of the Study

While much of the existing research has focused on deriving and analysing volatility for asset classes like equity and currencies in developed markets, there is a notable lack of literature that has explored the predictive power of implied volatility from USD/INR option contracts.

Additionally, studies on the existence of volatility risk premia as well as its influencing factors are quite scare. This gap in the literature presents an opportunity to explore these questions based on the unique market conditions in India. This study aims to address this gap and contribute to a deeper understanding of volatility dynamics in the Indian context.

5. Data and Methodology

Given the limited trading data on option contracts for tenors beyond 2 months, the quoted data USD/INR option has been considered. The quotes of implied volatility of At-the-Money contracts, for maturities ranging from 1 month, 2 months, 3 months, 6 months, 9 months and 12 months have been sourced through Refinitiv. The RICs for the tenors are "*INR1MO=*", *"INR2MO=", "INR3MO=", "INR6MO=", "INR9MO=", and "INR1YO=".*

The Realised volatility (RV) at time t is defined as annualised standard deviation of log returns for the daily closing USD/INR exchange rate. The equation for RV for day i is defined as:

$$RV_t = \sqrt{\frac{\mathrm{T}}{N-1} \sum_{i=1}^{N} \left[\ln\left(\left(\frac{\mathrm{U_i}}{\mathrm{U_{i-1}}} \right) - \mu \right) \right]^2} \qquad \text{...(1)}$$

where,

- N is defined as the number of trading days (i.e. 22 for one-month contracts, 43 for two months, 64 for three months, 127 for six months, and 252 for twelve months).
- T is 252 days
- U is the closing price
- μ is the average returns for the period N.

This analysis encompasses a daily data set from January 2006 to September 2024. It has been carried out taking into consideration both overlapping and non-overlapping datasets. An overlapping dataset allows for more observations, however, can introduce autocorrelation, making it challenging to assess the independence of observation. In contrast, non-overlapping periods analyses distinct segments of dataset, however comes at a cost of fewer observations used in the analysis.

The information content of implied volatility was assessed by estimating a regression of the form:

$$RV_t = \alpha + \beta \, IV_t + \varepsilon_t \qquad \text{...(2)}$$

where IV_t denotes the implied volatility for a given tenor, quoted at the beginning of period on day t. RV_t denotes the realized volatility for the same tenor in which IV_t was quoted on that day. If the implied volatility can predict volatility realised over time, β should be significantly different from zero. Further if implied volatility is an unbiased forecast of realized volatility, it would necessitate that α=0 and β =1. This condition is jointly testing with the null hypothesis, that $a = 0$ and $\beta = 1$.

It would be also be beneficial to explore how well historical volatility observed can predict future levels. This was analysed by using historical volatility measured over a backward-looking window, as a predictor for realized volatility, by employing the following equation:

$$RV_t = \hat{\alpha} + \hat{\beta}\, HV_t + \varepsilon_t \qquad \text{… (3)}$$

where HV_t is the Historical volatility defined for the window prior to day t. For example, in case of 1 month, the historical volatility would be computed as the annualised volatility for a 22-day period prior to day t, using the equation *(1)*. RV_t *i*s the annualised volatility for a 22-day period after day t. $\widehat{\alpha}$ is the intercept term and $\widehat{\beta}$ is the slope coefficient of HV_t.

In addition to the above equations, a third equation for regression model for RV_t can be estimated, where IV_t represents the forecast based on the more inclusive information set and HV_t represents the one which is conditional on the smaller set which only includes historical realisations of the volatility process (*Galati and Tsatsaronis*, *2014*).

$$RV_t = \alpha' + \beta'\, IV_t + \gamma\, HV_t + \varepsilon_t \qquad \text{…(4)}$$

A statistically significant β' coupled with an insignificant γ coefficient for the historical volatility, can be interpreted that implied volatility is a superior forecaster for future volatility.

In the next part of this study, the Volatility Risk Premia (VRP_t) is calculated using the difference between the measure of realized volatility of returns as defined in equation (*1*) and implied volatility. While considering the implied, one measure it is take the quoted implied volatility of at-the-money (ATM) options, while another way is to calculate the risk-neutral volatility from options with several strikes, and then take the square root[1]. This study uses the former approach, given its simplicity and ready availability of continuous data series across tenors.

$$VRP_t = RV_t - IV_t \qquad \text{…(5)}$$

Using this approach, VRP_t is computed by comparing realized volatility with the implied volatility, both considered for the same time horizon The volatility risk premium that is constructed, can be interpreted as the cost of insurance against volatility fluctuations in the underlying currency (*Corte, Ramadorai and Sarno, 2013*). When VRP_t is positive (Realised Volatility is higher than the Implied Volatility), insurance is relatively cheap. Likewise, when VRP_t is negative (Implied Volatility is greater than Realised Volatility) the cost of insurance against in the underlying currency volatility is more expensive)[2].

To provide more insight into the determining factors that of VRP_t, the following functional form has been defined:

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[1] The VIX index, the most known volatility index, is calculated by CBOE using several options on the S&P500 index, with different strikes is an example.

2 However, it is pertinent to note that this method has the challenge of relying on implied volatility data quoted at the beginning of the period. It implicitly assumes that IV_t serves as a perfect forecast by agents, but in reality, forecast errors do exist (Ornelas and Mauad, 2017). As a result, this measure includes both a volatility risk premium and a forecast error. Disentangling the volatility risk premium from the forecasting error is beyond the scope of current study.

$$VRP_t = \alpha + \beta_1\, dSpot_t + \beta_1\, FwdPrem_t + \beta_2\, DCovid + \beta_3\, DGFC + \beta_4\, DFedTaper + \beta_5\, CurDep + \epsilon_t \quad \text{...(6)}$$

where,

- $d\_Spot_{\ t}$ is the change in the USD/INR spot rate over the period during which the VRP_t is calculated. For example, in case of the 1-month tenor, $dSpot_{\ t}$ is computed as

$$dSpot_{\ t} = \frac{[\mathrm{Spot_{USDINR_{t+22}}} - \mathrm{Spot_{USDINR_t}}]}{\mathrm{Spot_{USDINR_t}}} \times 100 \quad \text{...(7)}$$

  A positive (negative) value of $dSpot_{\ t}$ indicates that the currency has depreciated (appreciated) over the period. Existing literature has documented a significant relationship between currency returns and volatility risk premia, particularly during periods of currency depreciation.

- The $FwdPrem_t$ reflects the forward premia rate for the given tenor. The forward premia increases when there is an increase in the hedging demand for the currency, particularly when market participants seek to protect themselves from uncertain or adverse currency movements in the future. During such times, the cost of insurance against the underlying volatility would also increase, i.e. the VRP_t ($RV_{t-T,t}$ - $IV_{t-T,t}$) would turn negative.

- $DCovid$ represents a dummy variable for the first wave of the COVID-19 from March 2020 to April 2020 period, a time characterized by a period of uncertainty and economic changes.

- Similarly, $DGFC$ accounts for the global financial crisis period from August 2008 to March 2009, which was a period marked by heightened risk across financial markets.

- In addition, $DFedTaper$ corresponds to the Fed taper tantrum from May to August 2013. The period witnessed a dramatic impact on emerging market currencies including USD/INR, due to the collective reactionary panic that triggered a spike in U.S. Treasury yields, after investors learned that the Federal Reserve was slowly putting the brakes on its quantitative easing program.

- The variable $CurDep$, uses a binary dummy variable to differentiate between days when there is a depreciation and appreciation in the USD/INR spot rate.

In addition to the multivariate regression model specified above, the inter-relationship between VRP_t, $dSpot_{\ t}$ and $FwdPrem_t$ were analysed using a Vector Autoregressive Model (VAR). Unlike multivariate regression model, which focus on a single dependent variable, a VAR model treats all the included variables as dependent and models their interdependencies over time. Each of these variables is explained by its own past values and the past values of other variables in the system, capturing a more complex feedback effect and lagged interactions between them. The VAR model of the following form was estimated:

$$\begin{bmatrix} VRP_t \\ dSpot_t \\ FwdPrem_t \end{bmatrix} = \mathbf{A_0} + \sum_{i=1}^{p} \begin{bmatrix} \beta_{11,i} & \beta_{12,i} & \beta_{13,i} \\ \beta_{21,i} & \beta_{22,i} & \beta_{23,i} \\ \beta_{31,i} & \beta_{32,i} & \beta_{33,i} \end{bmatrix} \begin{bmatrix} VRP_{t-i} \\ dSpot_{t-i} \\ FwdPrem_{t-i} \end{bmatrix} + \mathbf{D_1} \begin{bmatrix} DCovid_t \\ DGFC_t \\ DFedTaper_t \\ CurDep_t \end{bmatrix} + \boldsymbol{\varepsilon_t}$$

...(8)

where:

- VRP_t, $dSpot_t$ and $FwdPrem_t$ are the endogenous variables.
- A_0 is the intercept vector which consists of constant terms for each of the three endogenous variables.
- The matrix of beta coefficients captures how past values of the endogenous variables influence the current values and how changes in one variable might impact the others. For example, $\beta_{11,i}$ measures how past values of VRP_{t-1} affect the current value of VRP_t while $\beta_{12,i}$ measures how past values of $dSpot_{t-1}$ affect the current value of VRP_t, and so on.
- The exogenous variables (the dummy variables in the equation) influence the endogenous variables but are not affected by them. D_1 represents the matrix of the coefficient for the dummy variables.
- The error term ε_t captures all unexplained fluctuations in the endogenous variables.

The optimal lag length for the model specification for each of the tenors was selected using Hannan-Quinn Information Criterion and Schwarz Information Criterion.

6. Empirical Findings and Results

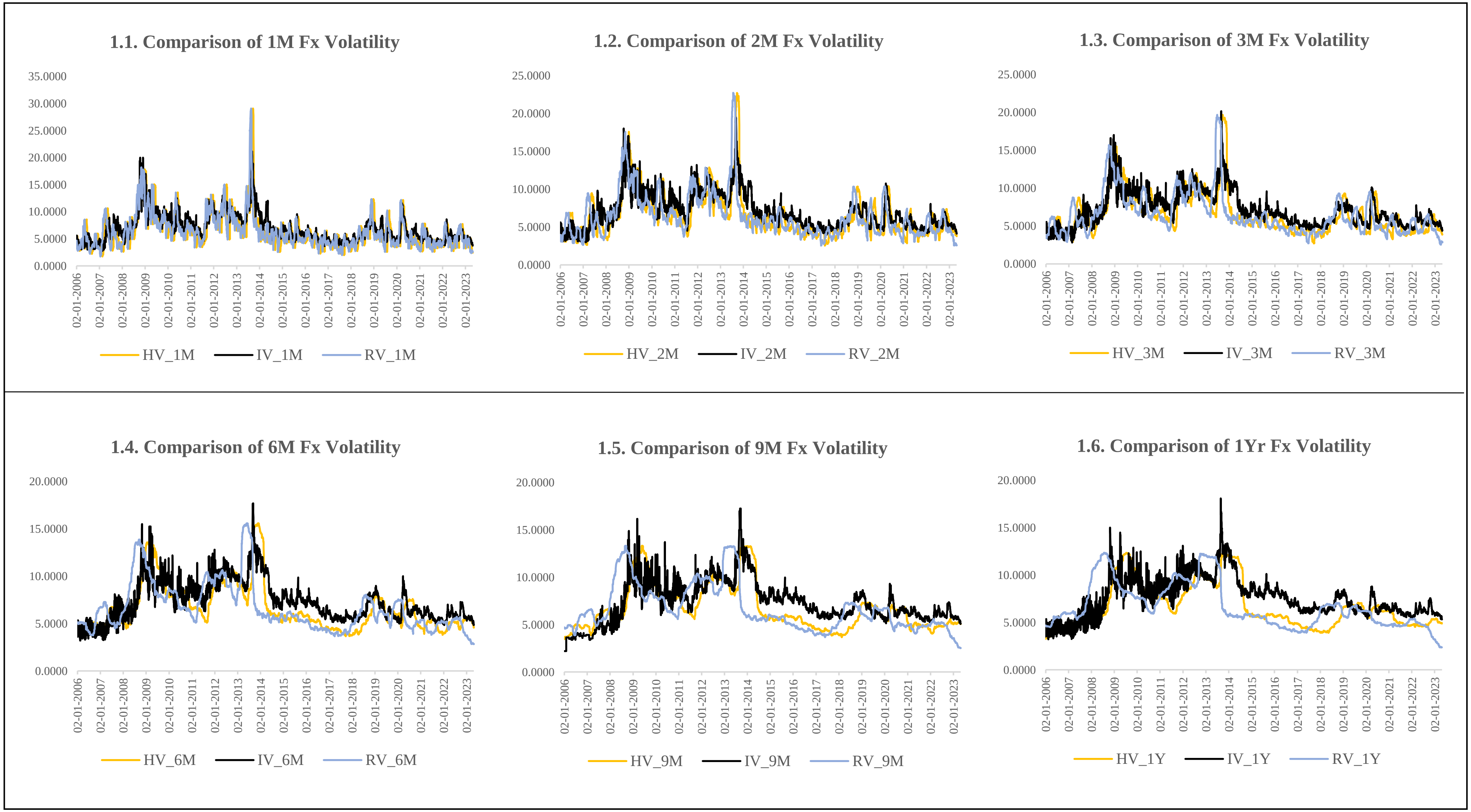
Table 6 provides the descriptive statitics of the volatility computed under various methods, and indicates that average implied volatility exceeded the average of the corresponding realized volatility and historical volatility series. The implied volatility was higher than the realised volatility for all the tenors considered. It was further found that this difference increased with an increase in tenors. The distributions of both implied and realized volatility are found to be positively skewed and leptokurtic.

Table 6: Descriptive Statistics for USD/INR Realised Volatility (RV), Implied Volatility (IV) and Historical Volatility (HV)

1 Month to 3 Months Tenor									
	RV_1M	*RV_2M*	*RV_3M*	*IV_1M*	*IV_2M*	*IV_3M*	*HV_1M*	*HV_2M*	*HV_3M*
Mean	6.3779	6.4915	6.5486	6.9048	7.0417	7.1170	6.3890	6.5079	6.5674
Median	5.6713	5.8260	5.8555	6.2500	6.4500	6.6000	5.6713	5.8260	5.8555
Mode	8.6579	2.6299	4.3659	7.5000	7.5000	9.5000	8.6579	2.6299	4.3659
Stdev	3.1334	2.9084	2.7832	2.5769	2.3841	2.2696	3.1242	2.8929	2.7643
Kurtosis	9.6374	6.1810	4.5188	2.9298	1.9323	1.4740	9.7441	6.3117	4.6450
Skewness	2.2828	1.9941	1.8256	1.3956	1.2056	1.0509	2.3003	2.0254	1.8644
Range	27.3436	20.1378	17.1242	18.3750	16.4500	17.3500	27.3436	20.1378	16.9361
Minimum	1.7549	2.5517	2.5338	2.8000	3.0000	2.8000	1.7549	2.5517	2.7219
Maximum	29.0985	22.6895	19.6579	21.1750	19.4500	20.1500	29.0985	22.6895	19.6579
Count	4520	4520	4520	4520	4520	4520	4520	4520	4520
6 Month to1 Year Tenor									
	RV_6M	*RV_9M*	*RV_1Y*	*IV_6M*	*IV_9M*	*IV_1Y*	*HV_6M*	*HV_9M*	*HV_1Y*
Mean	6.6342	6.6676	6.6900	7.3143	7.3363	7.5597	6.6604	6.6947	6.7163
Median	5.8339	5.8767	5.9176	6.9380	7.0000	7.2250	5.8339	5.8767	5.9176
Mode	9.6646	3.9893	-	10.0000	3.8000	9.5000	9.6646	3.9893	3.4756
Stdev	2.5604	2.4405	2.3572	2.1281	2.1938	2.0526	2.5321	2.4074	2.3207
Kurtosis	1.9012	0.5708	-0.1069	1.0557	1.0950	0.8330	2.0041	0.6240	-0.0995
Skewness	1.4363	1.1205	0.8887	0.8905	0.6836	0.6896	1.4916	1.1861	0.9653
Range	12.7410	10.8155	9.9808	14.5000	15.0500	14.9000	11.9186	9.8549	9.0702
Minimum	2.8345	2.5150	2.3614	3.2000	2.2000	3.2000	3.6570	3.4757	3.2721
Maximum	15.5755	13.3306	12.3422	17.7000	17.2500	18.1000	15.5755	13.3306	12.3422
Count	4520	4520	4520	4520	4520	4520	4520	4520	4520

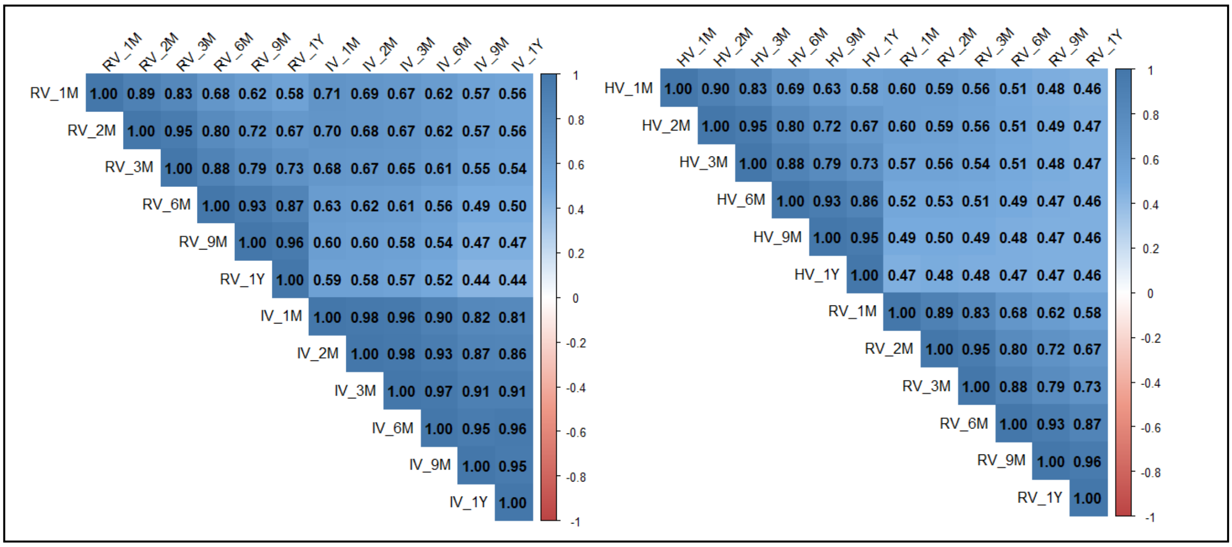
Chart 1 presents a tenor-wise comparison of volatility measures. An analysis of the historical trends reveals that, for shorter tenors up to 3 months, implied volatility closely tracks the movements of realized volatility and historical volatility. However, as the tenors lengthen, this co-movement weakens. It can also be observed that the movement between the historical volatility and realised volatility begins to weaken for the longer tenors of 9 months and 1 year.

Chart 1: Comparison of Volatility Measures across Tenors



A Cross-correlation analysis between realised volatility with implied volatility across tenors is depicted in *Chart 2*. A positive correlation was observed between tenors for the same volatility measure. The correlation of realised with implied volatility ranged between 0.44 to 0.71, with the highest correlation observed in the shorter tenors (1 month and 2 month). On the other hand, realised volatility had slightly lower correlation with historical volatility, with correlation coefficient ranging from 0.46 to 0.60.

Chart 2: Correlation heatmap of Implied (IV), Realised (RV) and Historical Volatility (HV)



6.1. Results of Unbiasedness Hypothesis Test

To test for the predictive ability of implied volatility for the dependant variable of realised volatility, the bi-variate regression model was estimated for 6 tenors. The results are highlighted in *Table 7*. The IV_t was found to be a significant predictor of RV_t for all the tenors considered at a 1% level of significance. The β Coefficients of IV_t was found to be positive and ranged from 0.50 to 0.85. However, the intercept term α was not found to be significantly different from 0 for the tenors of 1 month to 3 months. When testing for the joint null hypothesis of $\alpha = 0$ and $\beta = 1$, it was found that the IV_t was not an unbiased predictor of the RV_i, i.e. the joint test of α = 0 and β = 1, were rejected.

Table 7: Regression results for $RV_t = \alpha + \beta\, IV_t + \varepsilon_t$

	α					β					Test of α =0 and β =1			R^2
Tenor	Estimate	Std. Error	t value	Pr(>|t|)		Estimate	Std. Error	t value	Pr(>|t|)		Chisq	Pr(>Chisq)		
1M	0.4441	0.7228	0.6144	0.5390		0.8594	0.1245	6.9009	0.0000	***	47.6220	0.0000	***	0.50
2M	0.6147	0.7733	0.7949	0.4267		0.8346	0.1255	6.6521	0.0000	***	44.2500	0.0000	***	0.47
3M	0.8485	0.7394	1.1475	0.2512		0.8009	0.1207	6.6380	0.0000	***	44.0630	0.0000	***	0.43
6M	1.6821	0.6083	2.7654	0.0057	**	0.6770	0.0995	6.8038	0.0000	***	46.2920	0.0000	***	0.32
9M	2.8542	0.5690	5.0163	0.0000	***	0.5198	0.0907	5.7324	0.0000	***	32.8600	0.0000	***	0.22
1Y	2.8759	0.5481	5.2466	0.0000	***	0.5045	0.0865	5.8298	0.0000	***	33.9870	0.0000	***	0.19

*Notes: Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*

When testing for Historical Volatility as an efficient and unbiased estimate, the results indicated that HV_i was a poor predictor of RV_i for all the tenors considered. The intercept $\hat{\alpha}$ and slope $\hat{\beta}$ were found to be statistically insignificant (except 1 month). The results indicate that there was no information content in Historical volatility when trying to predict the future realised volatility. The results are summarised in *Table 8.*

Table 8: Regression results for $RV_t = \hat{\alpha} + \hat{\beta}\, HV_t + \varepsilon_t$

	$\hat{\alpha}$				$\hat{\beta}$				Test of $\hat{\alpha}$=0 and $\hat{\beta}$=1		R^2
Tenor	Estimate	Std. Error	t value	Pr(>|t|)	Estimate	Std. Error	t value	Pr(>|t|)	Chisq	Pr(>Chisq)	
1M	2.5599	1.3881	1.8442	0.0652 .	0.5976	0.2577	2.3193	0.0204 *	5.3794	0.0204 *	0.35
2M	2.6396	3.4740	0.7598	0.4474	0.5919	0.5955	0.9940	0.3203	0.9880	0.3202	0.35
3M	2.9751	3.0199	0.9852	0.3246	0.5441	0.513	1.0607	0.2889	1.1250	0.2888	0.29
6M	3.3271	4.4463	0.7483	0.4543	0.4965	0.7331	0.6773	0.4982	0.4588	0.4982	0.24
9M	3.4847	5.6479	0.6170	0.5373	0.4754	0.8887	0.5350	0.5927	0.2862	0.5927	0.22
1Y	3.5335	14.1111	0.2504	0.8023	0.4700	1.7197	0.2733	0.7846	0.0747	0.7846	0.21

*Notes: Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*

When HV_i was added to IV_t as explanatory variable to RV_t (*Table 9*), the coefficients of β' were found to be statistically significant at 1% for the tenors of 1 month to 6 months. The HV_i remained statistically insignificant in explaining RV_t in the multivariate regression in all cases. The γ coefficient was found to be in the range of 0.02 to 0.31.

The regression results presented in *Table 9*, which utilize non-overlapping data, further substantiate the findings from *Table 10*. By employing a non-overlapping dataset, the analysis reinforces the stability of the coefficients associated with IV_t, demonstrating that the original conclusions hold even when considering possible biases that may arise from overlapping observations. The γ coefficients suggest a limited impact of HV_t on RV_t.

In summary, the analysis indicates that implied volatility is found to be a significant predictor of realized volatility for tenors of one, two, three, and six months. However, as the length of the tenors increases, it was found that the nine-month and twelve-month tenors do not serve as significant predictors. Furthermore, historical volatility was found to have no meaningful impact on explaining realized volatility. Across all models tested, although implied volatility was significant, it was not an unbiased predictor of realized volatility, i.e., a perfect one-to-one relationship between these rates was not established.

The finding that implied volatility serves as a biased predictor for tenors of one to six months, while being insignificant predictor for longer maturities, suggests the presence of a volatility risk premium. This aligns with the notion that realized volatility is impacted by a broader array of factors, that cannot be explained by the implied volatility alone.

Table 9: Regression results for $RV_t = \alpha' + \beta' IV_t + \gamma HV_t + \varepsilon_t$ using Overlapping Data

	α'				β'				γ				Test of α'=0 and β'=1		R^2
Tenor	Estimate	Std. Error	t value	Pr(>|t|)	Estimate	Std. Error	t value	Pr(>|t|)	Estimate	Std. Error	t value	Pr(>|t|)	Chisq	Pr(>Chisq)	
1M	0.4586	0.7508	0.6108	0.5413	0.8340	0.1495	5.5780	0.0000 ***	0.0251	0.1090	0.2303	0.8178	31.1140	0.0000 ***	0.50
2M	0.6547	0.9517	0.6879	0.4916	0.7646	0.1483	5.1558	0.0000 ***	0.0696	0.2008	0.3466	0.7289	26.5830	0.0000 ***	0.47
3M	0.8602	0.7716	1.1149	0.2649	0.7776	0.1905	4.0812	0.0000 ***	0.0235	0.1590	0.1478	0.8825	16.6570	0.0000 ***	0.43
6M	1.7204	0.8104	2.1228	0.0338 *	0.5731	0.1343	4.2666	0.0000 ***	0.1084	0.1365	0.7939	0.4273	18.2040	0.0000 ***	0.32
9M	2.7585	2.4382	1.1313	0.2580	0.2868	0.1910	1.5019	0.1332	0.2696	0.3324	0.8111	0.4173	2.2558	0.1331	0.24
1Y	2.8379	2.5849	1.0979	0.2723	0.2337	0.1510	1.5475	0.1218	0.3105	0.2623	1.1836	0.2366	2.3947	0.1217	0.23

*Notes: Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*

Table 10: Regression results for $RV_i = \alpha' + \beta' IV_t + \gamma HV_t + \varepsilon_t$ using Non-overlapping Data

	α'				β'				γ				Test of α'=0 and β'=1		R^2
Tenor	Estimate	Std. Error	t value	Pr(>|t|)	Estimate	Std. Error	t value	Pr(>|t|)	Estimate	Std. Error	t value	Pr(>|t|)	Chisq	Pr(>Chisq)	
1M	0.6996	0.5007	1.3973	0.1639	0.8553	0.1522	5.6207	0.0000 ***	-0.0405	0.1130	-0.3581	0.7206	31.593	0.0000 ***	0.45
2M	0.5938	0.7424	0.7998	0.4257	0.7118	0.2261	3.1486	0.0021 **	0.1370	0.1594	0.8596	0.3920	9.9139	0.0016 **	0.45
3M	0.6340	0.7862	0.8063	0.4229	0.7582	0.1923	3.9426	0.0002 ***	0.0680	0.1213	0.5608	0.5768	15.5440	0.0001 ***	0.44
6M	2.1613	0.8154	2.6505	0.0123 *	0.5121	0.2090	2.4506	0.0197 *	0.1085	0.1939	0.5596	0.5795	6.0052	0.0143 *	0.24
9M	2.7418	0.8915	3.0756	0.0057 **	0.4764	0.2513	1.8960	0.0718 .	0.0574	0.2588	0.2219	0.8265	3.5947	0.0580 .	0.20
1Y	2.6049	0.7089	3.6745	0.0023 **	0.2641	0.3334	0.7923	0.4405	0.3157	0.2781	1.1351	0.2741	0.6277	0.4282	0.26

*Notes: Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*

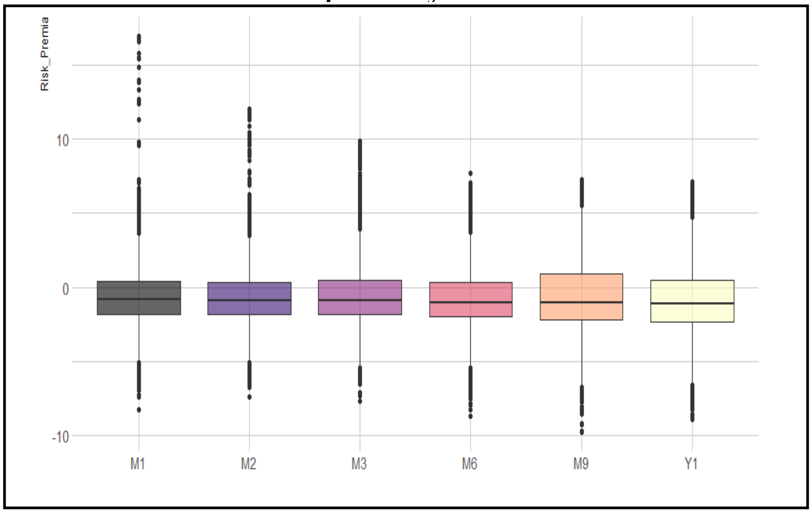
6.2. Currency Volatility Risk Premia

The Currency Volatility Risk Premia VRP_t represents the difference between realized and implied volatility, serving as a measure of the market's cost of insuring against fluctuations in underlying USD/INR currency. An analysis of the descriptive statistics (*Table 11*) shows that the average VRP_t is negative, suggesting that implied volatility tends to be higher than realized volatility for the USD/INR currency options. This indicates that market participants, on an average, have been pricing an additional risk or uncertainty that has not materialized, leading to higher implied volatility levels. It is also observed that VRP_t increases with tenor, indicating that longer-dated options were more expensive in terms of this insurance against volatility. It is also found that there has been a greater number of days when the VRP_t was negative then the instances when it was positive indicating an asymmetric distribution. Specifically, the VRP_t was found to be negative over 65% of the times for all the tenors considered.

Table 11: Descriptive Statistics of USD/INR Currency Volatility Risk Premia

	$VRP_t 1M$	$VRP_t 2M$	$VRP_t 3M$	$VRP_t 6M$	$VRP_t 9M$	$VRP_t 1Y$
Mean	-0.5269	-0.5502	-0.5684	-0.6801	-0.6687	-0.8696
Median	-0.8070	-0.8596	-0.8960	-1.0560	-1.0243	-1.1338
Standard Deviation	2.2461	2.1576	2.1555	2.2254	2.4011	2.3490
Kurtosis	8.8674	4.2149	2.6003	1.8799	0.9447	1.0482
Skewness	1.6832	1.2564	0.9675	0.6977	0.3202	0.3287
Range	25.1414	19.4487	17.5385	16.3646	16.9860	15.9718
Minimum	-8.2224	-7.4092	-7.6454	-8.6567	-9.7220	-8.8880
Maximum	16.9190	12.0395	9.8931	7.7079	7.2639	7.0838
No. of Days	4520	4520	4520	4520	4520	4520
No. of Days with Positive VRP	1432	1355	1390	1367	1566	1480
No. of Days with Negative VRP	3088	3165	3130	3153	2954	3040

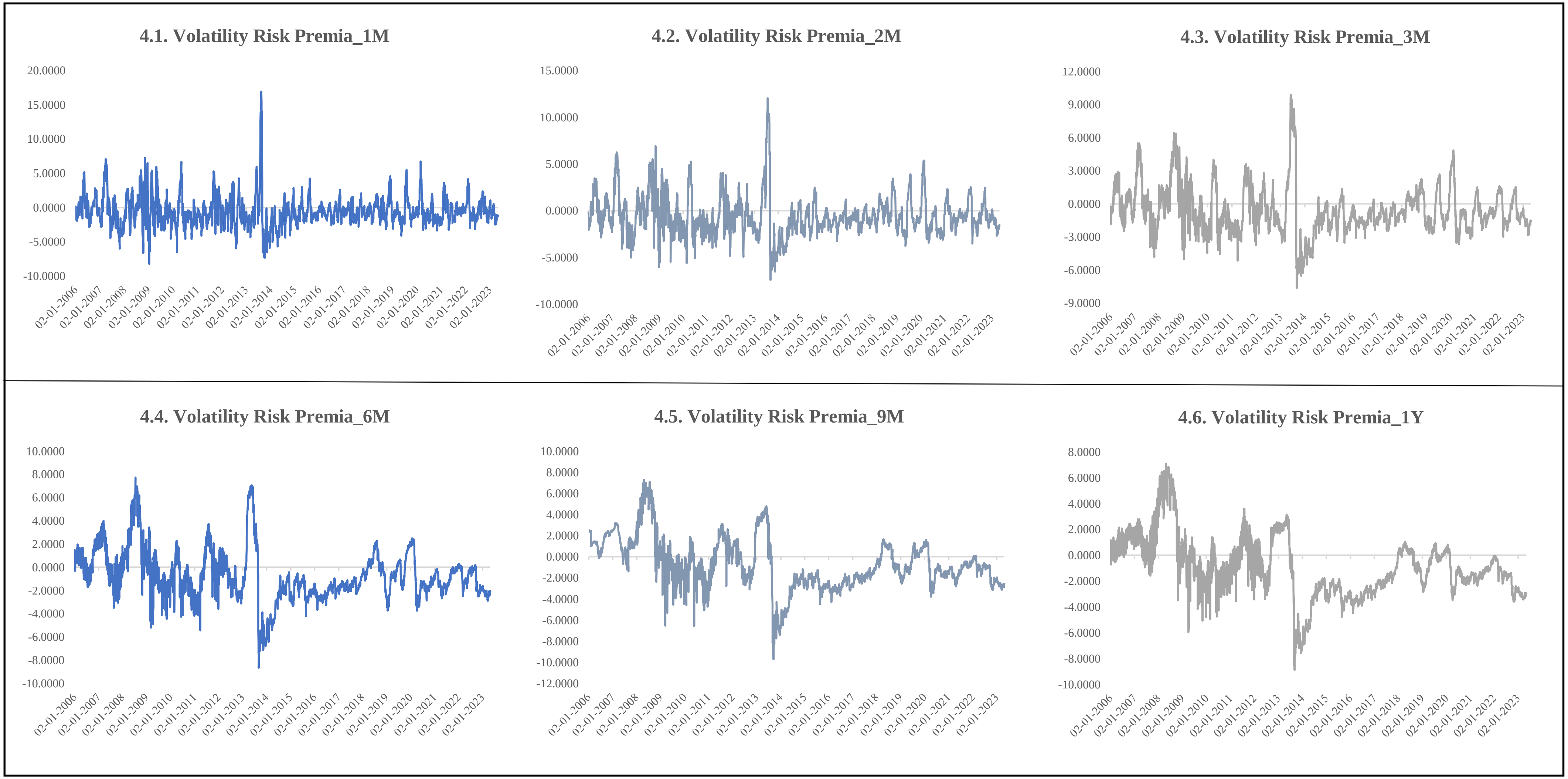
Chart 3: Distribution of Volatility Risk Premia across Tenors



A look at the distribution of the VRP_t (*Chart 3*) also indicates that this premium had fatter tails, more so in the short-term tenors of 1 month, 2 months and 3 months, suggesting that there were large, unexpected events that led to a substantial moves in the VRP_t.

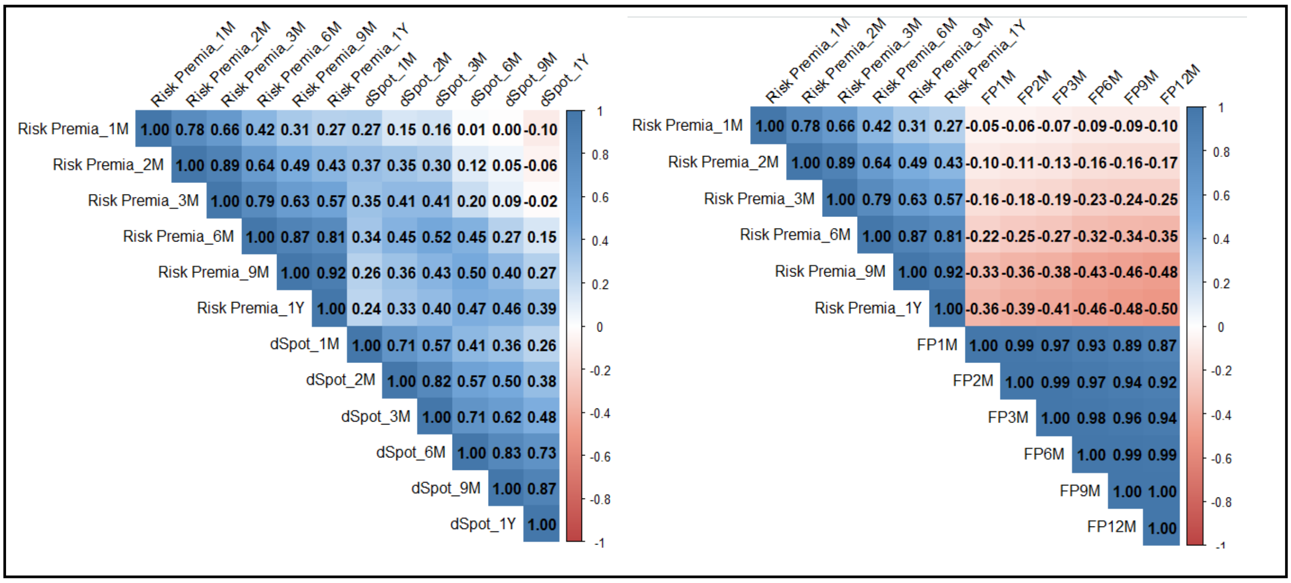
A look at the tenor-wise time series of the VRP_t (*Chart 4*), further indicate that there were extreme movements in the VRP_t during certain market stress events. For example, during 2008-09 Global financial crises, the VRP_t ranged from -7.62 to 7.08. The period of the Fed taper tantrum in 2013, the impact was more pronounced, with the VRP_t between -9.51 and 14.34. During the first wave of the covid pandemic in 2020 the VRP_t exhibited more negatively skewed characteristics with numbers ranging from -3.10 to 1.60.

Chart 4: Tenors wise Volatility Risk Premia from 2006-2023



A correlation heatmap of VRP_t with the changes in the spot rate and forward premia rate is presented in *Chart 5*. At first glance, the correlation between VRP_t and changes in spot rates was found to be positive while the correlation of VRP_t with forward premia was negative.

Chart 5: Correlation Heatmap of VRP_t with Changes in Spot Rate and Forward Premia



The relationship between VRP_t and the change in the USD/INR spot rate was further explored by segmenting historical data based on deciles of $dSpot_t$, where the changes in the spot rate range from the most negative (falling in the top decile, D1) to the most positive (falling in the last decile, D10). It is pertinent to note that, negative changes in the spot rate represent a percentage appreciation in the currency, while positive changes reflect depreciation. As such, the last decile (D10) typically corresponds to periods of heightened market stress, uncertainty, or significant turmoil, often leading to a depreciation of the currency.

The average VRP was computed under each decile bucket. It was observed (*Table 12*) that when the currency appreciated (associated with negative changes in the spot rate), the VRP_t tended to be negative, indicating that implied volatility was higher than realized volatility. In contrast, during periods captured in the last decile (D10), which correspond to instances of market turmoil or stress, there was a notable increase in realized volatility, leading to a positive VRP_t. This pattern was consistently observed across different tenors.

Table 12: Comparison of Average % Change in USD/INR Spot and the VRP_t

Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
1M										
Average $dSpot_t$	-3.32	-1.52	-0.90	-0.46	-0.09	0.33	0.80	1.40	2.25	4.62
Average VRP_t	-0.10	-1.03	-1.09	-1.31	-1.21	-0.97	-0.99	-0.46	0.01	1.86
2M										
Average $dSpot_t$	-4.39	-2.09	-1.15	-0.50	0.06	0.67	1.28	2.03	3.22	7.12
Average VRP_t	-0.29	-1.11	-1.41	-1.44	-1.44	-1.24	-0.81	-0.17	0.45	1.95
3M										
Average $dSpot_t$	-0.48	-1.15	-1.58	-1.85	-1.48	-1.08	-0.46	-0.19	0.64	1.97
Average VRP_t	-4.85	-2.52	-1.36	-0.53	0.16	0.88	1.74	2.65	4.07	9.14

Cont..

6M										
Average $dSpot_t$	-6.24	-3.38	-1.87	-0.39	0.68	1.69	2.92	4.58	7.07	13.60
Average VRP_t	-0.39	-1.83	-1.77	-1.59	-1.66	-1.21	-0.85	-0.18	0.02	2.64
9M										
Average $dSpot_t$	-8.39	-3.67	-1.76	-0.10	1.17	2.67	4.46	6.31	9.98	17.25
Average VRP_t	0.01	-1.78	-1.99	-1.61	-1.51	-1.11	-1.18	-0.86	0.45	2.90
1Y										
Average $dSpot_t$	-9.41	-3.91	-1.54	0.34	1.96	4.00	6.18	8.46	11.21	20.04
Average VRP_t	-0.02	-2.04	-1.93	-2.11	-2.14	-1.24	-1.35	-0.75	0.51	2.37

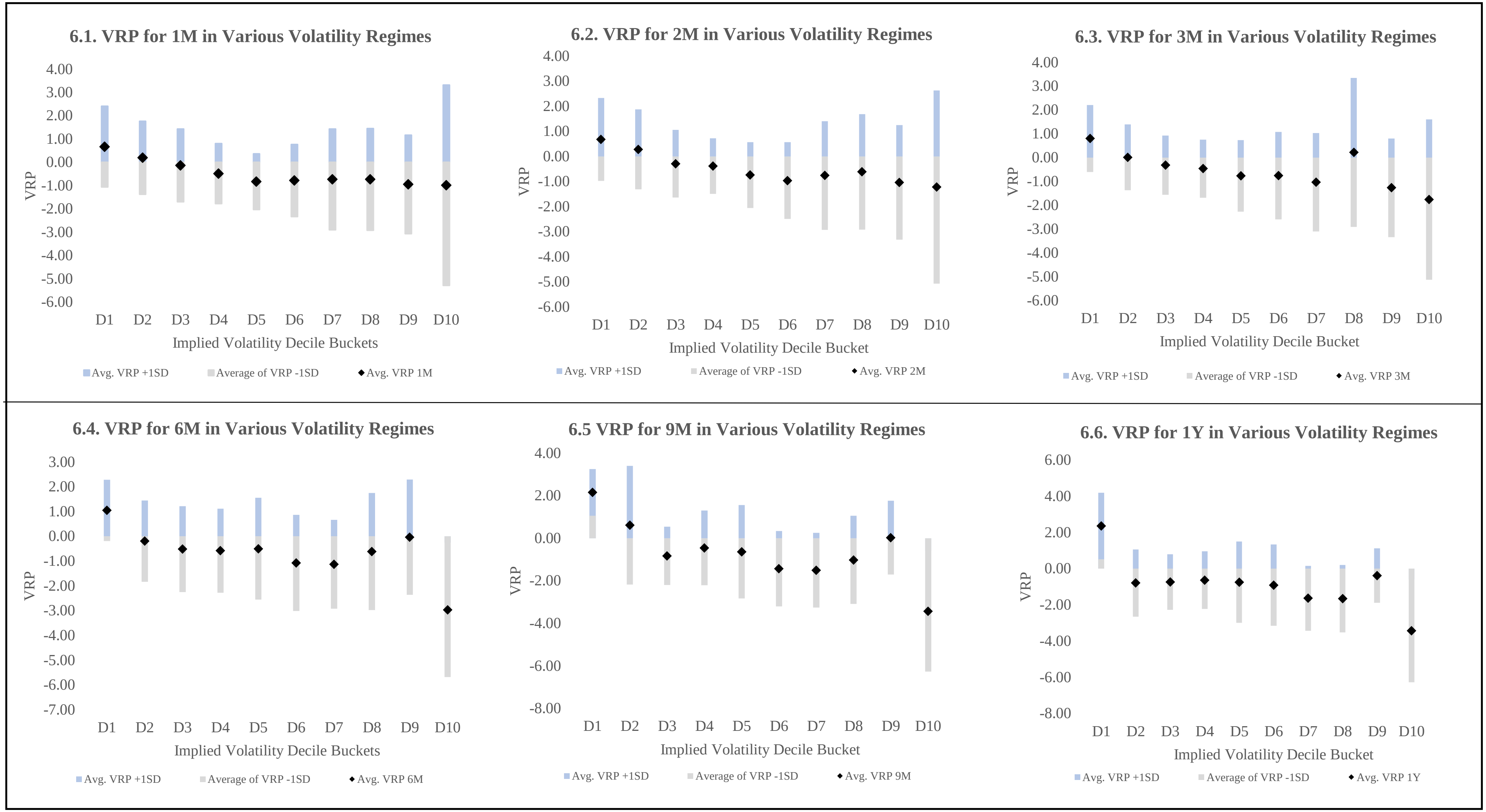
To explore the relationship between forward premia and VRP_t, the forward premium rates were also grouped into deciles (*Table 13*). A look at the VRP_t for each decile of forward premia indicated that as forward premia increased, the VRP_t became more negative. This observation aligns with the idea that heightened demand for hedging—driven by expectations of increased volatility—pushes up the cost of protection, thereby contributing to a negative VRP_t.

Table 13: Comparison of Average USD/INR Forward Premia % and the VRP_t

Variable	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
1M										
Average $FwdPrem_t$	1.03	2.53	3.25	3.62	4.07	4.65	5.87	6.68	7.52	8.86
Average VRP_t	-0.60	-0.64	-0.10	-0.33	-0.20	-0.57	-0.45	-0.32	-1.00	-1.06
2M										
Average $FwdPrem_t$	1.20	2.56	3.34	3.72	4.13	4.67	5.79	6.60	7.43	8.67
Average VRP_t	-0.58	-0.63	-0.14	-0.30	-0.10	-0.54	-0.16	-0.51	-0.99	-1.54
3M										
Average $FwdPrem_t$	1.23	2.56	3.30	3.78	4.15	4.62	5.64	6.53	7.34	8.54
Average VRP_t	-0.30	-0.72	0.10	-0.37	-0.20	-0.42	0.02	-0.79	-0.92	-2.11
6M										
Average $FwdPrem_t$	1.30	2.41	3.10	3.86	4.18	4.50	5.30	6.30	6.98	8.22
Average VRP_t	0.78	-0.54	0.04	-0.47	-0.37	-0.60	-0.67	-1.27	-0.28	-3.16
9M										
Average $FwdPrem_t$	1.29	2.24	2.95	3.83	4.19	4.45	5.09	6.05	6.73	8.02
Average VRP_t	1.82	-0.47	0.09	-0.31	-0.60	-0.78	-0.97	-1.14	-0.79	-3.60
1Y										
Average $FwdPrem_t$	1.24	2.14	2.85	3.81	4.17	4.40	4.95	5.83	6.54	7.80
Average VRP_t	1.92	-0.75	-0.34	-0.50	-0.80	-0.93	-1.19	-0.53	-1.78	-3.86

To further understand the behaviour of VRP_t under different volatility regimes, the implied volatility was grouped into deciles, where D1 indicated the lowest or most stable volatility regime, while D10 represented the highest volatility regime (*Chart 6*). For each decile of implied volatility, the average VRP_t, as well as VRP_t at +1 standard deviation and -1 standard deviation, were computed. The analysis revealed that the standard deviation of VRP_t increased in higher volatility regimes (D10), while it decreased in more stable, lower volatility regimes (D1). This finding underscores the sensitivity of the VRP_t to changes in volatility expectations, with greater volatility leading to higher variability in the VRP_t.

Chart 6 : Trends in VRP_t Under Various Volatility Regimes



Before estimating the multivariate regression model, the stationarity of the time series of the VRP_t, $d\_Spot_{\ t}$ and $FwdPrem_t$ was tested using the Augmented Dickey–Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The results highlighted in *Annexure A .1.* indicate that the three series were stationary at level.

To examine the determining factors of VRP_t, the multivariate regression model specified in equation *(6)* was estimated. The results are highlighted in *Table 12*. It was found that $d\_Spot_{\ t}$ was a significant predictor of VRP_t, with the slope coefficient ranging from 0.14 to 0.20. Th finding reconfirm that the VRP_t turned more positive during times when the currency depreciated vis-à-vis times when the currency appreciated.

The forward premia $FwdPrem_t$ had a negative beta coefficient ranging from -0.17 to -0.71 (at 1% level of significance), for all tenors except near month. An increase in the forward premia resulted in a decline in the VRP_t. This was expected as the forward premia is influenced by the hedging demand for the currency, particularly when market participants seek to protect themselves from uncertain or adverse currency movements. As hedging demand increased, the forward premia increased. During these times, market participants also factored in a higher insurance for volatility in their implied volatility of the option contract, thus leading to a negative VRP_t.

Market-specific events , such as the recent COVID-19 pandemic, also affected the VRP_t for tenors greater than 3 months. For these tenors where it was found to be significant, the negative coefficients, which ranged from -0.96 to -1.28, suggest that the market priced in higher volatility for USD/INR option contracts than what was actually observed for the specific tenors considered.

On the contrary, the VRP_t turned more positive during market events such as the global financial crises and the Fed taper tantrum. The coefficient for the GFC was found to range between 1.10 to 1.87 for tenors of 1 month, 2 month , 3 months and 6 months. The impact of the Fed taper tantrum was more pronounced with the coefficient ranging from 2.88 to 6.15.

It was further observed that the VRP_t was influenced by the asymmetry in USD/INR currency movement. Specifically, the VRP_t tended to increase during days when the currency depreciated compared to days when currency appreciated. This suggests that on days when the currency weakens, market participants may expect greater volatility, leading to higher volatility risk premia. Likewise, on days when the currency strengthens, market participants may experience lower volatility risk premia.

It is also interesting to note that the intercept term of the VRP_t was found to be positive and statistically significant for tenors of 6 month and above. The intercept term ranged from 0.79 to 1.64 for these tenors, suggesting that the $VRP_t$is not simply a function of market beta but does have an additional alpha, even after taking into account market specific stress event.

Table 12: Regression results of VRP_t Against Forward Premia and Event Driven Factors												
Variables	Estimate	HAC Std. Error	t value	Pr(>|t|)		Adj. R^2	Estimate	HAC Std. Error	t value	Pr(>|t|)		Adj. R^2
	Tenor 1M						**Tenor 2M**					
(Intercept)	-0.3285	0.3441	-0.9546	0.3398		0.1539	-0.0227	0.3291	-0.0689	0.9451		0.2941
d_Spot_t	0.2071	0.0914	2.2657	0.0235	*		0.1770	0.0650	2.7233	0.0065	**	
$FwdPrem_t$	-0.0931	0.0721	-1.2902	0.1970			-0.1793	0.0644	-2.7828	0.0054	**	
Dummy_Covid	-0.3631	0.3437	-1.0564	0.2909			-0.9282	0.5351	-1.7346	0.0829	.	
Dummy_GFC	0.7348	0.8041	0.9138	0.3609			1.3964	0.6300	2.2166	0.0267	*	
Dummy_Fed_Taper	4.6136	4.8984	0.9419	0.3463			6.1537	2.9639	2.0762	0.0379	*	
Cur_Dep	0.1355	0.0589	2.3001	0.0215	*		0.1128	0.0496	2.2767	0.0228	*	
	Tenor 3M						**Tenor 6M**					
(Intercept)	0.3049	0.2616	1.1658	0.2438		0.4043	0.7883	0.3015	2.6143	0.0090	**	0.4589
d_Spot_t	0.1879	0.0438	4.2855	0.0000	***		0.1907	0.0356	5.3637	0.0000	***	
$FwdPrem_t$	-0.2742	0.0549	-4.9962	0.0000	***		-0.4365	0.0628	-6.9495	0.0000	***	
Dummy_Covid	-1.2804	0.3910	-3.2747	0.0011	**		-1.0091	0.3160	-3.1938	0.00	**	
Dummy_GFC	1.8776	0.5118	3.6684	0.0002	***		1.6440	0.4436	3.7056	0.0002	***	
Dummy_Fed_Taper	6.3560	1.4294	4.4467	0.0000	***		4.7848	0.6286	7.6114	0.0000	***	
Cur_Dep	0.1387	0.0463	2.9946	0.0028	**		0.0769	0.0450	1.7074	0.0878	.	
	Tenor 9M						**Tenor 1Y**					
(Intercept)	1.6443	0.3682	4.4656	0.0000	***	0.4849	1.5655	0.3685	4.2482	0.0000	***	0.5136
d_Spot_t	0.1613	0.0264	6.1060	0.0000	***		0.1432	0.0171	8.3863	0.0000	***	
$FwdPrem_t$	-0.6486	0.0770	-8.4185	0.0000	***		-0.7144	0.0716	-9.9789	0.0000	***	
Dummy_Covid	-1.0980	0.2892	-3.7966	0.0001	***		-0.9647	0.2331	-4.1389	0.0000	***	
Dummy_GFC	1.1795	0.5337	2.2100	0.0272	*		1.1071	0.6115	1.8103	0.0703	.	
Dummy_Fed_Taper	3.8265	0.4224	9.0581	0.0001	***		2.8788	0.5921	4.8623	0.0000	***	
Cur_Dep	0.0576	0.0468	1.2301	0.2187			0.1189	0.0453	2.6272	0.0086	**	
*Notes: Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*												

The abridged results from the VAR model are presented in *Table 13* and support the earlier findings. The VRP_t was found to be predominantly autoregressive, with its past values significantly influencing its current level, particularly up to a 2 days lag, across all tenors considered. Additionally, the coefficient of the previous day's spot rates were found to be positive and have a significant impact on the current VRP_t. The lagged forward premium, however, were generally not significant for most tenors, with the exception of the 6-month tenor. Furthermore, among the exogenous variables considered. the dummy for the Fed's tapering policy was found to significantly affect VRP across all tenors, highlighting the importance of this surprise in US monetary policy actions, in influencing USD/INR volatility.

***Table 13: VRP_t Coefficient* Estimates from Vector Auto Regressive Results**

Independent Variable	**Lag length**	**1M**		**2M**		**3M**		**6M**		**9M**		**12M**	
VRP	1	0.8454	***	0.6984	***	0.6052	***	0.4977	***	0.5327	***	0.3791	***
d_Spot	1	0.0946	***	0.0972	***	0.1216	***	0.0774	***	0.0708	***	0.0895	***
FwdPrem	1	-0.0144		0.0570	.	-0.0071		0.1023	*	0.0262		0.0846	
VRP	2	0.0793	***	0.2017	***	0.2437	***	0.2320	***	0.2068	***	0.2204	***
d_Spot	2	-0.0106		-0.0345	.	-0.0531	**	-0.0193		-0.0281	.	-0.0420	*
FwdPrem	2	0.0526		-0.0410		-0.0132		-0.1511	*	-0.0027		-0.0295	
VRP	3	0.0197		0.0258		0.1145	***	0.1362	***	0.1423	***	0.1387	***
d_Spot	3	-0.0579	***	-0.0168		-0.0543	***	-0.0236		-0.0001		-0.0065	
FwdPrem	3	-0.0467	.	0.0606		0.0077		0.1759	*	0.0026		0.1413	
VRP	4	-	-	0.0328	*	-	-	0.1060	***	0.0965	***	0.0684	***
d_Spot	4	-	-	-0.0321	*	-	-	-0.0238	.	-0.0368	***	-0.0093	
FwdPrem	4	-	-	-0.0877	**	-	-	-0.1397	**	-0.0398		-0.1191	
VRP	5	-	-	-	-	-	-	-	-	-	-	0.0225	
d_Spot	5	-	-	-	-	-	-	-	-	-	-	-0.0078	
FwdPrem	5	-	-	-	-	-	-	-	-	-	-	-0.0495	
VRP	6	-	-	-	-	-	-	-	-	-	-	0.1457	***
d_Spot	6	-	-	-	-	-	-	-	-	-	-	-0.0181	
FwdPrem	6	-	-	-	-	-	-	-	-	-	-	-0.0462	
Constant	0	0.0425		0.0496	*	0.0284		0.0285		0.0346		0.0314	
Dummy_Covid	0	-0.1113		-0.1845	.	-0.1573	.	-0.1348		-0.0969		-0.1107	
Dummy_GFC	0	0.0115		0.0376		0.0377		-0.0294		-0.0154		-0.0286	
Dummy_Fed_Taper	0	0.2249	**	0.1700	*	0.1009		-0.1340	*	-0.1018	.	-0.1680	*
Cur_Dep	0	-0.0858	***	-0.0615	***	-0.0095		-0.0126		-0.0050		0.0154	

*Notes: Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*

The details of the tenor-wise VAR model results are provided in *Annexure A.2.1* through *A.2.6.* The analysis of the factors influencing the *d_Spot* revealed that the lagged values of *d_Spot* were the most significant determinants of its current values. This indicates that the change in spot prices is highly dependent on its own past behaviour, suggesting a persistence in price movements. Additionally, exogenous factors, particularly the Global Financial Crisis impact and impact of the Fed taper tantrum, were found to significantly influence the change in spot prices, especially for the longer tenors. In the case of the Forward Premium *FwdPrem*, it was observed that lagged values of both the forward premium and the spot price exerted an influence on the current rates.

7. Conclusion

This paper provides insights into the relationship between implied volatility from currency options and realized volatility in the Indian currency market, contributing to the broader understanding of volatility dynamics in this market. The study contributes to the literature for emerging markets such as India, an area that has been underexplored compared to developed economies.

The objective of the study was two-fold. The first was to test if the implied volatility could serve as an unbiased predictor of realized volatility, and the second was to estimate the factors influencing the volatility risk premium, taking into account the unique market conditions in India.

The findings indicate that while implied volatility can serve as a significant predictor of future realized volatility, its effectiveness is more pronounced over shorter time horizons and diminishes as the time to expiration increases. It further finds that implied volatility is not an unbiased predictor of realized volatility.

One of the key contributions of this research explaining the factors influencing volatility risk premium (the difference between implied and realised volatility). It was found that the change in spot rates were significant predictor of volatility risk premia, and the premia turned more positive during times of a currency depreciation versus times when the currency appreciated. It was also found that an increase in the forward premia resulted in a decline in the volatility risk premia, as the hedging demand for the currency increased the implied volatility relative to realised volatility. The study demonstrates that the movements in this premium tends to be more pronounced during periods of market uncertainty. External market events, such as the global financial crisis and the fed taper tantrum, also influence the magnitude of the VRP.

Overall, the research encourages further exploration of the factors that drive volatility dynamics in emerging markets such as India. Additionally, the results highlight the potential of looking at currency volatility as a distinct asset class, creating opportunities for trading products such as volatility derivatives. By focusing on volatility itself, rather than just the underlying currency, market participants can explore strategies that involve taking a directional view on volatility or strategies that can be used in hedging volatility.

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ANNEXURE

A.1.Test for Stationarity using ADF and KPSS tests				
	Dickey-Fuller Estimate	P-value	KPSS Estimate	P-value
Volatility Risk Premia (VRP_t)				
1M	-12.706	0.01	0.19122	0.02
2M	-8.3079	0.01	0.66311	0.01
3M	-6.4123	0.01	1.6842	0.01
6M	-4.5814	0.01	4.5063	0.01
9M	-3.8612	0.02	8.6169	0.01
1Y	-3.3122	0.06	9.8631	0.01
Change in Spot Rate (d_Spot_t)				
1M	-13.65	0.01	0.1242	0.10
2M	-8.6242	0.01	0.2114	0.10
3M	-6.6232	0.01	0.2955	0.10
6M	-4.158	0.01	0.5499	0.03
9M	-3.7392	0.02	0.7434	0.01
1Y	-3.2763	0.08	0.8723	0.01
Forward Premia ($FwdPrem_t$)				
1M	-3.6795	0.02	6.6400	0.01
2M	-3.1134	0.11	7.1597	0.01
3M	-2.8741	0.21	7.5697	0.01
6M	-2.4358	0.39	8.5933	0.01
9M	-2.2109	0.49	9.4208	0.01
1Y	-2.0375	0.56	10.1010	0.01

A.2. 1. Vector Autoregressive Results for Tenor of 1M														
		VRP_t				d_Spot_t				$FwdPrem_t$				
Variable	Lag length	Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		
VRP	1	0.8454	0.0149	56.6490	***	0.0162	0.0119	1.3650		0.0120	0.0083	1.4510		
d_Spot	1	0.0946	0.0167	5.6690	***	1.0020	0.0133	75.5750	***	-0.0134	0.0093	-1.4400		
FwdPrem	1	-0.0144	0.0265	-0.5410		0.0129	0.0211	0.6140		0.9874	0.0148	66.9230	***	
VRP	2	0.0793	0.0195	4.0660	***	-0.0193	0.0155	-1.2500		-0.0116	0.0108	-1.0670		
d_Spot	2	-0.0106	0.0232	-0.4550		-0.0480	0.0185	-2.6000	**	0.0008	0.0129	0.0620		
FwdPrem	2	0.0526	0.0373	1.4110		0.0004	0.0296	0.0150		-0.1390	0.0207	-6.7030	***	
VRP	3	0.0197	0.0149	1.3270		-0.0075	0.0118	-0.6400		0.0008	0.0083	0.1010		
d_Spot	3	-0.0579	0.0168	-3.4490	***	0.0264	0.0133	1.9850	*	0.0046	0.0093	0.4960		
FwdPrem	3	-0.0467	0.0265	-1.7600	.	-0.0134	0.0210	-0.6350		0.1377	0.0147	9.3400	***	
const	0	0.0425	0.0270	1.5760		0.3075	0.0214	14.3430	***	0.0967	0.0150	6.4430	***	
Dummy_Covid	0	-0.1113	0.1218	-0.9140		-0.0855	0.0967	-0.8840		-0.0293	0.0677	-0.4320		
Dummy_GFC	0	0.0115	0.0559	0.2060		0.0502	0.0443	1.1320		-0.0075	0.0311	-0.2420		
Dummy_Fed_Taper	0	0.2249	0.0835	2.6950	**	0.0686	0.0663	1.0350		0.1064	0.0464	2.2910	*	
Cur_Dep	0	-0.0858	0.0214	-4.0150	***	-0.6066	0.0170	-35.7370	***	-0.0565	0.0119	-4.7490	***	

*Notes: Model Adjusted R^2 is 0.901, F Stat P-value is <0.0000. Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*

A2.2. Vector Autoregressive Results for Tenor of 2M														
		VRP_t				d_Spot_t				$FwdPrem_t$				
Variable	Lag length	Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		
VRP	1	0.6984	0.0150	46.7300	***	-0.0054	0.0141	-0.3850		0.0128	0.0069	1.8640	.	
d_Spot	1	0.0972	0.0139	6.9840	***	1.0071	0.0131	76.8020	***	0.0001	0.0064	0.0210		
FwdPrem	1	0.0570	0.0323	1.7660	.	0.0391	0.0304	1.2860		1.0017	0.0148	67.5670	***	
VRP	2	0.2017	0.0183	11.0530	***	-0.0077	0.0172	-0.4460		-0.0147	0.0084	-1.7600	.	
d_Spot	2	-0.0345	0.0195	-1.7720	.	-0.0761	0.0184	-4.1480	***	-0.0018	0.0089	-0.2000		
FwdPrem	2	-0.0410	0.0458	-0.8960		-0.0896	0.0431	-2.0780	*	-0.1505	0.0210	-7.1650	***	
VRP	3	0.0258	0.0183	1.4150		0.0518	0.0172	3.0160	**	-0.0190	0.0084	-2.2650	*	
d_Spot	3	-0.0168	0.0195	-0.8630		0.0339	0.0184	1.8440	.	-0.0084	0.0089	-0.9380		
FwdPrem	3	0.0606	0.0458	1.3250		0.0971	0.0431	2.2510	*	0.0539	0.0210	2.5640	*	
VRP	4	0.0328	0.0149	2.2090	*	-0.0392	0.0140	-2.7990	**	0.0228	0.0068	3.3370	***	
d_Spot	4	-0.0321	0.0140	-2.2830	*	0.0278	0.0132	2.1050	*	0.0043	0.0064	0.6730		
FwdPrem	4	-0.0877	0.0323	-2.7150	**	-0.0399	0.0304	-1.3100		0.0881	0.0148	5.9420	***	
const	0	0.0496	0.0237	2.0990	*	0.3003	0.0223	13.4740	***	0.0608	0.0109	5.5990	***	
Dummy_Covid	0	-0.1845	0.1027	-1.7960	.	-0.0505	0.0967	-0.5220		-0.0303	0.0471	-0.6440		
Dummy_GFC	0	0.0376	0.0477	0.7880		-0.0432	0.0450	-0.9600		-0.0091	0.0219	-0.4170		
Dummy_Fed_Taper	0	0.1700	0.0744	2.2860	*	-0.1583	0.0700	-2.2600	*	0.0789	0.0341	2.3110	*	
Cur_Dep	0	-0.0615	0.0179	-3.4430	***	-0.6337	0.0168	-37.6370	***	-0.0478	0.0082	-5.8260	***	
*Notes: Model Adjusted R^2 is 0.9292, F Stat P-value is <0.0000. Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*														

A2.3. Vector Autoregressive Results for Tenor of 3M													
		VRP_t				d_Spot_t				$FwdPrem_t$			
Variable	Lag length	Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		Estimate	Std. Error	t-value	
VRP	1	0.6052	0.0148	40.8220	***	-0.0167	0.0155	-1.0730		-0.0003	0.0077	-0.0450	
d_Spot	1	0.1216	0.0126	9.6400	***	0.9920	0.0132	74.9570	***	0.0145	0.0066	2.2190	*
FwdPrem	1	-0.0071	0.0285	-0.2510		0.0243	0.0299	0.8120		0.8054	0.0148	54.3600	***
VRP	2	0.2437	0.0170	14.3430	***	-0.0007	0.0178	-0.0400		0.0050	0.0088	0.5710	
d_Spot	2	-0.0531	0.0176	-3.0090	**	-0.0430	0.0185	-2.3240	*	-0.0161	0.0092	-1.7580	.
FwdPrem	2	-0.0132	0.0366	-0.3590		-0.0175	0.0384	-0.4560		0.0778	0.0190	4.0860	***
VRP	3	0.1145	0.0147	7.7640	***	0.0098	0.0155	0.6320		-0.0054	0.0077	-0.7050	
d_Spot	3	-0.0543	0.0128	-4.2510	***	0.0476	0.0134	3.5540	***	-0.0010	0.0066	-0.1440	
FwdPrem	3	0.0077	0.0285	0.2700		-0.0048	0.0299	-0.1590		0.1091	0.0148	7.3620	***
const	0	0.0284	0.0219	1.2970		0.2994	0.0230	13.0350	***	0.0577	0.0114	5.0680	***
Dummy_Covid	0	-0.1573	0.0935	-1.6830	.	-0.1130	0.0980	-1.1520		-0.0199	0.0486	-0.4100	
Dummy_GFC	0	0.0377	0.0438	0.8600		-0.0790	0.0459	-1.7180	.	-0.0157	0.0228	-0.6890	
Dummy_Fed_Taper	0	0.1009	0.0686	1.4700		-0.0738	0.0720	-1.0250		0.0793	0.0357	2.2230	*
Cur_Dep	0	-0.0095	0.0162	-0.5840		-0.5979	0.0170	-35.1770	***	-0.0386	0.0084	-4.5820	***
*Notes: Model Adjusted R^2 is 0.937, F Stat P-value is <0.0000. Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*													

A2.4. Vector Autoregressive Results for Tenor of 6M													
		VRP_t				d_Spot_t				$FwdPrem_t$			
Variable	Lag length	Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		Estimate	Std. Error	t-value	
VRP	1	0.4977	0.0148	33.5580	***	-0.0203	0.0153	-1.3260		0.0043	0.0045	0.9610	
d_Spot	1	0.0774	0.0128	6.0670	***	1.0067	0.0131	76.5750	***	0.0027	0.0039	0.7010	
FwdPrem	1	0.1023	0.0490	2.0890	*	0.0768	0.0505	1.5220		1.0290	0.0148	69.3470	***
VRP	2	0.2320	0.0165	14.0970	***	0.0034	0.0170	0.2030		-0.0040	0.0050	-0.7990	
d_Spot	2	-0.0193	0.0179	-1.0790		-0.0647	0.0185	-3.5040	***	0.0154	0.0054	2.8340	**
FwdPrem	2	-0.1511	0.0701	-2.1540	*	-0.0060	0.0723	-0.0830		-0.1412	0.0213	-6.6450	***
VRP	3	0.1362	0.0165	8.2680	***	-0.0024	0.0170	-0.1440		-0.0111	0.0050	-2.2310	*
d_Spot	3	-0.0236	0.0179	-1.3160		0.0393	0.0185	2.1260	*	-0.0171	0.0054	-3.1430	**
FwdPrem	3	0.1759	0.0701	2.5090	*	-0.0788	0.0723	-1.0900		0.0501	0.0212	2.3580	*
VRP	4	0.1060	0.0148	7.1570	***	0.0068	0.0153	0.4460		0.0094	0.0045	2.0890	*
d_Spot	4	-0.0238	0.0129	-1.8480	.	0.0191	0.0133	1.4390		-0.0013	0.0039	-0.3320	
FwdPrem	4	-0.1397	0.0489	-2.8580	**	0.0050	0.0504	0.0990		0.0577	0.0148	3.8940	***
const	0	0.0285	0.0230	1.2360		0.3256	0.0237	13.7140	***	0.0414	0.0070	5.9340	***
Dummy_Covid	0	-0.1348	0.0943	-1.4300		-0.0749	0.0972	-0.7700		-0.0089	0.0286	-0.3110	
Dummy_GFC	0	-0.0294	0.0443	-0.6640		-0.0753	0.0457	-1.6470	.	-0.0115	0.0134	-0.8530	
Dummy_Fed_Taper	0	-0.1340	0.0656	-2.0430	*	-0.1403	0.0676	-2.0750	*	0.0418	0.0199	2.1020	*
Cur_Dep	0	-0.0126	0.0163	-0.7720		-0.6189	0.0168	-36.8490	***	-0.0422	0.0049	-8.5530	***
*Notes: Model Adjusted R^2 is 0.9400, F Stat P-value is <0.0000. Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*													

A2.5. Vector Autoregressive Results for Tenor of 9M													
		VRP_t				d_Spot_t				$FwdPrem_t$			
Variable	Lag length	Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		Estimate	Std. Error	t-value	
VRP	1	0.5327	0.0149	35.8550	***	0.0003	0.0179	0.0150		-0.0016	0.0050	-0.3200	
d_Spot	1	0.0708	0.0109	6.4830	***	1.0178	0.0132	77.2380	***	0.0137	0.0037	3.7010	***
FwdPrem	1	0.0262	0.0441	0.5930		0.0285	0.0533	0.5350		0.8570	0.0149	57.3700	***
VRP	2	0.2068	0.0167	12.3550	***	-0.0010	0.0202	-0.0480		-0.0057	0.0057	-0.9980	
d_Spot	2	-0.0281	0.0155	-1.8180	.	-0.0854	0.0187	-4.5730	***	-0.0056	0.0052	-1.0660	
FwdPrem	2	-0.0027	0.0581	-0.0470		-0.0047	0.0701	-0.0670		0.0349	0.0197	1.7740	.
VRP	3	0.1423	0.0167	8.5020	***	-0.0047	0.0202	-0.2340		0.0108	0.0057	1.9120	.
d_Spot	3	-0.0001	0.0155	-0.0040		0.0435	0.0187	2.3270	*	0.0037	0.0052	0.7130	
FwdPrem	3	0.0026	0.0581	0.0440		-0.0617	0.0701	-0.8790		0.0479	0.0197	2.4350	*
VRP	4	0.0965	0.0148	6.5120	***	-0.0034	0.0179	-0.1900		-0.0051	0.0050	-1.0190	
d_Spot	4	-0.0368	0.0110	-3.3480	***	0.0237	0.0133	1.7870	.	-0.0120	0.0037	-3.2230	**
FwdPrem	4	-0.0398	0.0441	-0.9020		0.0340	0.0532	0.6380		0.0555	0.0149	3.7150	***
const	0	0.0346	0.0216	1.6010		0.3520	0.0261	13.4870	***	0.0382	0.0073	5.2240	***
Dummy_Covid	0	-0.0969	0.0843	-1.1500		-0.1298	0.1016	-1.2770		-0.0064	0.0285	-0.2250	
Dummy_GFC	0	-0.0154	0.0394	-0.3920		-0.1270	0.0475	-2.6720	**	-0.0143	0.0133	-1.0700	
Dummy_Fed_Taper	0	-0.1018	0.0563	-1.8070	.	-0.2366	0.0680	-3.4810	***	0.0370	0.0191	1.9390	.
Cur_Dep	0	-0.0050	0.0146	-0.3460		-0.6459	0.0176	-36.7780	***	-0.0338	0.0049	-6.8700	***

*Notes: Model Adjusted R^2 is 0.9588, F Stat P-value is <0.0000. Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*

A.2.6. Vector Autoregressive Results for Tenor of 1Y													
		VRP_t				d_Spot_t				$FwdPrem_t$			
Variable	Lag length	Estimate	Std. Error	t-value		Estimate	Std. Error	t-value		Estimate	Std. Error	t-value	
VRP	1	0.3791	0.0148	25.6630	***	-0.0197	0.0151	-1.3010		0.0050	0.0033	1.5190	
d_Spot	1	0.0895	0.0129	6.9270	***	1.0032	0.0132	75.8640	***	0.0095	0.0029	3.3100	***
FwdPrem	1	0.0846	0.0667	1.2680		0.0867	0.0683	1.2690		0.9574	0.0149	64.3320	***
VRP	2	0.2204	0.0158	13.9340	***	0.0068	0.0162	0.4170		-0.0051	0.0035	-1.4450	
d_Spot	2	-0.0420	0.0182	-2.3110	*	-0.0539	0.0186	-2.8970	**	-0.0005	0.0041	-0.1170	
FwdPrem	2	-0.0295	0.0923	-0.3190		-0.0370	0.0945	-0.3920		-0.0363	0.0206	-1.7620	.
VRP	3	0.1387	0.0161	8.6040	***	0.0041	0.0165	0.2470		-0.0023	0.0036	-0.6530	
d_Spot	3	-0.0065	0.0182	-0.3580		0.0488	0.0186	2.6260	**	-0.0089	0.0041	-2.1960	*
FwdPrem	3	0.1413	0.0922	1.5320		-0.0726	0.0944	-0.7690		0.0216	0.0206	1.0500	
VRP	4	0.0684	0.0161	4.2400	***	0.0368	0.0165	2.2310	*	0.0084	0.0036	2.3390	*
d_Spot	4	-0.0093	0.0182	-0.5100		0.0565	0.0186	3.0360	**	-0.0024	0.0041	-0.5850	
FwdPrem	4	-0.1191	0.0922	-1.2920		-0.1151	0.0944	-1.2200		0.0325	0.0206	1.5810	
VRP	5	0.0225	0.0158	1.4210		-0.0187	0.0162	-1.1560		-0.0045	0.0035	-1.2830	
d_Spot	5	-0.0078	0.0182	-0.4320		-0.0103	0.0186	-0.5510		0.0013	0.0041	0.3300	
FwdPrem	5	-0.0495	0.0922	-0.5370		0.0836	0.0944	0.8850		0.0480	0.0206	2.3340	*
VRP	6	0.1457	0.0147	9.8870	***	-0.0127	0.0151	-0.8420		-0.0023	0.0033	-0.7040	
d_Spot	6	-0.0181	0.0130	-1.3880		-0.0466	0.0133	-3.4940	***	0.0005	0.0029	0.1800	
FwdPrem	6	-0.0462	0.0667	-0.6940		0.0568	0.0682	0.8320		-0.0265	0.0149	-1.7840	.
const	0	0.0314	0.0259	1.2150		0.3253	0.0265	12.2910	***	0.0326	0.0058	5.6580	***
Dummy_Covid	0	-0.1107	0.0996	-1.1110		-0.0415	0.1020	-0.4070		-0.0045	0.0222	-0.2030	
Dummy_GFC	0	-0.0286	0.0470	-0.6100		-0.1080	0.0481	-2.2450	*	-0.0145	0.0105	-1.3810	
Dummy_Fed_Taper	0	-0.1680	0.0658	-2.5520	*	-0.1745	0.0674	-2.5890	**	0.0216	0.0147	1.4730	
Cur_Dep	0	0.0154	0.0172	0.8960		-0.6309	0.0176	-35.7650	***	-0.0338	0.0038	-8.7930	***

*Notes: Model Adjusted R^2 is 0.9399, F Stat P-value is <0.0000. Significance codes are '***' 0.001, '**' 0.01, '*' 0.05, and '.' 0.1.*