# OPTION CHAIN DYNAMICS: ANALYSING OPEN INTEREST, TRADING VOLUME, AND LAST TRADED PRICE RELATIONSHIPS

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**ABSTRACT:** This paper investigates the dynamic interplay between option chain metrics—specifically open interest (OI), trading volume, and last traded price (LTP)—within financial markets. Utilizing data spanning multiple market cycles, we explore how changes in these metrics influence one another and impact underlying asset prices. Drawing upon existing literature and empirical analysis, we seek to elucidate the predictive power of these indicators on market movements and volatility.

KEYWORDS: Option Chains, Open Interest, Trading Volume, Last Traded Price, Market Dynamics, Investor Sentiment

## Introduction:

The options market represents a dynamic arena where investors, traders, and institutions navigate financial opportunities and risks through the use of derivative instruments. At the heart of this market lie key metrics such as open interest (OI), trading volume, and the last traded price (LTP), each playing critical roles in shaping market dynamics and influencing investment decisions. Open interest serves as a fundamental gauge of market activity within options contracts. It represents the total number of outstanding contracts that have not been offset by opposite transactions and thus indicates the level of investor interest in specific strike prices and expiration dates. Changes in open interest can signal shifts in market sentiment and expectations regarding future price movements. For instance, a significant increase in open interest at a particular strike price may suggest growing anticipation of price movements in that direction as investors position themselves accordingly. Trading volume, on the other hand, reflects the number of contracts traded during a given period. It provides insights into the level of market participation and the intensity of transactions occurring within the options market. High trading volumes often coincide with periods of heightened market activity, where information dissemination and investor reactions to news or events can influence price movements. Analyzing trading volume trends helps market participants gauge market liquidity and potential areas of price support or resistance. Last traded price (LTP) represents the price at which the most recent trade occurred for a particular option contract. It serves as a crucial benchmark for market participants, indicating the prevailing market price at which buyers and sellers are willing to transact. The LTP plays a pivotal role in price discovery, as it reflects the culmination of market supply and demand dynamics at any given point in time. Changes in the LTP can provide insights into short-term price movements and help traders assess the immediacy and direction of market sentiment.

Understanding the relationships among these metrics is essential for market participants seeking to interpret market dynamics and make informed trading decisions. For instance, increases in open interest coupled with rising trading volumes can signify growing investor interest and potential upcoming volatility in the underlying asset. Conversely, discrepancies between trading volume and open interest levels may indicate divergent views among market participants regarding future price directions. Empirical studies have consistently demonstrated the predictive power of these metrics in forecasting market movements and identifying potential trading opportunities. Research has shown that shifts in open interest often precede significant price movements, highlighting its role as an early indicator of market sentiment. Similarly, trading volume spikes can signal abrupt changes in investor behavior or the emergence of new market trends, providing valuable signals for traders and analysts alike. In this study, we leverage comprehensive datasets and employ advanced statistical techniques to explore the dynamic interactions between open interest, trading volume, and the last traded price across various market conditions and asset classes. By examining these relationships, we aim to uncover deeper insights into investor behavior, market efficiency, and the underlying factors driving options market dynamics. Ultimately, a nuanced understanding of option chain dynamics—fueled by insights into open interest, trading volume, and the last traded price—can empower market participants to navigate volatility, manage risk effectively, and capitalize on emerging opportunities in the everevolving landscape of financial markets. This research contributes to the broader understanding of market mechanics and reinforces the importance of these metrics in shaping investment strategies and market outcomes.

## Literature Review:

Previous research (e.g., O'Hara and Oldfield, 1986; Easley et al., 1998) has established foundational insights into the roles of open interest and trading volume in financial markets. These studies highlight how changes in open interest can signal market sentiment and future price movements, while trading volume often reflects the intensity of market participation and information dissemination. Additionally, studies on implied volatility (Cremers et al., 2008) underscore the predictive power of option-derived metrics on underlying asset prices.

## Methodology

In this study, we employ a rigorous methodology to investigate the dynamic relationships between open interest (OI), trading volume, and last traded price (LTP) in the options market. Our approach integrates comprehensive datasets spanning multiple market cycles and employs advanced statistical techniques to analyze the interplay of these key metrics. This section outlines our methodology, including data collection, statistical analysis, and modeling techniques.

# **Data Collection**

Our analysis draws upon daily trading data from a diverse range of options contracts across various sectors and asset classes. The dataset includes information on OI, trading volumes, LTPs, strike prices, expiration dates, and underlying asset prices. Data is sourced from reputable financial databases and exchanges, ensuring accuracy and reliability.

#### **Descriptive Statistics**

To gain initial insights into the characteristics of our dataset, we conduct descriptive statistical analysis. This includes calculating measures such as mean, median, standard deviation, and distribution plots for OI, trading volume, and LTP across different options contracts. Descriptive statistics help us understand the central tendencies, variability, and distributional properties of our variables of interest.

## **Correlation Analysis**

We begin by examining the pairwise correlations between OI, trading volume, and LTP. Correlation analysis provides insights into the strength and direction of relationships between these metrics. The Pearson correlation coefficient ( $\rho$ ) is calculated as follows:

 $\rho XY = Cov(X,Y)\sigma X\sigma Y \ln_{XY} = \frac{\cot(X,Y)}{\sin(X,Y)}$ 

where Cov(X,Y)\text{Cov}(X, Y)Cov(X,Y) is the covariance of variables XXX and YYY, and  $\sigma X, \sigma Y$ \sigma\_X, \sigma\_Y  $\sigma X, \sigma Y$  are the standard deviations of XXX and YYY, respectively. A positive correlation suggests that changes in one metric are associated with changes in the other in the same direction, while a negative correlation indicates an inverse relationship.

Side	Build Up	Trend	Interpretation
CALL	LONG BUILDUP or SHORT COVERING	BULLISH	Longs are getting added on the Call side or Shorts are being reduced, both of which are seen Bullish.
CALL	SHORT BUILDUP or LONG UNWINDING	BEARISH	Shorts are getting added on the Call side or Longs are being reduced (Profit Booking), both of which are seen Bearish.
PUT	SHORT BUILDUP or LONG UNWINDING	BULLISH	Shorts are getting added on the Put side or Longs are being reduced (Profit Booking), both of which are seen bullish.
PUT	LONG BUILDUP or SHORT COVERING	BEARISH	Longs are getting added on the Put side or Shorts are being reduced, both of which are seen Bearish.

## **Regression Analysis**

To further explore the relationships among OI, trading volume, and LTP, we employ regression models. Specifically, we consider multiple linear regression to examine how OI and trading volume predict variations in LTP. The regression equation can be expressed as:

 $LTP=\beta0+\beta1\cdot OI+\beta2\cdot Volume+\epsilon LTP = \beta_0 + \beta_1 \cdot \text{OI} + \beta_2 \cdot \text{Volume} + \eqref{Volume} + \eqref{Volume} + \beta_0+\beta1\cdot OI+\beta2\cdot Volume+\epsilon$ 

where LTPLTPLTP represents the dependent variable (last traded price), OI\text{OI}OI and Volume\text{Volume} Volume are the independent variables (open interest and trading volume, respectively),  $\beta$ 0\beta\_0 $\beta$ 0 is the intercept,  $\beta$ 1\beta\_1 $\beta$ 1 and  $\beta$ 2\beta\_2 $\beta$ 2 are the regression coefficients, and  $\epsilon$ \epsilon $\epsilon$  is the error term.

By estimating regression coefficients  $\beta_1$  and  $\beta_2$  and  $\beta_2$ , we assess the impact of changes in OI and trading volume on LTP. A significant  $\beta_1$  beta  $1\beta_1$  indicates that changes in

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	200	78	340		323.45	241.35	1,450	324.18	124.09	980	18,850,00	8,410	11.70	11.75	2,900	7.33	33.70	14.44	4,20,839	3,872	28,500	12
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	8427	458	2,828		285.25	-252.75	80	235.20	235.78	500	19,056,80	59	22.15	22.25	3,800	15.80	22.15	18.78	7,75,568	10,094	82,802	
15	3,873	603	22,79				rib.	104.00	194.30	1,680	19,100.00	42,100	31.00	25.18	11,250	28.00	31.00	13.67	14/02/276	22,089	83,188	1.00
25	2,243	2,081	37.82	Pre	emi	um	50	155.35	185.78	-300	19,150.00	700	42.40	42.55	350	Dre	omi		1307	13,795	18,054	
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812	23,829	22,916	1.85,105	10.54	91,70	007.18	300	91.70	.93.5	-	ka D			78.75	780	29.10	78.50	12.95	12,90,472	16,559	47,219	100
82	72,826	67,013	7,37,346	10.92	68.05	185.35	350	67.85	68.8	Suri	ke P	LICE	3	104.40	100	78.15	104.13	13.81	311, 53, 5-8.4	8,784	10.803	25
13	81,452	49,413	16.27,804	11.06	\$7.78	183.70	350	47.79	42,99	2,800	17.899.00	1,850	138.00	131.35	3,980	99.30	134.00	18.97	15,45,211	12,060	46,2799	
12	1.96,311	1,95,622	22,56,650	-1177	35.85	-143.35	0.400	32.55	32.45	0.000	19,400.00	209	169.45	140.85	200	122.45	169.50	1000	30,67,256	-29,301	84,970	12
12	1,02,811	94,139	21,17,891	11.62	22.95	1118.30	4,508	22.30	23.45	2,990	38,650.00	18,250	288.05	208,95	90	745.00	224.3	24,00	23,111,558	(11,343	28.615	10
12	2,34,015	1.45,782	38,10,294	12.00	1.00	PE 20	1,730	35.30	18.28	1,990	39,908.00	28,250	281.00	251.50	50	108,79	22.05	35.90	29,66,288	-26,435	1,30,845	-
82	1,45,607	76,005	22,91,159	12.41	33.40	-24.58	450	10.95	11.00	10.650	19,558,00	458	296.00	296.30	100	198.35	96.00	18.65	10.72,099	-25.699	30,799	
83	2.33,181	72,797	Ch	an	00	in (		7,90	7.95	5,850	18.609.90	50	342.55	24	The	na	- in	0	1 1	-27,124	72,824	10
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62	82,654	8,311	10,82,814	14.74	6.10	18.70	16,790	4.05	4.10	12,890	18,758,89	60	489.00	480.00	8,813	248.38	ARS.BD	21.47	22,825	-1,990	8,357	15
22	2,08,675	43,71/5	14,38,930	12.17	3.00	11.90	12,650	8.60	3.60	19,900	18,800.00	300	540.92	541.50	1,3592	254.65	043.00	24.89	10.452	-0.320	48,994	10
152	88,977	11,487	8,16,863	18.47	2.20	4 90	18,2563	3,20	3.25	16,800	18,859,00	100	089.30	1941.25	543	256.45	589,30	28.08	5.261	11,721	2,666	2
12	1,899,7024	24,392	11,08,143	17.30	4.75		41,0%)	2.79	2.78	44,100	19,909,00	0.0	0.00.00	439.05	300	200.00	129.05	47.29	10,131		18,874	
12	10.752	7.2.87	11.10.002	18.31	2.00	2.05	0.000	0.00	1.90	00,130	19,908,00	200	1000.00	000100	200		A104.40	30.20	2,402		1.204	2
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10	79.676	10.000	4,04,700	10.04	2.10	4.50	78,000	a.00	0.10	10,000	20,050,00		225.10		100	100.00	234.90	22.00	1.0104		2.000	
100	78.636	30,334	0,00,797	20.95	5.10	0.70	18,600	2.10	2.15	38,750	10,108.00	300	00010	039.70	100	260.53	0.16.15	33.94	1.074	-3.87	1.308	

OI have a statistically significant effect on LTP, while a significant  $\beta_2$  beta  $2\beta_2$  suggests that trading volume influences LTP.

## **Time Series Analysis**

Given the temporal nature of options market data, we conduct time series analysis to explore trends and patterns in OI, trading volume, and LTP over time. This includes techniques such as moving averages, autocorrelation functions (ACF), and partial autocorrelation functions (PACF) to identify seasonality, trends, and potential cyclical patterns in our variables of interest.

#### **Event Study Methodologies**

Event study methodologies are employed to investigate the impact of specific events or market occurrences on OI, trading volume, and LTP. Events of interest may include earnings announcements, economic releases, corporate actions, or geopolitical developments. The event study framework typically involves the following steps:

1. **Event Identification:** Define the event window around the occurrence of the event. For instance, a typical event window might include several days before and after the event date to capture market reactions.

2. Estimation of Abnormal Returns: Calculate abnormal returns (AR) for each event using a benchmark model such as the market model or an asset pricing model. Abnormal returns represent the difference between actual returns and expected returns based on the model.

The market model for calculating abnormal returns is typically expressed as:

$$\label{eq:result} \begin{split} Rit-Rtf=&\alpha i+\beta i (Rtm-Rtf)+\varepsilon it R_{it} - R^f_t = \\ alpha_i + beta_i (R^m_t - R^f_t) + epsilon_{it} Rit-Rtf=&\alpha i+\beta i (Rtm-Rtf)+\varepsilon it \\ -Rtf)+\varepsilon it \end{split}$$

where RitR\_{it}Rit is the return of asset iii at time ttt, RtfR^f\_tRtf is the risk-free rate at time ttt, RtmR^m\_tRtm is the return of the market portfolio at time ttt,  $\alpha i = \pi \beta i$  and  $\beta i = \pi \beta i$  are the asset-specific intercept and slope coefficients, and  $\epsilon i \geq 1$  is the error term.

- 3. **Cumulative Abnormal Returns (CAR):** Sum the abnormal returns over the event window to obtain the cumulative abnormal return for each event. CAR provides a measure of the total impact of the event on the asset's returns during the event period.
- 4. **Analysis of Options Metrics:** Extend the event study methodology to analyze changes in OI, trading volume, and LTP during the event window. Calculate abnormal changes in OI and trading volume to assess whether the event triggers significant adjustments in market sentiment or expectations regarding future price movements.
- 5. **Statistical Inference:** Conduct statistical tests such as t-tests or rank tests to evaluate the significance of abnormal returns and changes in options metrics during the event window. This helps determine whether observed changes are statistically significant and not merely due to random fluctuations.

#### **Advanced Modelling Techniques**

To enhance our understanding of the complex interactions within the options market, we explore advanced modelling techniques such as machine learning algorithms and Bayesian inference. These techniques allow us to capture nonlinear relationships, identify latent patterns, and make probabilistic forecasts based on historical data. **Validation and Sensitivity Analysis** 

To ensure the robustness of our findings, we conduct validation exercises and sensitivity analyses. This includes cross-validation techniques to assess model stability and generalizability across different subsets of data. Sensitivity analysis helps us evaluate the impact of variations in input parameters and assumptions on our results, ensuring the reliability and reproducibility of our findings. Our comprehensive methodology integrates quantitative analysis with advanced statistical techniques to uncover the intricate relationships between open interest, trading volume, and last traded price in the options market. By leveraging a rich dataset and employing rigorous modeling approaches, we contribute to the broader understanding of market dynamics, investor behavior, and the predictive power of options market metrics. This study provides actionable insights for market participants, analysts, and policymakers seeking to navigate volatility, manage risk effectively, and capitalize on emerging opportunities in today's dynamic financial markets.

#### **Empirical Analysis:**

The dataset used in our empirical analysis comprises daily trading data from a diverse range of options contracts across various sectors and asset classes. For each option contract, we have recorded variables such as OI, trading volumes, LTPs, strike prices, expiration dates, and underlying asset prices. The data spans multiple years to capture different market conditions and cycles.

#### **Descriptive Statistics**

We begin our analysis by examining the descriptive statistics of the key variables: OI, trading volume, and LTP. Descriptive statistics provide insights into the central tendencies, variability, and distributional properties of these metrics across different options contracts. Key descriptive statistics include mean, median, standard deviation, skewness, and kurtosis.

## **Correlation Analysis**

Next, we investigate the pairwise correlations between OI, trading volume, and LTP. Correlation analysis helps us understand the strength and direction of relationships between these variables. The Pearson correlation coefficient ( $\rho$ ) is computed as follows:





where Cov(X,Y)\text{Cov}(X, Y)Cov(X,Y) denotes the covariance between variables XXX and YYY, and  $\sigma X, \sigma Y$ \sigma\_X, \sigma\_Y  $\sigma X, \sigma Y$  are the standard deviations of XXX and YYY, respectively. Positive correlations indicate that increases in one variable are associated with increases in the other, while negative correlations suggest an inverse relationship.

## **Regression Analysis**

To further explore the relationships among OI, trading volume, and LTP, we employ multiple linear regression models. Our regression model is specified as follows:

 $LTPi=\beta0+\beta1\cdot OIi+\beta2\cdot Volumei+\epsilon i LTP_i = \langle beta_0 + \langle beta_1 \rangle (dot \langle text{OI}_i + \langle beta_2 \rangle (dot \langle text{Volume}_i + \langle epsilon_i LTPi=\beta0+\beta1\cdot OIi+\beta2\cdot Volumei+\epsilon i \rangle (dot \langle text{OI}_i + \langle beta_1 \rangle (dot \langle text{OI}_i + \langle beta_2 \rangle (dot \langle text{Volume}_i + \langle beta_1 \rangle (dot \langle text{OI}_i + \langle beta_2 \rangle (dot \langle text{Volume}_i + \langle beta_2 \rangle (do$ 

where LTPiLTP\_iLTPi represents the LTP for option contract iii, OIi\text{OI}\_iOIi is the OI for contract iii, Volumei\text{Volume}\_iVolumei is the trading volume for contract iii,  $\beta$ 0\beta\_0 $\beta$ 0 is the intercept,  $\beta$ 1\beta\_1 $\beta$ 1 and  $\beta$ 2\beta\_2 $\beta$ 2 are the regression coefficients, and  $\epsilon$ i\epsilon\_i $\epsilon$ i is the error term.



The regression coefficients  $\beta_1$  and  $\beta_2$  beta\_2 $\beta_2$  indicate the magnitude and direction of the impact of OI and trading volume on LTP, respectively. Statistical tests such as t-tests are performed to assess the significance of these coefficients.

## **Time Series Analysis**

Given the time-dependent nature of options market data, we conduct time series analysis to examine trends and patterns in OI, trading volume, and LTP over time. Techniques such as moving average smoothing, autocorrelation function (ACF), and partial autocorrelation function (PACF) are utilized to identify seasonality, trends, and potential cyclical patterns in our variables of interest.

#### **Event Study Analysis**

Incorporating event study methodologies, we analyze the impact of specific events or market occurrences on OI, trading volume, and LTP. Events of interest include earnings announcements, economic releases, corporate actions, or geopolitical developments. The event study framework involves:

## **Advanced Modeling Techniques**

In addition to traditional regression and time series analysis, we explore advanced modeling techniques such as machine learning algorithms and Bayesian inference. These methods allow us to capture nonlinear relationships, identify latent patterns, and make probabilistic forecasts based on historical data.

## Validation and Sensitivity Analysis

To ensure the robustness of our findings, we conduct validation exercises and sensitivity analyses. This includes cross-validation techniques to assess model stability and generalizability across different subsets of data. Sensitivity analysis helps us evaluate the impact of variations in input parameters and assumptions on our results, ensuring the reliability and reproducibility of our findings.

# **Results and Analysis**

In this section, we present the results and provide in-depth analysis of our research findings on the relationships between open interest (OI), trading volume, and last traded price (LTP) in the options market. Our empirical study employed robust methodologies, including descriptive statistics, correlation analysis, regression models, time series analysis, event studies, and advanced statistical techniques, to uncover insights into market dynamics and investor behavior.

IF THIS PART IS RED		CALLS						1			-	PUTS				
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		5.07,000	15,82,300	12224.455		49.95	18186	142.00	44.00	47.05,251	1.94200	16,221				
		12,11,350	42,77,400	632,66,400	4.11	12.10	16200	111.78	-44.70		2.550.950	70,000	IF THIS PART IS GREEN			
		1,27,850	16,27,600	2.95.28.450	4.85	23.00	10200	212.44	47.20	1.54,900	28.550	15,000	MEANS MARKET IS BEARI			
		12,41,450	40,88,450	430.36356	1.00	12.85		296.29	-48.25	1222.400	45,200	18,192				
		11,85,400	12,36,800	2,5421,300	4.96	1.28	16266	279.23	41.6	1,00,000	10,850	1,700				
		1571.000	\$8,85,158	411,71410	-4.80	4.21	16600	BAT.YE	48.86	2,17,701	27,756	17,458	HEAVE MADVETIC			
		ADADIE	11,97,288	1.02,05,400	-6.40	2.88	1948	80.00	4125	1.005	1330	1,000	BEARISH			

#### **Conclusion:**

The findings of this study underscore the importance of monitoring option chain dynamics for market participants seeking to gauge investor sentiment and predict future price movements. By understanding how open interest, trading volume, and last traded price interact, investors can better navigate market uncertainties and capitalize on emerging opportunities. Future research could further explore the impact of option chain dynamics on market stability and the efficacy of regulatory measures in maintaining market integrity.

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