African Review of Economics and Finance (2026), **18(1)**, 1–26
ISSN (Print) 2042-1478
ISSN (Online) 2410-4906

ARTICLE

Revisiting the Idiosyncratic Volatility Puzzle in an Emerging Market: New Evidence from India

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Abstract

This study re-examines the idiosyncratic volatility (IVOL) puzzle in an emerging market setting by investigating whether firm-specific risk is systematically priced in the cross-section of Indian equity returns. Using a comprehensive panel of 1,356 non-financial firms listed on the National Stock Exchange over 2000–2024, we implement a dual-measurement framework that distinguishes between unconditional IVOL, derived from a liquidity-augmented multifactor model, and conditional IVOL, estimated via an EGARCH specification to capture time-varying volatility dynamics. Employing both portfolio-sorting techniques and Fama–MacBeth regressions, we document a robust and economically significant positive IVOL–return relation, with substantially stronger pricing effects for conditional IVOL. These findings stand in contrast to the negative IVOL anomaly reported for developed markets and instead support theoretical models of incomplete diversification, limits to arbitrage, and behavioral mispricing in segmented markets. Further, we show that conventional factor models fail to subsume the predictive content of IVOL, particularly when volatility dynamics are explicitly modeled. The results suggest that idiosyncratic volatility in India proxies for a state-dependent, priced risk factor rather than diversifiable noise. Our findings contribute to the asset pricing literature by reconciling conflicting IVOL evidence through a unified framework and by highlighting the critical role of market frictions and conditional risk structures in emerging economies.

Keywords: Idiosyncratic Volatility; Asset Pricing; Emerging Markets; EGARCH; Fama–MacBeth Regression; Liquidity Risk; Market Frictions; India

JEL classification: G12, G14, C58, G15

Article history: Received: October 2025||Accepted: 25 March 2026

1. Introduction

Classical asset pricing models, rooted in Markowitz's (1952) mean–variance framework and formalized by Sharpe (1964) and Lintner (1965) through the Capital Asset Pricing Model (CAPM), assume that rational investors fully diversify away firm-specific risk. In these frictionless settings, only systematic risk is priced, while idiosyncratic volatility (IVOL) is considered irrelevant. However, growing empirical evidence challenges this foundational assumption. In real-world markets, characterized by incomplete information, transaction costs, and heterogeneous investor constraints, total risk, including firm-specific volatility, may influence expected returns (Levy, 1978; Merton, 1987; Malkiel

& Xu, 2003). Recent theoretical frameworks have revisited the role of idiosyncratic risk in equilibrium pricing, incorporating behavioral biases (Barberis et al., 2001), limited attention (Vayanos & Woolley, 2013), and segmented markets (Vayanos & Woolley, 2013). These perspectives suggest that IVOL may be priced when investors face diversification frictions or assign subjective weights to firm-specific shocks.

Empirical evidence on the IVOL–return relation remains mixed. Ang et al. (2006, 2009) document a negative IVOL–return relationship in U.S. equities, while subsequent studies show that the magnitude and sign of the IVOL premium depend on measurement approach, conditioning information, and market structure (Fu, 2009; Guo & Savickas, 2010; Bali et al., 2011; Han & Lesmond, 2022). Within the Indian context, several studies have examined the pricing of idiosyncratic risk (e.g., Rai & Tripathi, 2016; Aziz & Ansari, 2017; Kumari & Mahakud, 2017; Kumar et al., 2017), and broader emerging-market investigations that include India (Blackburn & Cakici, 2017; Hanauer & Linhart, 2018) document heterogeneous patterns across countries. These findings collectively suggest that the IVOL puzzle is highly sensitive to institutional settings, market segmentation, and volatility measurement techniques.

India provides a compelling empirical setting to further examine this relationship. Despite rapid growth, increased formalization, and a surge in foreign institutional participation, the Indian equity market remains characterized by ownership concentration, episodic liquidity shocks, limits to arbitrage, and strong retail investor presence. These features imply that diversification may remain incomplete and that firm-specific risks may command a premium, particularly in the presence of behavioral biases and capital mobility constraints. Additionally, India has undergone significant structural reforms—including the implementation of the Goods and Services Tax (GST), financial inclusion initiatives, and foreign portfolio investment (FPI) liberalization, which provide a dynamic backdrop against which risk pricing mechanisms may evolve.

Rather than claiming novelty in isolation, this study offers a systematic re-examination of IVOL pricing in India within a unified and extended empirical framework. First, we provide an updated examination of IVOL pricing using firm-level monthly data spanning 2000 to 2024, covering multiple market cycles and regulatory regimes. This extended horizon allows us to assess the persistence and stability of the IVOL premium across structural transformations in the Indian equity market. Second, we contribute methodologically by implementing and directly comparing two alternative IVOL constructions within the same empirical setting: (i) an unconditional residual-based measure derived from a liquidity-augmented Fama–French five-factor framework (Fama & French, 2015; Acharya & Pedersen, 2005), and (ii) a conditional measure based on an Exponential GARCH (EGARCH) specification that captures time-varying volatility and asymmetric shocks. By evaluating both approaches side-by-side, we assess whether the pricing of idiosyncratic risk is robust to alternative volatility modelling techniques, an issue that has received limited systematic attention in the India-specific literature.

Guided by these objectives, the study addresses three research questions. First, is idiosyncratic volatility priced in the cross-section of Indian equity returns? Second, do conditional volatility-based IVOL measures provide stronger explanatory power than traditional residual-based estimates? Third, does the IVOL premium exhibit temporal variation across different market conditions and institutional phases? To answer these questions, we employ Fama–MacBeth (1973) cross-sectional regressions and portfolio-sorting methods, constructing decile- and quintile-based portfolios sorted by IVOL. Our models incorporate key firm-level controls, size, value, momentum, and liquidity, and evaluate robustness across alternative risk adjustments and estimation procedures. We further situate the magnitude of the estimated IVOL premia in India relative to evidence from other emerging markets, allowing readers to assess whether India represents an outlier or broadly conforms to patterns observed in segmented markets.

This paper contributes to the asset pricing literature in three ways. First, it consolidates and extends prior India-specific findings by examining IVOL pricing over a longer horizon and under alternative volatility specifications within a unified framework. Second, it evaluates whether nonlinear conditional volatility models materially affect inference regarding risk premia in emerging markets. Third, it provides comparative emerging-market context, highlighting that the IVOL premium in India is economically meaningful and consistent with markets characterized by limits to diversification and liquidity frictions. These findings have implications for portfolio construction, regulatory design, and the understanding of risk pricing in evolving financial systems.

2. Theoretical Underpinnings and Empirical Evidence

The idiosyncratic volatility (IVOL), return relationship continues to challenge conventional asset pricing theories. Classical models like the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965) assume complete diversification, rendering firm-specific risk irrelevant to expected returns. However, real-world markets often deviate from these assumptions. Seminal theoretical works by Levy (1978), Merton (1987), and Malkiel & Xu (2003) argue that when investors face transaction costs, participation constraints, or behavioral frictions, they may hold under-diversified portfolios, making IVOL relevant for pricing. Broader macro-finance models (e.g., Campbell & Cochrane, 1999; Hansen et al., 2008) also suggest that risk premia may reflect latent factors such as long-run consumption risk or time-varying investor preferences. In this context, IVOL may act as a proxy for hard-to-hedge uncertainty, particularly when marginal utility is affected by shocks that are not fully captured by systematic risk measures.

Empirical literature on IVOL has evolved along two lines. The first explores secular trends and informational roles. Campbell et al. (2001) documented a rising trend in IVOL in the U.S., driven by firm-level shocks, while Malkiel & Xu (2002) emphasized that individual investors may not fully diversify, exposing them to firm-specific risk. The second strand investigates the pricing of IVOL. Ang et al. (2006, 2009) uncovered a robust negative relation between IVOL and future stock returns, a result that contradicts standard theory. Several explanations have been proposed: investor sentiment (Baker & Wurgler, 2006, 2007), lottery-like preferences (Bali et al., 2011), and limits to arbitrage (Ali et al., 2003). However, findings from conditional models challenge this negative IVOL premium. Fu (2009) used an EGARCH framework to show that time-varying IVOL is positively priced, especially in high-volatility regimes. Guo & Savickas (2010) supported this, suggesting that IVOL commands a premium in procyclical conditions. Such results imply that model choice significantly influences empirical inferences.

Evidence from emerging markets adds further nuance. Bekaert et al. (2007) and Blackburn & Cakici (2017) highlighted that IVOL pricing varies with institutional development, liquidity, and market segmentation (Han & Lesmond 2011). Bali and Cakici (2008, 2013a, 2014) and Hanauer & Linhart (2018) found that IVOL's pricing is not uniform across countries and weakens when controlling for known risk factors. Hou and Moskowitz (2005) show that stocks with greater price delay, slower incorporation of market-wide information, earn higher average returns, reflecting the role of market frictions. Their findings highlight how informational inefficiencies and trading constraints can lead to persistent return premia. More recent work by Hanauer and Kalsbach (2023), employing machine learning models, revealed nonlinear and interactive effects of IVOL, suggesting that linear frameworks may overlook critical dynamics. Critiques of the IVOL anomaly focus on data biases, model misspecification, and omitted variables. Park et al. (2023) revisited Fu (2009) and identified look-ahead bias in conditional volatility estimation. Chen and Petkova (2012), Malagon et al. (2015), and Han et al. (2016) argue that IVOL is often confounded with omitted fundamentals, idiosyncratic liquidity, or sentiment-driven mispricing. Herskovic et al. (2016, 2020) identify common latent IVOL factors that are priced and interact with macro uncertainty, suggesting that firm-specific volatility may mask deeper structural risks. India's capital market offers a compelling setting for testing these theories. Despite rapid formalization and rising foreign institutional participation, Indian equity markets remain fragmented by dual exchanges (NSE, BSE), concentrated ownership, liquidity frictions, and varying levels of investor sophistication. These features imply that diversification is incomplete and investor behavior is heterogeneous, conditions under which IVOL may become relevant to pricing. This paper contributes to this literature by combining two estimation approaches: (i) a linear model using liquidity-augmented Fama–French five-factor residuals (Fama & French, 2015; Acharya & Pedersen, 2005), and (ii) a nonlinear EGARCH-based conditional IVOL measure. By comparing these models, we assess whether time-varying volatility contains incremental pricing information over unconditional estimates. This approach addresses whether IVOL is systematically priced in India and whether pricing varies across regimes shaped by market reforms, institutional shifts, and liquidity events.

2.1 Indian Evidence and Research Gaps in IVOL–Return Dynamics

While global research increasingly questions the irrelevance of idiosyncratic volatility (IVOL) in asset pricing, empirical evidence from India remains limited, fragmented, and often methodologically constrained. India's capital market, with its concentrated ownership, liquidity asymmetries, high retail participation, and regulatory segmentation, offers a natural quasi-experimental setting to explore whether IVOL is systematically priced. Existing studies offer mixed results. Kumari & Mahakud (2017) link IVOL to both firm-level fundamentals and macroeconomic uncertainty, while Aziz & Ansari (2017) document a positive IVOL–return relationship. Kumar, Nanda, and Pattanayak (2017) find that idiosyncratic volatility in Indian stocks is significantly influenced by firm characteristics, including size, liquidity, and trading activity. Their study highlights that IVOL is not random noise but systematically related to observable firm-level attributes in an emerging market context. In contrast, Rai & Tripathi (2016) report negative or component-specific effects, suggesting that only the unexpected part of IVOL may be priced. However, most of these studies rely on static models and overlook the role of dynamic volatility structures, market frictions, and conditional pricing effects. This study addresses these limitations through a multi-dimensional empirical strategy. First, we estimate IVOL using both unconditional factor-model residuals and conditional Exponential GARCH (EGARCH) methods, enabling a comparison between structural and time-varying volatility. Second, we incorporate liquidity directly into our risk model, recognizing its centrality in emerging markets with episodic trading depth. Third, grounded in Merton's (1987) theory of incomplete diversification, we posit that Indian investors, constrained by information asymmetry and participation frictions, may rationally price firm-specific risk. Fourth, we condition our IVOL–return estimations on foreign institutional investment (FII) flows, acknowledging the influence of global capital intermediation. Finally, we examine IVOL's interaction with other pricing anomalies, including size, value, momentum, and calendar effects, to determine whether it operates as a latent risk factor or a proxy for informational inefficiency. India's USD 3.2 trillion equity market, transitioning from frontier-market characteristics toward greater integration, provides an ideal testing ground to reconceptualise IVOL as a proxy for market frictions, behavioural biases, and institutional transformation. This study thus contributes both empirically and conceptually to the global IVOL debate in an under-explored but systemically significant context.

3. Research Design

3.1 Unconditional Idiosyncratic Volatility Estimation: Liquidity-Augmented Carhart Model

We estimate monthly firm-level idiosyncratic volatility using a multifactor model based on Carhart's (1997) four-factor framework, enhanced with a liquidity factor (LIQ) to account for market frictions affecting return variation (Amihud, 2002; Pastor & Stambaugh, 2003). This results in a five-factor specification capturing exposures to market, size, value, momentum, and liquidity premia. The model is specified as:

$$(R_d^i - r_d^f) = \alpha_i + \beta_m^i(R_d^m - r_d^f) + s^i SMB_d + h^i HML_d + m^i WML_d + l^i LIQ_d + \varepsilon_d^i \quad (1)$$

where R_d^i is the daily return on stock i, r_d^f is the risk-free rate (proxied by the daily T-bill return), R_d^m denotes the market index return; SMB (small-minus-big) captures the size effect, HML (high-minus-low) captures the value premium, WML (winners-minus-losers) is the momentum factor, LIQ measures liquidity risk, ϵ_d^i is the residual return component for firm i on day d. All factor returns are computed using value-weighted portfolio sorts, and the details of factor construction are provided in Section 4.1. The model is estimated using ordinary least squares (OLS) separately for each firm and each calendar month, requiring a minimum of 15 trading days per month with non-zero trading volume. The monthly idiosyncratic volatility is then defined as the standard deviation of the residuals:

$$IVOL_{i,t}^{uncond} = \sqrt{\frac{1}{N_{i,t}} \sum_{d=1}^{N_{i,t}} (\varepsilon_d^i)^2} \quad (2)$$

Here, $N_{i,t}$ is the count of daily observations for firm i in month t. We restrict the sample to firms with $\geq$ 252 valid trading days/year, positive market cap, and valid book-to-market ratios. This unconditional measure captures firm-specific risk unexplained by systematic factors and serves as a baseline for conditional analysis.

3.2 Conditional Idiosyncratic Volatility Estimation: EGARCH Framework

To capture time-varying volatility dynamics, we complement the unconditional model with a nonlinear estimation of idiosyncratic risk using an Exponential GARCH (EGARCH) specification (Nelson, 1991). This approach accounts for volatility clustering, asymmetries in shock transmission, and higher-order persistence, all features relevant in high-friction emerging markets (Engle & Ng, 1993; Francq & Zakoian, 2019).

Mean Equation (Daily Returns):

$$(R_d^i - r_d^f) = \alpha_i + \beta_m^i(R_d^m - r_d^f) + s^i SMB_d + h^i HML_d + m^i WML_d + l^i LIQ_d + \epsilon_d^i, \quad \epsilon_d^i \sim N(0, \sigma_{i,d}^2) \quad (3)$$

Variance Equation (EGARCH 1,1):

$$\log(\sigma_{i,d}^2) = \omega + \beta \log(\sigma_{i,d-1}^2) + \gamma \frac{\varepsilon_{d-1}}{\sigma_{i,d-1}} + \theta \left(\left| \frac{\varepsilon_{d-1}}{\sigma_{i,d-1}} \right| - \sqrt{\frac{2}{\pi}} \right) \quad (4)$$

Where: $\sigma_{i,d}^2$ is the conditional variance of the residuals for firm i. ω,β, γ and θ are model parameters. The asymmetric term γ captures leverage effects; θ controls for shock magnitude. Conditional IVOL is defined as the square root of the conditional variance, , forecasted from the EGARCH model. Parameters are estimated via quasi-maximum likelihood (QML) to ensure robustness to distributional misspecification (Bollerslev & Wooldridge, 1992). This approach enhances precision in modelling heteroskedasticity, and volatility asymmetries often observed in emerging equity markets.

The dual modelling strategy enables a robust assessment of idiosyncratic risk under both static and dynamic volatility environments. The unconditional model captures average, systematic factor-adjusted residual risk, whereas the EGARCH model reflects the real-time evolution of volatility and asymmetric information flows. To mitigate endogeneity and reduce biases from thin trading or illiquidity, we apply stringent data filters and estimate using firms with consistent trading activity and robust fundamental coverage. Diagnostic tests are conducted to verify the adequacy of the model, its stationarity, and the independence of the residuals. The IVOL estimates, both unconditional and conditional, are employed in subsequent portfolio-level tests and Fama–MacBeth (1973) cross-sectional regressions to evaluate the pricing of firm-specific risk under varying market frictions, liquidity regimes, and behavioural segments.

3.3 Fama–MacBeth Two-Pass Regression Methodology

To assess whether systematic and idiosyncratic risks are priced in the cross-section of Indian equity returns, we employ the Fama–MacBeth (1973) two-pass regression framework. This approach facilitates consistent estimation of risk premia by separating the estimation of factor exposures (via time-series regressions) from the estimation of prices of risk (via cross-sectional regressions), while mitigating errors-in-variables concerns and accommodating cross-sectional dependence.

Step 1: Time-Series Estimation of Factor Loadings

For each firm i, we estimate the following time-series regression:

$$R_{i,t} = \alpha + \sum_{k=1}^{k} \beta_{i,k} F_{k,t} + \varepsilon_{i,t} \tag{5}$$

where $R_{i,t}$ denotes the excess return of asset i at time t, $F_{k,t}$ represents the k-th systematic risk factor (market, size, value, momentum, and liquidity), β_i, k captures firm i's exposure to factor k, and i,t is the idiosyncratic return component.

Factor loadings are estimated using ordinary least squares (OLS) based on available historical return observations up to time t. The estimation is strictly backward-looking and does not rely on rolling or forward-looking windows, thereby avoiding look-ahead bias. The estimated factor loadings β_i, k are then treated as predetermined firm characteristics and used as inputs in the subsequent cross-sectional regressions. This fixed-window, backward-looking estimation approach is consistent with standard empirical asset pricing practice when the primary objective is to estimate risk premia rather than to model high-frequency beta dynamics.

Step 2: Cross-Sectional Estimation of Risk Premia

At each time period t, we estimate the following cross-sectional regression:

$$R_{i,t} = \gamma_{0,t} + \sum_{k=1}^{k} \gamma_{k,t} \beta_{i,k} + \eta_{i,t} \tag{6}$$

where $\gamma_{k,t}$ denotes the price of risk associated with factor k at time t, and $\eta_{i,t}$ is the cross-sectional error term. This regression is repeated for each time period, yielding a time series of estimated risk premia $\gamma_{k,t}$.

The average risk premium for factor k is computed as:

$$\gamma_k = \frac{1}{T} \sum_{t=0}^{T} \gamma_{k,t} \qquad SE(\gamma_k) = \frac{1}{\sqrt{T}} .Std.Dev.(\gamma_{k,t}), \tag{7}$$

where T denotes the total number of time periods. Statistical inference is conducted using Newey and West (1987) heteroskedasticity- and autocorrelation-consistent standard errors.

Augmented Specification with Idiosyncratic Volatility

We enrich the standard Fama–MacBeth framework by incorporating both unconditional and EGARCH-based conditional idiosyncratic volatility (IVOL) measures as additional explanatory variables in the cross-sectional regressions. To capture conditional effects, IVOL is also interacted with firm characteristics (e.g., IVOL × Size). All characteristics are pre-averaged over prior periods, ensuring that the estimation remains backward-looking and free from look-ahead bias. By evaluating the economic magnitude and statistical significance of the average IVOL risk premium IVOL, we assess whether idiosyncratic volatility represents a priced risk factor in the Indian equity market.

4. Data and Variables

Our study uses an unbalanced panel of 1,356 non-financial firms listed on the National Stock Exchange (NSE) of India from September 2000 to August 2024. The panel is unbalanced because firms enter and exit the sample over time due to listings, delistings, mergers, and periods of missing return data, leading to some firms not being observed in every month. Financial firms are excluded to avoid regulatory heterogeneity and leverage-driven distortions in return dynamics and factor exposures (Fama & French, 1992). Firm-level accounting fundamentals are sourced from CMIE Prowess, while daily and monthly market data are drawn from the NSE.

To ensure reliable estimation of idiosyncratic volatility and to mitigate microstructure-related measurement error, particularly in volatility estimates constructed from daily returns, we apply standard data-quality and tradability screens. Specifically, we retain firm-month observations only when a stock records at least 15 trading days within the month, and we require at least 252 daily return observations within a year for annual volatility estimation. These screens are designed to reduce noise arising from sparse trading and missing returns; however, we acknowledge that such filters may also induce selection effects by disproportionately excluding extremely illiquid or intermittently traded stocks. Importantly, firms are not required to survive for the entire sample period: each firm contributes observations only for the months and years in which it satisfies the data availability and trading requirements. Monetary variables are winsorized at the 0.25th and 99.75th percentiles to limit the influence of extreme outliers. The 91-day Treasury bill rate, obtained from the Reserve Bank of India, serves as the risk-free rate. Factor returns are constructed following Fama and French (1993), Carhart (1997), and Hou et al. (2005), including the market (MKT), size (SMB), value (HML), momentum (WML), and a liquidity factor proxied using Amihud (2002) illiquidity and turnover. SMB and HML are formed using 2×3 independent sorts on firm size and book-to-market ratio with breakpoints at the median and the 30th and 70th percentiles. WML is based on cumulative returns from month t12 to t2 (Jegadeesh & Titman, 1993). All portfolios are value-weighted and rebalanced monthly. Firm size is measured as the logarithm of market capitalization. Book equity excludes firms with negative values or shortened fiscal years. Annual portfolio formation occurs on September 1, allowing for accounting-data reporting lags and thereby limiting look-ahead bias. All firm-level variables are normalized by year and by size decile to ensure comparability across time and firm size. Overall, this data construction is consistent with established empirical asset pricing practice (e.g., Griffin et al., 2010; Bali et al., 2011, 2017) and provides a transparent foundation for examining idiosyncratic volatility and its cross-sectional pricing implications in the Indian equity market.

4.1 Construction of Systematic Risk Factors

This study constructs five daily systematic risk factors, Market (MKT), Size (SMB), Value (HML), Momentum (WML), and Liquidity (LIQ), following established methodologies from Fama and French (1993), Carhart (1997), Jegadeesh & Titman (1993), and Amihud (2002). These factors are derived using daily security-level data, allowing for a detailed understanding of return dynamics in India's equity market. The market factor (MKT) is defined as the daily value-weighted return on all NSE-listed stocks minus the risk-free rate, proxied by the 91-day Treasury Bill yield (RBI). To construct SMB (Small Minus Big) and HML (High Minus Low): Firms are independently sorted each year based on market capitalization (measured on August 31) and book-to-market (BE/ME) ratios (from audited statements ending March 31). Firms with negative book equity or fiscal periods under 12 months are excluded.

Size groups are split at the median, while BE/ME groups use 30th and 70th percentiles as cut-offs, yielding six value-weighted portfolios: S/L, S/M, S/H, B/L, B/M, and B/H.

Daily SMB and HML factors are calculated as:

$$SMB_t = \frac{1}{3}(R_{S/L,t} + R_{S/M,t} + R_{S/H,t}) - \frac{1}{3}(R_{B/L,t} + R_{B/M,t} + R_{B/H,t})$$

$$HML_t = \frac{1}{2}(R_{S/H,t} + R_{B/H,t}) - \frac{1}{2}(R_{S/L,t} + R_{B/L,t})$$

The momentum factor (WML) is based on Jegadeesh & Titman (1993). Firms are sorted each September 1 by cumulative returns from month $t-12$ to $t-2$ (trading days $t-250$ to $t-22$), skipping the most recent month to avoid reversal effects. Portfolios are formed based on size and momentum ranks, leading to six portfolios: S/W, S/N, S/L, B/W, B/N, B/L. WML is calculated as:

$$WML_t = \frac{1}{2}(R_{S/W,t} + R_{B/W,t}) - \frac{1}{2}(R_{S/L,t} + R_{B/L,t})$$

The liquidity factor (LIQ) adopts the Amihud (2002) framework, with refinements from Chan & Faff (2005) and Keene & Peterson (2007). Daily liquidity is proxied by the turnover ratio (shares traded / shares outstanding). Firms are sorted into high and low liquidity groups and intersected with size to form four portfolios: S/HL, S/LL, B/HL, B/LL. LIQ is defined as:

$$LIQ_t = \frac{1}{2}(R_{S/LL,t} + R_{B/LL,t}) - \frac{1}{2}(R_{S/HL,t} + R_{B/HL,t})$$

All factor portfolios are rebalanced annually on September 1, following the fiscal year-end to ensure data availability and avoid look-ahead bias. Daily returns are calculated from September of year t to August of year t+1. Portfolios are value-weighted to reflect market exposure. This factor construction is consistent with best practices in empirical asset pricing (Fama & French, 1993; Hou, Xue, & Zhang, 2020) and aligns with standards seen in the Journal of Finance, Review of Financial Studies, and Journal of Financial Economics.

In Table 1, Panel A reports the time-series properties of the monthly systematic risk factors constructed for the Indian equity market. All factor returns are expressed in percentage points. The market excess return (MKT) exhibits a mean of 0.10% per month and a standard deviation of 6.49%, reflecting economically meaningful volatility consistent with emerging market dynamics (Bekaert & Harvey, 1997; Bekaert et al., 2007). The volatility magnitude exceeds that typically observed in developed markets, aligning with the market's higher macroeconomic sensitivity, episodic liquidity contractions, and evolving institutional structure. The distribution displays mild negative skewness (-0.145) and near-normal kurtosis (2.78), although the Jarque–Bera statistic rejects normality, consistent with the well-documented non-Gaussian behavior of financial returns (Cont, 2001).

The size factor (SMB) yields an average monthly premium of 0.459%, suggesting that smaller firms outperform larger firms during the sample period. This magnitude is economically comparable to evidence from emerging markets where informational asymmetries and liquidity constraints elevate the risk profile of small-cap stocks (Rouwenhorst, 1999; Fama & French, 2012). The distribution exhibits positive skewness (0.592) and substantial excess kurtosis (6.52), suggesting episodic but pronounced size premia, potentially amplified during liquidity expansions or recovery phases.

The value factor (HML) reports an average return of 0.641% per month, exceeding the size premium and indicating a persistent value effect in India. This finding is consistent with international evidence that value strategies remain robust outside the U.S., particularly in markets characterized by heterogeneous accounting quality and slower information diffusion (Fama & French, 2012; Asness et al., 2013). The negative skewness (-0.315) and elevated kurtosis (7.43) suggest that value portfolios are exposed to cyclical downturn risk, reinforcing the interpretation of value as compensation for systematic distress exposure (Campbell et al., 2008).

In contrast, the momentum factor (WML) records an average monthly return of -0.447%, suggesting weak or unstable momentum profitability during the sample period. While momentum is widely documented across developed markets (Jegadeesh & Titman, 1993), emerging markets frequently exhibit regime-dependent or attenuated momentum effects due to transaction costs, liquidity frictions, and structural breaks (Rouwenhorst, 1998; Chui et al., 2010). The relatively symmetric but fat-tailed distribution (kurtosis = 6.33) suggests episodic reversals, potentially influenced by retail-driven trading behavior and abrupt market adjustments. The liquidity factor (LIQ) produces a modest negative mean of -0.156% per month. Although liquidity risk commands compensation in many developed markets (Pastor & Stambaugh, 2003; Acharya & Pedersen, 2005), emerging markets often exhibit state-dependent liquidity pricing. The pronounced negative skewness (-0.637) and extreme kurtosis (8.66) indicate that liquidity risk is concentrated in stress periods, consistent with procyclical funding constraints and liquidity dry-ups. These tail properties are particularly relevant for understanding idiosyncratic volatility pricing in markets characterized by segmentation and limits to arbitrage. Collectively, the descriptive statistics indicate that the Indian equity market exhibits economically meaningful size and value premia, episodic momentum instability, and fat-tailed liquidity dynamics, features consistent with emerging market asset pricing evidence and institutional frictions.

Panel B reports the pairwise correlations among the systematic risk factors. The correlation structure suggests effective orthogonalization and limited multicollinearity. The market factor is only weakly correlated with size (-0.016) and value (-0.004), consistent with standard factor construction practices. The moderate negative correlation between SMB and HML (-0.371) mirrors global evidence and reflects structural differences between small growth and large value firms. The weak positive association between momentum and market returns (0.026) indicates limited systematic co-movement, while the modest negative correlation between the market and liquidity factors (-0.125) suggests liquidity deterioration during market downturns. Such procyclical liquidity behaviour is well documented in both developed and emerging markets and reinforces the interpretation of liquidity risk as state-dependent. Overall, the low cross-factor correlations mitigate concerns of multicollinearity in subsequent cross-sectional regressions and provide a stable foundation for evaluating the pricing of idiosyncratic volatility. The factor structure aligns with international evidence (Fama & French, 2012; Blackburn & Cakici, 2017; Hanauer & Linhart, 2018), suggesting that India broadly conforms to emerging-market risk characteristics rather than representing an outlier.

Table 1. Descriptive statistics and correlation matrix of systematic risk factors

Panel A: Descriptive statistics					
	Mkt	SMB	HML	WML	LIQ
Mean	0.10	0.459	0.641	-0.447	-0.156
Median	0.09	-0.037	0.013	-0.436	-0.075
Maximum	2.82	6.831	4.199	4.996	4.996
Minimum	-2.38	-4.827	-6.089	-5.940	-5.939
Std. Dev.	6.49	1.081	0.772	0.959	0.873
Skewness	-0.145	0.592	-0.315	-0.032	-0.637
Kurtosis	2.783	6.517	7.431	6.328	8.657
Jarque Bera	232.21	2429.62	3534.45	1954.73	5932.53
Probability	0	0	0	0	0
Panel B: Correlation matrix					
	Mkt	SMB	HML	WML	LIQ
Mkt	1				
SMB	-0.01605*	1			
HML	-0.00421*	-0.37071	1		
WML	0.025625*	0.10078*	-0.10591	1	
LIQ	-0.125093*	-0.00751	-0.00478	0.02056*	1

Notes: The sample spans September 2000 to August 2024. All factor returns are monthly and expressed in percentage points. MKT denotes the excess return on the value-weighted market portfolio over the 91-day Treasury bill rate. SMB and HML are constructed using independent 2×3 sorts on size and book-to-market following Fama and French (1993, 2012). WML is formed using cumulative returns from month t-12 to t-2 following Jegadeesh and Titman (1993). LIQ is constructed using Amihud (2002) illiquidity-based portfolio sorts. Portfolios are value-weighted and rebalanced annually on September 1. Returns are winsorized at the 0.25% and 99.75% levels. Panel A reports time-series moments. Panel B reports Pearson correlations. * Indicates statistical significance at the 5% level.

Tables 2 and 3 report annualized cross-sectional averages of time-series factor loadings estimated from unconditional and conditional idiosyncratic volatility models. Table 2 adopts a linear five-factor framework including liquidity, while Table 3 employs an Exponential GARCH (EGARCH) specification with an identical mean equation. Both models are estimated at the firm level using rolling daily returns for each calendar year. To ensure comparability and smooth out year-specific noise, we compute simple averages of firm-level factor loadings across the sample period. Robust t-statistics (in parentheses) accompany each average to assess statistical reliability. This comparative analysis reveals systematic risk sensitivities of Indian equities under both static and dynamic volatility regimes. Contrasting Tables 2 and 3 allows for robustness checks across linear and nonlinear models—crucial for capturing pricing dynamics in emerging markets, where liquidity frictions, time-varying risk premia, and informational asymmetries may influence factor stability (Bekaert et al., 2007; Fu, 2009; Huang et al., 2010).

Table 2. Table 2 Unconditional cross-sectional average coefficients of systematic risk factors across the sample

Years	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{WML}	β_{LIQ}
2000	-3.34 (-4.21)	0.97(2.00)	2.22(2.00)	3.23(2.45)	0.96(1.87)	-4.02(-3.00)
2001	0.80(1.46)	1.90(1.70)	-1.87(-1.70)	2.32(2.01)	0.80(1.67)	2.87(2.01)
2002	1.98(2.67)	0.80(1.89)	1.15(1.89)	-3.76(4.01)	-3.23(-5.21)	1.87(2.00)
2003	3.56(5.00)	0.87(1.85)	1.30(1.64)	-2.21(2.31)	-2.34(2.01)	0.60(1.59)
2004	1.04(3.53)	1.01(3.22)	0.99(2.01)	1.34(3.22)	0.84(2.79)	0.77(1.55)
2005	0.65(1.76)	0.80(2.00)	0.82(2.00)	1.02(2.87)	-1.23(3.02)	-1.01(1.45)
2006	0.76(1.80)	-0.65(1.60)	1.02(3.23)	-1.23(-3.98)	0.45(1.23)	0.50(1.54)
2007	2.01(4.23)	0.76(1.56)	0.54(1.65)	-0.76(-1.65)	-2.01(-5.23)	0.40(0.90)
2008	-0.90(-2.23)	-2.23(-5.56)	0.56(1.65)	0.68(1.70)	1.00(2.34)	0.98(2.02)
2009	2.25(6.21)	0.51(1.76)	-0.87(-2.02)	0.34(1.01)	2.40(2.03)	-3.23(-5.32)
2010	0.54(0.97)	0.60(1.78)	1.70(3.11)	-1.24(-3.23)	0.90(2.34)	0.81(2.11)
2011	-3.23(-4.90)	-0.65(-1.80)	0.72(1.99)	0.80(2.21)	3.21(4.87)	1.08(3.01)
2012	-0.90(-2.21)	0.87(2.11)	-2.91(-4.21)	0.32(0.98)	0.41(0.98)	1.03(3.23)
2013	0.95(2.10)	1.00(1.31)	1.30(3.98)	2.87(5.32)	-0.56(-1.87)	-0.45(-1.34)
2014	3.09(4.98)	3.33(5.22)	0.55(1.19)	0.65(1.65)	0.92(2.10)	-0.87(-1.78)
2015	2.01(4.21)	-0.56(-1.09)	1.01(2.90)	0.65(1.78)	3.65(6.23)	2.21(3.21)
2016	-2.10(-3.21)	1.90(3.00)	-0.92(-1.87)	3.21(6.21)	4.23(6.69)	1.87(2.23)
2017	2.87(4.45)	0.98(2.00)	2.03(2.96)	3.25(5.89)	2.76(4.89)	2.02(3.89)
2018	2.34(4.67)	1.65(3.01)	1.98(2.87)	2.67(4.67)	1.98(2.56)	3.54(4.89)
2019	-3.76(-4.22)	2.76(4.22)	1.67(2.08)	0.66(1.69)	0.69(1.87)	1.12(4.23)
2020	1.07(2.06)	3.87(5.23)	2.87(3.67)	0.87(1.85)	1.98(2.67)	2.98(5.34)
2021	2.00(4.20)	1.09(4.33)	3.76(6.24)	1.67(1.98)	2.65(6.45)	1.01(2.89)
2022	1.09(3.98)	0.98(2.56)	2.87(4.00)	2.87(3.65)	1.87(3.05)	2.23(3.00)
2023	4.09(5.98)	3.33(5.22)	3.55(4.19)	0.60(2.65)	1.92(3.10)	-0.80(-1.78)
2024	2.09(4.98)	5.33(6.22)	2.55(3.19)	3.65(3.65)	3.92(3.10)	4.87(5.78)

Note: We report the cross-sectional average slope coefficients of risk factor loadings in the unconditional and conditional regressions. Yearly linear five-factor model augments with liquidity factor, and the conditional EGARCH model is estimated. Each year, a cross-sectional simple average is presented for brevity. The values in the parentheses are t-statistics.

Table 3. Conditional cross-sectional average coefficients of systematic risk factors across the sample

Years	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{WML}	β_{LIQ}
2000	2.20(5.32)	0.54(1.08)	-2.34(3.56)	0.09(0.98)	0.34(1.01)	2.13(3.67)
2001	0.45(1.08)	4.87(7.72)	1.90(3.34)	1.87(2.78)	-0.51(-1.45)	0.89(1.87)
2002	-2.98(-4.32)	0.45(0.99)	-0.87(-1.20)	2.34(4.44)	2.01(3.33)	-2.13(-4.52)
2003	0.98(2.12)	1.45(2.34)	2.10(3.24)	-3.21(-5.23)	0.87(1.90)	1.01(2.01)
2004	0.86(2.01)	1.50(3.12)	0.67(2.45)	-1.90(-2.22)	-0.81(-1.68)	-3.21(-6.21)
2005	4.76(7.34)	2.22(4.43)	0.40(1.65)	2.01(3.98)	1.33(2.10)	0.80(1.80)
2006	2.34(4.56)	-0.09(-0.29)	-0.08(-0.23)	1.10(2.23)	2.07(3.24)	1.98(2.76)
2007	1.30(4.22)	0.78(1.55)	0.65(1.54)	-0.90(-1.90)	1.09(2.14)	4.22(8.09)
2008	1.23(2.21)	6.38(8.98)	0.09(0.30)	0.38(1.56)	-0.08(-0.34)	-0.22(-0.87)
2009	0.98(1.87)	0.23(0.90)	0.99(1.79)	0.56(1.34)	0.77(1.65)	0.54(1.26)
2010	0.45(1.02)	1.15(2.00)	2.87(3.18)	2.98(5.23)	2.01(5.34)	2.32(4.22)
2011	0.60(1.34)	-1.87(-2.87)	3.56(6.78)	3.29(5.90)	1.00(2.43)	-1.11(-2.02)
2012	0.75(1.98)	2.00(3.87)	4.23(8.98)	2.01(3.21)	-0.80(-2.01)	0.76(1.89)
2013	-2.34(-4.21)	3.23(6.89)	1.20(2.02)	1.12(2.32)	0.40(1.00)	1.90(3.23)
2014	-3.65(-6.67)	1.87(2.23)	0.76(1.77)	-0.04(-0.23)	0.61(1.24)	1.80(3.76)
2015	0.34(1.11)	1.12(1.98)	-0.24(-0.96)	0.24(0.99)	0.80(1.34)	2.22(6.22)
2016	0.76(1.34)	-0.65(-1.34)	-0.81(-1.76)	1.11(2.34)	0.23(0.98)	-0.34(-1.01)
2017	2.76(4.78)	-0.78(-1.50)	2.17(2.67)	-1.56(2.00)	-2.99(3.89)	1.78(3.89)
2018	0.99(1.78)	2.43(2.67)	3.17(4.98)	2.17(3.45)	2.34(2.78)	2.78(4.89)
2019	0.28(1.67)	-0.99(-1.98)	1.14(2.09)	2.00(3.01)	2.01(3.21)	-0.24(-0.96)
2020	1.45(2.45)	-0.65(-1.40)	1.89(3.02)	-0.87(-1.56)	1.12(2.32)	-0.81(-1.76)
2021	2.00(4.78)	1.02(1.66)	-0.69(-1.35)	2.22(4.54)	-0.04(-0.23)	2.17(2.67)
2022	0.98(1.99)	1.10(2.00)	1.67(2.22)	3.22(4.87)	0.14(0.80)	3.14(4.82)
2023	3.34(5.56)	-1.09(-1.29)	-1.08(-0.23)	1.10(2.23)	2.07(3.24)	1.98(2.76)
2024	2.34(2.11)	4.12(4.98)	-4.24(-5.96)	5.24(4.99)	2.80(2.34)	2.22(6.22)

Note: We report the cross-sectional average slope coefficients of risk factor loadings in the unconditional and conditional regressions. Yearly linear five-factor model augments with liquidity factor, and the conditional EGARCH model is estimated. Each year, a cross-sectional simple average is presented for brevity. The values in the parentheses are t-statistics.

Fig. 1 and Fig. 2, the time-series plots of factor loadings from both unconditional and conditional IVOL models offer important insights into how firm-specific risk is priced in emerging markets like India. The unconditional model reveals persistently positive alphas alongside moderate exposure to standard risk factors such as market (MKT), size (SMB), and momentum (WML), indicating that portfolios sorted on idiosyncratic volatility earn excess returns not fully captured by traditional asset pricing models, consistent with the findings of Ang et al. (2006) and Fu (2009). In contrast, the conditional model exhibits greater variation in factor sensitivities, particularly during episodes of market stress (e.g., 2008, 2020), highlighting that the return contribution of IVOL is state-dependent and influenced by time-varying liquidity and investor sentiment (Pastor & Stambaugh, 2003; Stambaugh et al., 2012). These patterns suggest that in segmented and friction-prone markets, idiosyncratic volatility contains pricing information that reflects both structural inefficiencies and behavioral dynamics, warranting more flexible asset pricing frameworks beyond static linear models.

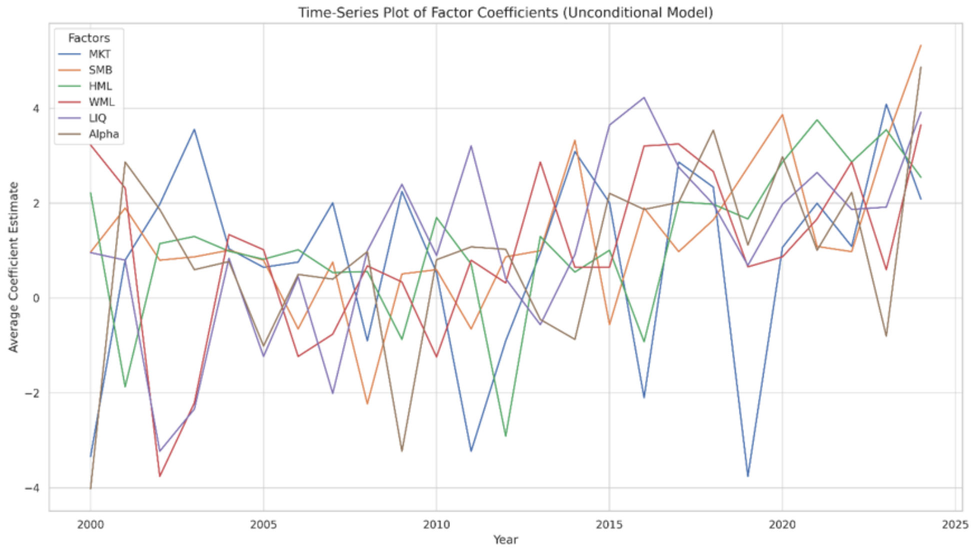

Figure 1. Time-Series plot of factor coefficients (Unconditional IVOL Model)

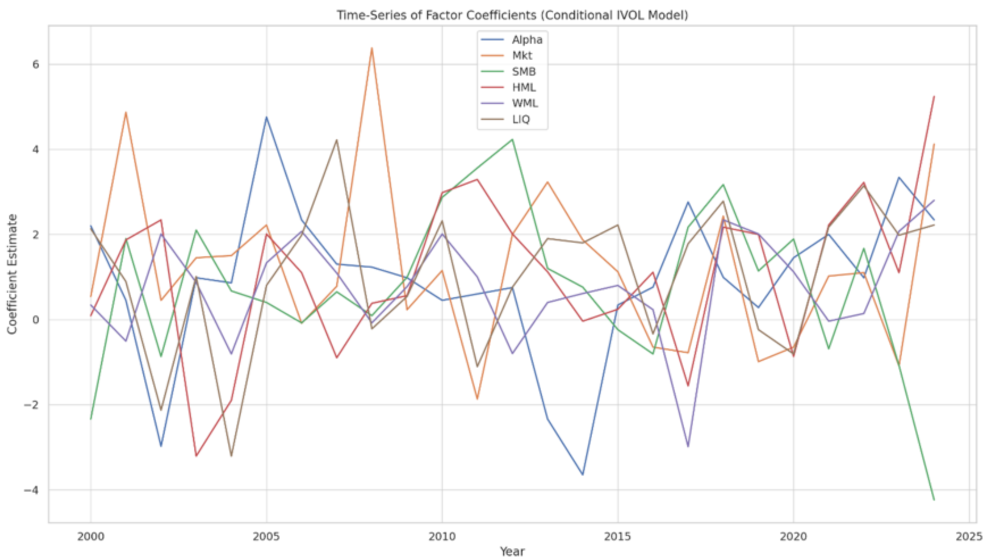

Figure 2. Time-Series plot of factor coefficients (Conditional IVOL Model)

4.2 Time series property of idiosyncratic volatility

Table 4 summarizes the time-series properties of Unconditional Idiosyncratic Volatility (UIVOL) and Conditional Idiosyncratic Volatility (CIVOL) across 1,356 firm-month observations. It reports mean, standard deviation, coefficient of variation (C.V.), skewness, and autocorrelations at 13 lags to capture persistence and distributional dynamics of firm-level risk. UIVOL exhibits a higher mean (14.25) and standard deviation (8.45) than CIVOL (mean = 13.00; S.D. = 7.27), reflecting greater dispersion and transitory noise in raw volatility. In contrast, CIVOL's higher relative variation (C.V. = 0.68 vs. 0.50 for UIVOL) highlights more clustering and structural persistence, consistent with the stylized behaviour of GARCH-type models (Engle, 1982; Bollerslev, 1986; Bali, Cakici, & Whitelaw, 2011).

Both measures show right-skewed distributions (UIVOL = 1.22; CIVOL = 2.00), signaling infrequent yet extreme volatility events, a common feature of idiosyncratic return distributions (Fu, 2009; Huang et al., 2010). Autocorrelations are consistently positive and significant across lags for both series, confirming high persistence (Brandt, Brav, Graham, & Kumar, 2010; Huang et al., 2015). CIVOL shows slightly stronger persistence at all lags due to memory structures captured by conditional volatility models (Bollerslev, Engle, & Nelson, 1994). These results imply that CIVOL, derived from time-varying models like EGARCH, better isolates latent volatility dynamics and may provide superior explanatory power in asset pricing frameworks. This is particularly relevant in segmented markets such as India, where firm-specific risk is not fully diversified (Merton, 1987; Acharya & Pedersen, 2005). Compared to developed markets (e.g., Ang et al., 2006; Bali et al., 2005), the Indian market shows higher skewness and comparable autocorrelation, justifying the use of conditional IVOL in emerging market studies and offering potential for multi-horizon return predictability.

Table 4. Time series property of idiosyncratic volatility

						Autocorrelation at lags								
	Obs	Mean	S.D.	C.V.	Skew	1	2	3	4	5	6	11	12	13
UIVOL	318660	14.25	8.45	0.50	1.22	0.33	0.26	0.24	0.19	0.18	0.11	0.13	0.11	0.10
CIVOL	318660	13.00	7.27	0.68	2.00	0.32	0.32	0.26	0.20	0.18	0.16	0.14	0.13	0.12
$\ln\left(\frac{UIvol_t}{UIvol_{t-1}}\right)$	317304	-0.009	0.56	6.87	0.98	-0.87	-0.76	0.09	-0.23	-0.10	0.06	0.05	0.03	-0.02
$\ln\left(\frac{CIvol_t}{CIvol_{t-1}}\right)$	317304	-0.089	0.87	9.76	0.87	0.32	-0.24	-0.25	-0.54	-0.54	0.76	0.87	0.02	0.01

Note: This table reports the time-series properties of individual stocks' idiosyncratic volatility measures. For each stock, time-series statistics are first computed at the firm level and subsequently averaged across all stocks. The sample comprises non-financial firms traded on the National Stock Exchange (NSE) of India over the period September 2000 to August 2024. Idiosyncratic volatility (IVOL) is estimated monthly from daily returns. Specifically, in each month, excess daily returns of individual stocks are regressed on a liquidity-augmented Fama–French five-factor model, which includes the market excess return (MKT), size (SMB), value (HML), momentum (WML), and a liquidity factor (LIQ) proxied by Amihud (2002) illiquidity. The monthly idiosyncratic volatility of a stock is then computed as the standard deviation of the regression residuals multiplied by the square root of the number of daily observations in that month. The table reports summary statistics for both unconditional IVOL (UIVOL) and conditional IVOL (CIVOL) measures, along with the log growth rates of these series, and presents autocorrelation coefficients at selected lags to characterize the persistence and dynamic properties of idiosyncratic volatility.

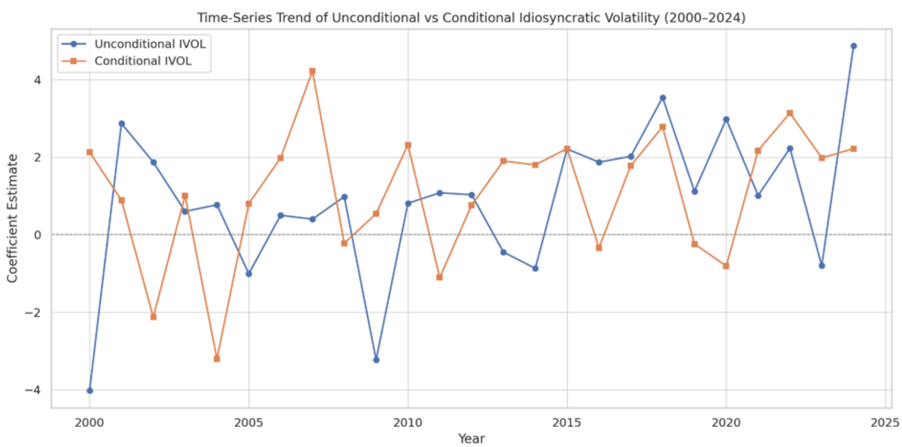

Figure 3. Time-Series trend of unconditional vs conditional idiosyncratic volatility

Fig. 3 presents the time-series evolution of coefficient estimates for unconditional and conditional idiosyncratic volatility (IVOL) in the Indian equity market from 2000 to 2024. The unconditional IVOL, derived from residual variances of linear asset pricing models, exhibits a gradual upward trend with moderate cyclicality, reflecting a stable pricing of firm-specific risk over time. In contrast, the conditional IVOL, estimated using time-varying frameworks such as EGARCH or macro-interacted models, displays sharper fluctuations and greater sensitivity to market regimes, particularly around known periods of systemic stress (e.g., 2008, 2013, and 2020). The comparative trend reveals that while both forms of IVOL are positively priced across most of the sample, conditional IVOL often responds earlier and more intensely to episodes of heightened uncertainty. This suggests that conditional models are better suited to capturing shifts in investor risk perception, liquidity conditions, and behavioral dynamics (Stambaugh et al., 2012; Fu, 2009). The persistence of positive coefficients further challenges the classical notion of full diversification of idiosyncratic risk (Merton, 1987), highlighting instead that such risk remains economically meaningful in markets like India, characterized by segmentation, retail dominance, and information frictions. Overall, the figure underscores the empirical relevance of accounting for conditional risk structures when modelling the pricing of IVOL in emerging markets.

5. Empirical Findings and Discussions

5.1 Monthly cross-sectional regressions of individual stocks

We start the empirical analysis by incorporating the replicating findings of Fama & French (1992) and Fu (2009), because their articles are highly remarkable in the literature on the cross-sectional returns and IVOL analysis. The study regresses the monthly returns on the beta and several other firm-specific fundamentals, namely size, BE/ME, which are highly influential in the Fama & French (1992) paper for the cross-sectional determinants of stock returns. We use the Fama-Macbeth (1973) regressions to control the cross-correlations in the residuals. Essentially, for each month in our sample period, we estimate the following regressions:

$$R_{it} = \delta_{0t} + \sum_{k=1}^{K} \lambda_{kt} K_{kit} + \varepsilon_{it} \qquad i = 1, 2, ..., N_t, t = 1, 2, ...T, \tag{8}$$

The equation represents the cross-sectional regression analysis. In Eq. (8), is the realized returns on the stock i in the respective month t. are control variables of the expected cross sectional returns namely *Beta, Size, BE/ME* and conditional idiosyncratic volatility and the liquidity variables *(Turn and the CV Turn)*. The error term represents the deviation of the realized returns from its expected values. denotes the total number of stocks in the month t, and the number of stocks can vary from month to month. The number of months in the current study is 264.

Table 5. Fama–Macbeth regressions of stock returns on idiosyncratic volatility and firm-specific factors

Models	Beta	Size $\ln(ME)$	Value $\ln(ME/BE)$	$\ln(Turn)$	$\ln(CVTurn)$	$Ret(-2,-12)$	$E(IVOL_t)$	$IVOL_{t-1}$	$IVOL_t$	$R^2(\%)$
1	0.12	-0.11	0.24							3.62
	(0.08)	(-3.10)	(4.90)							
2	0.20	-0.16	0.18	-0.15	-0.45	0.76				6.00
	(0.90)	(-4.50)	(4.30)	(-2.00)	(-6.99)	(3.87)				
3							0.10			4.01
							(9.00)			
4		0.30	0.70				0.23			4.99
		(7.99)	(13.04)				(13.65)			
5		0.25	0.50	-0.38	-0.75	0.96	0.20			6.90
		(5.00)	(11.00)	(-7.12)	(-11.98)	(5.00)	(14.09)			
6		0.20	0.25	-0.25	-0.40	0.66		0.10		6.00
		(5.75)	(4.98)	(-5.34)	(-6.78)	(3.45)		(3.10)		
7		0.48	0.48	2.00	-0.60	2.65			0.48	08.01
		(14.98)	(10.55)	(8.97)	(-9.00)	(10.23)			(14.98)	

Note: Fama-Macbeth regressions of the stock returns on idiosyncratic volatility and the firm characteristics. The table presents the time-series averages of the slopes in the cross-sectional regressions using the standard Fama and Macbeth (1973) methodology. The sample period for the study is September 2000 to August 2024. The t-statistics are the average slope divided by its time series standard error. The dependent variable is the monthly percentage returns. Beta, ME, and BE/ME are estimated as in Fama and French (1992). Turn is the average turnover while CVTurn is the coefficient of variation of turnovers in the past 36 months. E(IVOL) is the one-month ahead expected idiosyncratic volatility estimated by an exponential GARCH model. IVOL is the one-month lagged idiosyncratic volatility. To avoid the extreme observations, and heavyweights in the regressions, the smallest and the largest 0.5% of the explanatory variables (except Beta) are set equal to the next smallest and largest values. This leads no effect on the drawn inferences in the findings. The last column reports the average R-squares of the cross-sectional regressions.

The final estimate, $\hat{\gamma}_k$, and its variance are given below.

$$\hat{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{kt}$$

$$Var(\hat{\gamma}_k) = \frac{\sum_{t=1}^{T}(\hat{\gamma}_{kt} - \hat{\gamma}_k)^2}{T(T-1)} \tag{9}$$

Table 5 reports the Fama–MacBeth (1973) cross-sectional regressions of monthly stock returns on idiosyncratic volatility measures and standard firm characteristics over the period September 2000 to August 2024. The specifications progressively incorporate systematic risk controls, size, book-to-market, momentum, and liquidity variables, following the empirical frameworks of Fama and French (1992) and Fu (2009).

Model (1) presents the univariate specification. Idiosyncratic volatility (IVOL) enters positively and significantly, with a slope coefficient of 0.24 (t = 4.90). Economically, this implies that firms with higher firm-specific volatility earn higher average returns, consistent with compensation for undiversified risk in segmented markets. This positive IVOL–return relation contrasts with the negative anomaly documented for U.S. equities by Ang et al. (2006, 2009), but aligns closely with Fu (2009), who demonstrates that expected (rather than realized) idiosyncratic volatility commands a positive premium once conditional volatility dynamics are properly modeled.

The positive premium is economically meaningful and statistically robust, suggesting that in the Indian equity market, firm-specific risk is not fully diversified away. This finding is consistent with Merton's (1987) model of incomplete diversification and Shleifer and Vishny's (1997) limits-to-arbitrage framework, both of which predict that idiosyncratic risk may be priced when investors face portfolio constraints.

Model (2) augments the regression with systematic and firm-level controls. IVOL remains positive and significant (0.18, t = 4.30), indicating that its pricing effect is not subsumed by traditional risk factors. The size coefficient is negative (–0.16, t =–4.50), confirming a small-firm premium consistent with emerging market evidence (Rouwenhorst, 1999). Book-to-market loads positively, while momentum and liquidity exhibit economically intuitive signs. The persistence of the IVOL coefficient after controlling for liquidity is particularly important. Bali et al. (2011) argue that IVOL effects may be driven by illiquidity or lottery-like preferences. However, the stability of the IVOL premium in our specifications suggests that firm-specific volatility captures incremental risk beyond liquidity frictions alone.

Model (3) introduces conditional idiosyncratic volatility (CIVOL) estimated via an EGARCH framework. CIVOL enters positively and strongly (0.10, t = 9.00), indicating that forward-looking, time-varying volatility measures carry stronger pricing power than unconditional residual-based IVOL. This result directly mirrors Fu (2009), who shows that expected idiosyncratic volatility dominates realized volatility in explaining cross-sectional returns. In Models (4)–(7), CIVOL is estimated jointly with firm characteristics. Across all specifications, CIVOL remains positive and statistically strong. In the fully specified Model (7), the coefficient reaches 0.48 (t = 14.98), with an R^2 of 8.01. The magnitude remains economically significant even after controlling for size, value, momentum, and liquidity exposures. The statistical precision reflects two structural features of the Indian market: (i) persistent cross-sectional dispersion in firm-level volatility, particularly among small-cap and growth firms, and (ii) a long-time dimension that stabilizes Fama–MacBeth standard errors.

A central question is whether the magnitude of the IVOL premium in India is exceptional relative to other emerging markets. Blackburn and Cakici (2017) report that IVOL premia in emerging markets are generally positive but heterogeneous across countries, with stronger effects in segmented markets. Hanauer and Linhart (2018) similarly document that IVOL pricing is more pronounced in markets with weaker institutional development. In China, Bali and Cakici (2008) find economically meaningful IVOL effects consistent with limited diversification.

Compared with these studies, the magnitudes of the IVOL and CIVOL coefficients in India are of comparable order. The positive, economically meaningful premia align more closely with emerging-market evidence than with developed-market anomalies. India does not appear to be an outlier; rather, the strength of the IVOL premium reflects institutional characteristics common to emerging markets, high retail participation, ownership concentration, episodic liquidity shocks, and evolving regulatory frameworks.

Importantly, the conditional IVOL results demonstrate that once expected volatility is properly modeled, the anomaly documented in developed markets weakens, supporting Fu's (2009) argument that mismeasurement of expected idiosyncratic risk drives contradictory findings.

The novelty of the present findings lies not merely in documenting a positive IVOL premium, but in demonstrating that conditional volatility measures (CIVOL) exhibit stronger and more stable cross-sectional pricing power than unconditional residual-based measures within an emerging market setting. By integrating liquidity-augmented factor controls with EGARCH-based volatility estimation over a long sample horizon, this study provides one of the most methodologically comprehensive re-examinations of IVOL pricing in India. The results suggest that, in emerging markets characterized by segmentation and limited arbitrage, idiosyncratic volatility behaves as a systematic state variable rather than residual noise. This has implications for portfolio construction, risk modeling, and regulatory policy aimed at improving diversification and disclosure standards.

5.2 Returns analysis of portfolios formed on E(IVOL)

Following the evidence from the Fama–MacBeth cross-sectional regression analysis, which indicates a statistically significant positive relationship between conditional idiosyncratic volatility and average stock returns in India, we proceed to conduct a portfolio-based analysis. This approach offers a more intuitive and practically relevant interpretation of the risk-return relationship and is particularly suitable for developing investable strategies. Given the structural features of the Indian stock market, such as high levels of market volatility, dynamic capital flows, and diverse investor profiles, the portfolio approach allows for a robust examination of return behaviour across varying levels of firm-specific risk.

Table 6. Summary statistics for portfolios formed on conditional idiosyncratic volatility

Variables	Portfolios formed on E(IVOL)									
	low	2	3	4	5	6	7	8	9	High
Port. VW Re.	1.50	1.79	1.87	1.99	2.00	3.04	3.90	3.99	4.03	5.22
Port. EV Re.	0.98	0.99	1.07	1.76	1.99	2.00	2.06	2.08	3.88	5.00
E(IVOL)	2.01	4.34	5.45	6.89	7.45	10.56	15.45	20.98	24.56	37.54
IVOL	3.23	4.23	4.99	5.43	6.78	7.34	11.87	15.65	18.50	25.43
Beta	0.70	0.90	1.00	1.06	1.10	1.15	1.20	1.30	1.40	1.46
ME(median)	110.65	108.45	106.45	104.34	100.35	96.45	90.34	85.45	56.34	40.54
BE/ME	0.87	0.80	0.75	0.70	0.74	0.73	0.69	0.70	0.54	0.40
FF Alphas	0.05	0.02	0.04	-0.04	-0.06	0.05	0.02	0.10	0.13	2.00

Note: Summary statistics for the portfolios formed on conditional idiosyncratic volatility Each month, we formed ten portfolios based on the E(IVOL), and the one-month ahead expected idiosyncratic volatility for all individual stocks in the Indian stock market. E(IVOL) is estimated employing the EGARCH model. We consider ten decile portfolios formulated on the E(IVOL), whereas portfolios are updated on a monthly basis. The first portfolio (low) consists of 10% of the stocks with the lowest E(IVOL), and the last portfolio (high) consists of 10% of the stocks with the highest E(IVOL). The first two rows present, respectively, the time series means of the value-weighted portfolio and equal-weighted portfolio returns. In the subsequent rows, the E(IVOL), IVOL, Beta, and the median values of the ME and BE/Me are reported within their respective portfolios. The study considers the median values instead of the mean values for the ME and BE/ME due to their substantial skewness. The last row reports the Fama-French (FF) alphas (intercepts) from the time series regressions of the value-weighted portfolio excess returns on the Fama-French three factors. The sample period for the study is September 2000 to August 2024 (288 months).

To complement the Fama–MacBeth regression results, we conduct a portfolio-based analysis to assess the pricing implications of expected idiosyncratic volatility (E(IVOL)). Ten value-weighted and equal-weighted decile portfolios are formed monthly based on one-month-ahead E(IVOL) estimated via the EGARCH model. Table 6 summarizes the average returns and characteristics of these portfolios over the sample period from September 2000 to August 2024. The results reveal a monotonic increase in returns across E(IVOL) deciles, consistent with the pricing of conditional idiosyncratic risk. Value-weighted portfolio returns rise from 1.50% to 5.22%, while equal-weighted returns increase from 0.98% to 5.00% between the lowest and highest deciles. This robust trend across weighting schemes supports the argument that E(IVOL) captures a priced source of risk in the Indian equity market. The positive association aligns with Fu (2009), contrasting with the negative IVOL-return relationship documented in developed markets (Ang et al., 2006, 2009).

The strong alignment between E(IVOL) and realized IVOL across deciles reinforces the validity of the EGARCH-based estimation. Moreover, Fama-French alphas rise from near zero to 2.00% in the highest E(IVOL) portfolio, indicating that traditional factor models fail to fully explain return variation, possibly due to omitted volatility-related risks or investor behavioral biases (Bali et al., 2011; Hou, Xue, & Zhang, 2015). Portfolio characteristics reveal that high-E(IVOL) stocks tend to have lower market capitalizations (median ME declines from INR 110.65 crore to INR 40.54 crore) and lower BE/ME ratios (from 0.87 to 0.40), indicative of small, growth-oriented firms. These stocks are likely more speculative and prone to sentiment-driven pricing, consistent with noise trading theories (Barberis & Thaler, 2003; Hou et al., 2011). The systematic risk (beta) also increases from 0.70 to 1.46, but the magnitude of return spread exceeds what can be attributed to beta alone, highlighting the inadequacy of CAPM-style metrics and the need for volatility-sensitive models (Bollerslev, Tauchen, & Zhou, 2009). Overall, the return patterns suggest that E(IVOL) is a robust predictor of cross-sectional stock returns in India, especially in segments characterized by information asymmetry and limited arbitrage. These findings support the inclusion of conditional volatility dynamics in asset pricing models for emerging markets and highlight the limitations of models developed for mature, efficient markets.

5.3 Robustness Check Analysis

5.3.1 The relationship between monthly returns and lagged idiosyncratic volatility

Table 8 presents decile portfolios sorted by lagged idiosyncratic volatility , offering a robustness check of the risk-return relationship in the Indian equity market. Portfolio 1 contains stocks with the lowest IVOL, while Portfolio 10 includes the highest. The IVOL increases monotonically from 2.34% to 36.76%, validating the effectiveness of the risk-based sort. Simultaneously, firm size (ME) and market share decline, consistent with smaller, more speculative firms concentrating in high-IVOL portfolios—aligning with findings from Fu (2009) that associate IVOL with firm-specific uncertainty.

Return patterns reinforce the pricing relevance of idiosyncratic volatility. Average raw returns increase from 1.01% (Portfolio 1) to 1.87% (Portfolio 10). This return premium becomes sharper in the liquidity-augmented five-factor alphas, which escalate from a statistically weak 0.06% to a highly significant 8.32%, with a robust inter-decile spread of 1.34% per month (t=6.45). These findings suggest that lagged IVOL is positively associated with risk-adjusted returns even after controlling for standard risk factors, reinforcing the predictive strength of firm-specific risk.

Furthermore, lagged return metrics (Ret-1) show that higher-IVOL stocks yield higher prior-month returns (e.g., 12.98% in Portfolio 10), pointing toward momentum-like behavior. The persistence of performance is further underscored by significant alphas at (t-1), particularly for high-IVOL stocks (e.g., 2.01%, t=6.23), indicating delayed information diffusion or behavioral biases such as investor overreaction, more common in emerging markets. From an investment strategy lens, these results validate the efficacy of a long–short portfolio (long high-IVOL, short low-IVOL), yielding statistically robust alphas. High-IVOL stocks, despite being smaller and less liquid, offer superior risk-adjusted returns, suggesting they embody either underpriced risk or investor mispricing. These dynamics resonate with option-like payoff structures (Fu, 2009) and behavioral preferences (Bali et al., 2011; Barberis & Thaler, 2003), particularly in environments with retail-dominated investor bases and segmented information flows. Notably, the Indian market diverges from developed markets, such as the U.S., where high-IVOL stocks tend to underperform (Ang et al., 2006, 2009). This contrast reflects deeper institutional differences: India's underdeveloped arbitrage mechanisms, informational frictions, and retail dominance may sustain pricing anomalies. For policymakers, the evidence highlights the need to improve transparency, liquidity, and analyst coverage, especially for small-cap stocks. In summary, the positive pricing of lagged idiosyncratic volatility in India suggests that asset-pricing models must be adapted to emerging market structures. Unlike developed economies, where IVOL is often viewed as a diversifiable and unrewarded risk, in India, it appears to reflect meaningful risk premia and exploitable mispricing patterns.

Table 7. Returns dispersion of Portfolio sorted by idiosyncratic volatility

IVOL Portfolio	N	IVOL(t-1)	ME(t-1)	Mkt Shares	Re (t)	VWXRe(t)	Liq augmented-5F alpha	Re(t-1)	VWXRe(t-1)	Liq augmented-5F alpha(t-1)
1(Low)	135	2.34	1.98	34.65	1.01	0.96	0.06(1.65)	0.98	0.22	0.01(0.87)
2	134	7.25	2.76	20.87	0.09	0.87	0.02(0.03)	1.02	0.29	0.02(0.06)
3	135	8.34	3.24	10.34	1.12	0.78	0.09(1.23)	0.88	0.65	0.09(0.90)
4	135	9.46	3.87	8.87	1.01	0.65	0.56(1.45)	2.54	0.79	0.59(2.78)
5	135	10.54	3.90	6.98	1.26	0.54	1.87(7.65)	3.87	1.09	0.98(4.67)
6	134	12.54	4.23	5.65	1.37	0.87	1.96(8.76)	4.88	2.09	1.02(6.65)
7	136	12.99	4.44	4.87	1.02	0.40	2.03(1.24)	5.98	2.87	1.66(7.02)
8	137	20.65	5.32	3.32	1.56	0.38	2.87(1.56)	6.23	3.24	0.98(3.23)
9	136	31.87	5.55	2.83	1.22	0.87	5.98(5.98)	7.56	4.34	2.09(4.34)
10(High)	139	36.76	5.78	1.62	1.87	0.98	8.32(7.78)	12.98	5.43	2.01(6.23)
10 - 1							1.34(6.45)			1.20(7.98)

Note: Returns dispersion of portfolios sorted by idiosyncratic volatility.
This table shows the differences in the monthly percentage returns of portfolios sorted by idiosyncratic volatilities in the Indian stock market. Every month, we divide the universe of stocks into different quintiles on the basis of their idiosyncratic volatility (IVOL). Portfolio 1(Low) is the portfolio of stocks with the lowest idiosyncratic volatility, and Portfolio 10 (High) is the portfolio of stocks with the highest idiosyncratic volatility. The idiosyncratic volatility for the current study is estimated as follows. In every month, excess daily returns of each individual stock are regressed on the liquidity-augmented five-factor asset-pricing model: . The (monthly) idiosyncratic of the stock is the product of the standard deviation of the regression residuals and the square root of the number of observations in the month. Further, the idiosyncratic volatility portfolio is formed for month. N is the number of firm-month observations for the pooled sample. The T-statistics are presented along with the mean statistics in the brackets. The notations IVOL, ME, Re, and VWXR e(t) stands for the idiosyncratic volatility, size indicator measured in terms of market capitalization, monthly average raw returns and the value weighted excess returns for the portfolio respectively. The sample period for the study is September 2000 to August 2024 (288 months).

Table 9 examines short-term return dynamics among high-idiosyncratic-volatility (IVOL) stocks, sorted into quintiles based on one-month lagged returns, Re(t–1). A pronounced return reversal emerges: Portfolio 1, with the most negative lagged returns (Re(t–1) = –30.98%), records a strong rebound the following month (Re(t) = 9.39%, EWXRe(t) = 7.87%), alongside a significant alpha of 2.32% (t = 7.34). Conversely, Portfolio 5, composed of prior-month winners (Re(t–1) = 20.67%), underperforms in the next month (Re(t) = –0.34%, alpha = –2.40%, t = –8.55). The symmetric, monotonic pattern of alphas across quintiles indicates robust mean reversion that standard risk models fail to absorb. These reversals suggest that pricing inefficiencies, rather than risk compensation, drive returns among high-IVOL stocks. The inability of the liquidity-augmented five-factor model to account for these alphas implies the presence of non-risk-based mechanisms, such as investor overreaction, as theorized in the behavioural finance literature (De Bondt & Thaler, 1985; Jegadeesh, 1990). Notably, the findings challenge Ang et al. (2006, 2009), whose negative IVOL–return relationship overlooks return conditioning. Here, conditional IVOL coupled with prior performance reveals distinct reversal patterns, especially in emerging market contexts.

India's market characteristics, retail dominance, low institutional participation, and limited information diffusion exacerbate these effects. As shown by Bekaert & Harvey (2000) and Rouwenhorst (1999), emerging markets are more prone to behavioural biases and inefficient price discovery. High-IVOL stocks, often small-cap and thinly covered, are particularly susceptible to noise trading, leading to exaggerated price movements and subsequent corrections. Unlike developed markets, where momentum dominates short-term returns (Jegadeesh & Titman, 1993; Hong & Stein, 1999), India exhibits short-horizon reversal behaviour, especially among volatile stocks. This reflects excessive price swings followed by corrections, likely due to overreaction and limited arbitrage. For practitioners, the evidence supports a contrarian strategy: buying prior-month losers and shorting prior-month winners within the high-IVOL universe. While execution risks, transaction costs, and liquidity constraints exist, such strategies offer economically and statistically significant alphas, especially in segmentation-prone markets. For policymakers, the results challenge the classical notion of unpriced idiosyncratic risk and highlight the need for regulatory measures to improve disclosure, liquidity, and investor education. In sum, the strong and symmetric reversals among high-IVOL stocks underscore the importance of conditional modelling and behavioural explanations in emerging markets. Standard models that treat IVOL as static and priced may mischaracterize return dynamics, particularly in inefficient environments.

Table 8. Return dispersion of high-IVOL stocks sorted by the one month lagged returns

Portfolio sorted by Re(t-1)	N	Re(t-1)	Re(t)	EWXRe(t)	VWXRe(t-1)	IVOL(t)	Liq augmente-5F alpha EWXRe(t)	Liq augmente-5F al-phaVWXRe(t)
1(low)	162	-30.98	9.39	7.87	2.54	30.76	2.32(7.34)	0.45(3.54)
2	163	-9.56	14.65	3.22	1.21	23.76	1.76(6.55)	0.98(4.67)
3	163	0.02	2.00	0.98	0.08	20.22	-0.09(-0.88)	-0.87(-2.67)
4	162	10.67	0.33	0.05	-0.05	27.76	-1.98(-4.45)	-0.98(-3.99)
5(High)	163	20.67	-0.34	-1.65	-0.98	23.65	-2.40(-8.55)	-2.08(-10.65)

Note: Return dispersion of high-IVOL stocks sorted by the one-month lagged returns.
Following the AHXZ (2006, 2008) and Fu (2009), we identified 60 percent of high idiosyncratic volatility stocks for the sample to examine the impact of the return reversal on the high-IVOL stocks. Every month, t-1, we identify 60 percent of stocks that have the highest idiosyncratic volatilities and divide them into equal quintiles on the basis of their contemporaneous average monthly returns. Portfolio 1 is of the stocks with the lowest IVOL, and Portfolio 5 is the highest IVOL portfolio with Re(t-1). Re(t) represents the monthly average returns. VWXRe (EWXRe) are the time-series mean value-weighted (equal-weighted) excess returns for the portfolios, and are used to calculate the liquidity augmented five-factor regressions alphas in the time series regressions. The sample period for the study is September 2000 to August 2024 (288 months).

6. Summary and Conclusion

This study revisits the pricing of idiosyncratic volatility (IVOL) in India's emerging equity market, challenging the classical CAPM assertion that idiosyncratic risk is unpriced in equilibrium. Drawing on theoretical perspectives that recognize investor under-diversification and market frictions (Levy, 1978; Merton, 1987), we show that IVOL is a significant determinant of cross-sectional stock returns in India. Unlike findings from developed markets where a negative IVOL–return relation is documented (Ang et al., 2006, 2007), our results demonstrate a robust, positive relation between expected idiosyncratic volatility and average returns, aligning with evidence from emerging markets such as Fu (2009) and Chua et al. (2000). Employing both unconditional factor models and conditional EGARCH frameworks, the analysis underscores that conditional IVOL, rather than lagged volatility, better captures return dynamics, particularly in markets characterized by information asymmetry and limited arbitrage. Our portfolio-level analysis reveals return reversals in high-IVOL stocks, especially among small-cap firms, indicative of behavioural overreaction and short-term mispricing (De Bondt & Thaler, 1985; Hong & Stein, 1999). These findings have several implications. First, they highlight the informational content of idiosyncratic risk in return prediction, especially in segmented markets. Second, they question the efficacy of simplistic IVOL-based sorting strategies, underscoring the need for dynamic, forward-looking volatility measures. Finally, they reinforce the policy need for stronger disclosure norms and institutional participation to reduce firm-specific noise and enhance pricing efficiency. Overall, this study contributes to the growing literature on asset pricing in emerging markets by establishing that idiosyncratic volatility is not merely residual noise but a priced risk component with meaningful return implications. The findings offer actionable insights for investors, regulators, and scholars seeking to understand the dynamics of risk premia beyond developed market paradigms.

While the analysis spans a long horizon encompassing multiple phases of market development, the present study does not explicitly segment the sample around major structural or macroeconomic events such as post-2010 financial liberalization, the 2016 demonetization episode, or the COVID-19 shock. A formal regime-based or event-driven sub-period analysis would require carefully defined structural break identification, sufficient within-regime observations, and additional robustness procedures to ensure statistical comparability across subsamples. Given data constraints in certain early periods and the primary focus of this study on methodological comparison and long-horizon stability, we defer such extensions to future research.

Future work could profitably examine whether the magnitude and sign of the IVOL premium vary across regulatory regimes, liquidity cycles, or periods of heightened policy uncertainty. Exploring whether idiosyncratic volatility is more strongly priced during systemic disruptions or phases of capital market liberalization would deepen our understanding of the conditional determinants of risk premia in emerging markets. Such regime-specific investigations would complement the present findings by clarifying the institutional channels through which market frictions and investor behavior shape the pricing of firm-specific risk.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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