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Determinants of idiosyncratic volatility: Evidence from the Indian stock market

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ABSTRACT

This paper investigates whether firm-specific characteristics explain idiosyncratic volatility in the stocks of non-financial firms traded in the Indian stock market. It employs the linear time series five-factor model, augmented with a liquidity factor and the conditional EGARCH model, to extract yearly idiosyncratic volatility. We estimate a panel data regression to quantify the relationship between firm-specific characteristics and the volatility of individual securities. The results show that idiosyncratic volatility is significant in emerging markets such as India, and that cross-sectional return variations of firms are associated with firm-specific characteristics such as firm size, book-to-market ratio, momentum, liquidity, cash flow-to-price ratio, and returns on assets. We find that the idiosyncratic risk documented in this study is associated with smaller size of company, higher liquidity, low momentum, high book-to-market ratio, and low cash flow-to-price ratio. The findings suggest need to develop alternative tools to make investment decisions in emerging markets.

1. Introduction

The conventional portfolio theory of finance holds that rational investors in perfect capital markets diversify unsystematic risk completely by holding uncorrelated assets in their portfolio (Markowitz, 1952), and early theoretical models hypothesize that systematic market risk is the sole determinant of expected stock returns (*e.g.*, Sharpe, 1964; Lintner, 1965; Black, 1976). The extant literature documents anomalies in modern finance such as firm size; book-to-market ratio (BM); price-earnings (P/E) ratio; firm leverage; momentum returns (MM); cash flow-to-price ratio (CF/P); and profitability ratios such as returns on equity (ROE) and returns on assets (ROA), sales growth, assets growth, dividend yield, *etc.* The pertinent literature on asset pricing shows that the capital asset pricing model (CAPM) does not capture the role of these firm-specific factors; therefore, alternative asset pricing models are proposed to explain the expected returns of the stocks. Some studies analyze the role of the idiosyncratic volatility (Ivol) of stock returns in the determination of expected stock returns across countries by following the approach of an imperfect capital market and under-diversification. Merton (1987) and Malkiel and Xu (2002) argue that poorly diversified portfolios require an extra risk premium for holding stocks with high Ivol and thus suggesting a strong relationship between idiosyncratic risk and expected stock returns. Campbell et al. (2001) document the increasing idiosyncratic risk in the stock market over the past four decades.

In this light, further investigation of Ivol is needed. No study examines the factors that influence Ivol in emerging markets (EMs) such as India. This study aims to estimate idiosyncratic risk in the Indian stock market and identify its determinants by employing a liquidity-augmented five-factor model in under-diversification conditions at equilibrium. By bridging the gap in the literature on EMs, we contribute to the literature on Ivol in the following ways.

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First, while a few studies in developed financial markets show evidence of pricing of idiosyncratic risk and receipt of risk premium by investors (Ang et al., 2006, 2009; Fu, 2009), these findings do not apply to EMs, which have peculiar characteristics and are heterogeneous. Research into volatility in stock markets in EMs has assumed significance over the years because of economic liberalization, faster economic growth, increase in stock market size, and international portfolio flows. In this context, India is an ideal candidate to examine research issues on Ivol that have not yet been explored.

Second, while alternative asset pricing models have been employed to measure the Ivol (*e.g.*, Fama and French, 1993; Carhart, 1997), and also generalized autoregressive conditional heteroscedasticity (GARCH)-class models on alternative asset-pricing models – to estimate conditional Ivol – liquidity plays a vital role in firm performance, and stock returns are expected to respond to it. Liquidity affects investment, as illiquid stocks cost more to buy, and sell for less and, hence, illiquidity reduces the expected return of stocks. Nevertheless, no study uses a liquidity-augmented five-factor asset-pricing model to estimate Ivol in a developed or emerging market; this is the first study to do so.

Third, investors may hold under-diversified portfolios because of idiosyncratic risk pricing as a component of total risk in any specified portfolio in imperfect capital markets such as India. Thus, under-diversified portfolios demand an extra risk premium. The present study account for such premium and thus extend the literature on EMs.

Fourth, unlike developed markets, where retail investors dominate equally, institutional investors largely dominate the Indian stock market. Markets are informationally inefficient in EMs such as India (Hiremath, 2014), in which institutional investors irrationally trade against market fundamentals that lead to the increase in total risk, including the idiosyncratic risk of the portfolio. The remainder of the paper is organized as follows. Section 2 presents the related theoretical and empirical research. Section 3 explains the methodology. Section 4 discusses the variables and empirical results. Section 5 presents the conclusion.

2. Idiosyncratic volatility and emerging markets

As recognition of the relevance of Ivol deepens, the literature on the role of company-specific characteristics that explain Ivol is growing. Pastor and Veronesi (2002) show that persistence of idiosyncratic risk changes during the life cycle of the firm. Chen and Petkova (2012) note that Ivol pricing depends on the standard deviation of the residuals of estimated asset-pricing models such as Fama and French (1993). Therefore, Ivol is sensitive to the factor loadings in the pricing models. These findings are compatible with the study of Ang et al. (2006, 2009), Berggrun et al. (2016), who conclude that stocks with high (low) Ivol provide low (high) expected returns, because assets provide hedging opportunities than the increase in the idiosyncratic risk of the stock. When average stock risk goes up, investment opportunities deteriorate. Therefore, investors are willing to pay an insurance premium for high Ivol stocks because their payoff is negative when average return variance is significant.

The pertinent literature shows that Ivol is a new dimension to Markowitz's (1952) theory. Hence, the Ivol is expected to be all the more important in EMs, which are characterized by a number of market frictions and lack of information. The peculiar features and frictions in EMs pose more challenges to the theory of finance and portfolio investment than do developed markets. The lack of tradable fixed income instruments makes the financial valuation further difficult. Hence, Bruner et al. (2003) suggest that portfolio managers in EMs need to depart from conventional investment practices, and global investors need to adapt to this peculiar structure and develop alternative tools to analyze and make investment decisions in these markets.

Emerging markets are accumulating capital at a faster rate than developed markets, and their market capitalization and share in world capitalization is growing, but they lag far behind developed markets, such as the US and European markets, in terms of growth, number of stocks listed, foreign investment, liquidity, and risk. In a global portfolio, Harvey (1995) advocate, weight needs to be assigned to these markets to generate higher returns because of growth potential.

Some important features of EMs are higher transaction costs, multiple tax regimes, lack of transparency, illiquidity, non-synchronous trading, substandard accounting systems, lack of regulations, and weak enforcement of contracts. Financial markets cannot function smoothly because the physical and institutional infrastructure is poor or underdeveloped, and governance is weakened by corruption, an uncertain legal environment, political instability, and lack of transparency. The extant literature suggests that these markets are informationally inefficient (Hiremath and Kumari, 2014), and Lagoarde-Segot and Lucey (2008) show that liberalization and trading infrastructure is necessary but not sufficient to improve the quality of information in EMs. As the EMs integrate with developed markets, the higher positive correlation exposes these markets to global shocks and volatility (Nasser and Hajilee, 2016). Often, during crises, EMs devalue their currency, and fuel exchange rate volatility which, in turn, affect global portfolios. As institutions and infrastructure are weak, EMs rarely experience benefits from foreign portfolio investment (FPI) as documented in the theoretical literature; rather, shocks trigger FPI outflows and higher volatility. Against this backdrop, Ivol assumes further significance in EMs.

From the empirical perspective, if the idiosyncratic risk of a given security can be potentially mis-estimated because of limited information in the EMs, firm characteristics related to idiosyncratic risk provide supplemental information to risk analysis. If firm-specific fundamentals play a significant role in explaining the idiosyncratic risk at cross-sectional securities, these unique fundamentals can be good predictors of Ivol, and can be used in forecasting the risk of an existing portfolio of securities over time. So far, researchers have focused on the practical relevance of the theory and on the cross-sectional relationship between Ivol and expected cross-sectional returns, but investigation into the practical implications of these relationships and the determinants of idiosyncratic risk has been scant.

We attempt to fill these gaps and extend the literature by investigating whether firm-specific characteristics play any role in determining trends in Ivol and by attempting to explain its future dynamics in EMs such as India. With its institutional heterogeneity, the Indian stock market provides an interesting opportunity to examine the issue. The characteristics of India are peculiar and hardly

in line with the assumptions of modern finance. The market frictions hinder arbitrage, and a fully diversified portfolio in the sense of Markowitz (1952) is far from the reality. Despite financial sector reforms, studies show, the Indian stock market is not informationally efficient. Hiremath and Narayan (2016) document that India performs poorly in terms of informational quality and corporate governance in comparison with some of its peers.

In India, the ownership structure of firms is complex, and includes closed business groups, concentrated ownership, and cross-holdings. The controlling group that owns private information grabs private benefits over outside investors (Kim and Yi, 2006). As a result, the cost of acquiring private information is likely to be higher and the profitability of informed trading is likely to be lower in EMs than in developed markets (Farooq and Zarouali, 2016). This evidence suggests that stock prices less informative in EMs because of lack of informed trading and thus leading to increase in total risk of assets.

India is the second fastest among growing EMs and is more open than other EMs. Until the 1990s, financial markets were subject to controls and the dominance of public sector banks. Reforms and liberalization measures in financial systems and corporate governance after the 1990s aimed to revitalize financial markets and improve their functioning. Capital market liberalization and microstructure reforms fostered exponential growth in the stock market and FPI. India had followed a gradualist approach in liberalizing its financial system, which helped it to sustain the global financial shocks in 2008.

The degree of company-specific information available in EMs is lower than in developed markets, but also varies from one emerging market to another. Firm-level information plays a significant role in attributing substantial total variance to company-specific factors. In the absence of such information, investment analysis has to rely on the market as a whole (Bruner et al., 2003; Roggi et al., 2017). In the wake of increasing integration between India and developed markets, idiosyncratic risk assumes further importance. The investment is profitable only when the portfolio manager considers company-specific factors to analyze idiosyncratic risk. Therefore, India is an ideal sample for the analysis of determinants of idiosyncratic volatility. A single-market study such as this allows for better attention to market-specific data and modeling issues and is more useful for investment strategy than a large cross-country sample. The implications of cross-country studies are seldom applicable universally because of heterogeneity. This study, therefore, helps to gain better insights into the issue.

To foreshadow the key results, we find that Ivol is related to firm characteristics such as size, book-to-market, momentum, liquidity, cash flow-to-price, and returns on assets. These relationships imply that these firm fundamentals predict the idiosyncratic risk of time series and cross-sectional expected returns. Further, our estimates suggest that high idiosyncratic risk is associated with smaller company size, higher liquidity, low momentum, high book-to-market, and low cash flow-to-price.

3. Methodology

3.1. Unconditional idiosyncratic volatility estimation

We use a five-factor model that augments Carhart's (1997) four-factor model with the liquidity factor to estimate each firm's yearly unconditional Ivol by using daily data. The model is specified as follows:

$$(R_{it}^d - r_{ft}^d) = \alpha_{it}^d + \beta_{it}^d (R_{mt}^d - r_{ft}^d) + s_{it}^d SMB_t^d + h_{it}^d HML_t^d + m_{it}^d WML_t^d + l_{it}^d LIQ_t^d + \varepsilon_{it}^d it \tag{1}$$

where R_{it}^d is the daily return on the stock i, the corresponding subscript d is the day, R_{mt}^d is the market index return, r_{ft}^d represents the Treasury bill rate, SMB_t^d, HML_t^d, LIQ_t^d and WML_t^d are the FF model factor loadings. In Eq. (1), $R_{it}^d - r_{ft}^d$ is market excess returns over the risk-free rate, SMB (small minus big) represents the size factor – the difference between the daily value-weighted average return on portfolios of small stocks minus the daily value-weighted average returns of big stock portfolios. HML (high minus low) represents the value factor. The momentum factor is represented by the winners minus losers (WML) and the difference between low liquid minus high liquid (LIQ) is proxy for the liquidity factor (see Section 4). We perform yearly time series regressions for each firm. The Ivol is computed as the standard deviation of the residuals estimated from time series regression. We choose sample trading days between 252 and 275 days. The daily returns with non-zero market capitalization and positive book-to-market values for 252 days are required to reduce the impact of infrequent trading on Ivol estimates.

3.2. Conditional idiosyncratic volatility estimation

Following Fu (2009), we estimate the conditional Ivol with the exponential GARCH (EGARCH) (1 1) model. The mean and variance equation of the model are specified as follows:

$$(R_{it}^d - r_{ft}^d) = \alpha_{it}^d + \beta_{it}^d (R_{mt}^d - r_{ft}^d) + s_{it}^d SMB_t^d + h_{it}^d HML_t^d + m_{it}^d WML_t^d + l_{it}^d LIQ_t^d + \varepsilon_{it}^d it \tag{2}$$

where

$$\begin{aligned} &\varepsilon_{it} \sim N(0, \sigma_{it}^2) \\ &\log(h_{it}) = \omega + \textstyle\sum_{j=1}^{q} \alpha_{i,j} \left[\left| \frac{\varepsilon_{i,t-j}}{\sqrt{h_{i,t-j}}} - E\left(\frac{\varepsilon_{i,t-j}}{\sqrt{h_{i,t-j}}} \right) \right| \right] + \textstyle\sum_{k=1}^{m} \delta_k \frac{\varepsilon_{i,t-k}}{\sqrt{h_{i,t-k}}} + \textstyle\sum_{i=1}^{p} \beta_{it} h_{i,t-i} \end{aligned} \tag{3}$$

Eq. (2) represents the mean equation where the excess returns of individual stocks depend on the five-factor model augmented by Carhart's (1997) four-factor model along with the liquidity factor. The conditional distribution of residuals ε_{it} is assumed to be normal with the $iid\,(0, \sigma_{it}^2)$ where $\omega_0 > 0$, $\alpha_i + \beta_i < 1$, and $\delta_k < 0$, if volatility is asymmetric. Eq. (3) represents the variance equation. The

$\log(h_t)$ is the log of conditional variance of stock returns, β the vector of coefficient, ε_{it} represents the white noise term, and δ_i is the asymmetric coefficient. The log of conditional variance makes the leverage effect exponential instead of quadratic and, therefore, the estimates of the conditional variance are guaranteed to be non-negative. The leverage effect is shown by $\delta_k < 0$ if the impact of news is asymmetric. The EGARCH model is highly significant in determining the effect of volatility magnitude, the persistence of volatility in the market, and the leverage effect.

3.3. Panel data models

After estimating Ivol with the help of yearly time series regression analysis, we have specified a panel model to identify its determinants:

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \tag{4}$$

where $i = 1, \ldots, N$; $t = 1, \ldots, T$ with i denoting individuals and t denoting time. The i subscript, therefore, denotes the cross-section dimension whereas the t denotes the time series dimension. y_{it} is the unconditional and conditional Ivol of each firm across the year estimated from the previous models in Eqs. (1)–(3). The α is the intercept term, X_{it}^{i} is the vector of explanatory variables, β is the coefficient of the explanatory variables and u_{it} is a stochastic error term assumed to have mean zero and constant variance.

4. Variables

The data set comprises security returns, firm-specific characteristics, and daily systematic risk factor loadings. We employ the daily security returns of 516 non-financial publically traded firms listed on the National Stock Exchange (NSE) of India.[1] Financial and insurance companies are excluded from the sample because their specific asset and liability structure typically produces high financial leverage, which hinders the compatibility of their BM ratios with those of non-financial firms. The period of study stretches from September 1996 to August 2013 (204 months). To minimize outliers, we exclude the 0.25 per cent of firms having smallest and largest return observations. We collected the data from the NSE, the Prowess database of the Centre for Monitoring the Indian Economy (CMIE), and the Reserve Bank of India (RBI).

We follow the factor models devised by Fama and French (1993), Jegadeesh and Titman (1993), and Carhart (1997) to construct daily factor loadings – market risk premium (Mkt), size factor (SMB), value factor (HML), momentum (WML) and liquidity factor (LIQ) – which we use in the multivariate regression to estimate the unconditional and conditional yearly Ivol. To construct size and value factors, we employ data on common book equity and shares outstanding obtained from the CMIE database. If a firm publishes individual and consolidated financial statements, we use consolidated balance sheet data on common book equity. We exclude firms with negative book values and short fiscal years (*i.e.*, fiscal year with less than 12 months) from our analysis. We measure size by the natural log of the market value of equity (stock price times shares outstanding) on 31 August every year. We define the BM of the firm in year y as the ratio of a firm's book equity at fiscal year-end in calendar year y to the market value of equity at the end calendar year y. WML is the cumulative return of a stock in month $t - 12$ to $t - 2$ of the month of August in the previous year y. LIQ is the annual average of the daily turnover ratio, *i.e.*, shares traded to the numbers of shares outstanding.[2] We rank all firms by size and BM on 1 September of every year t from 1996 to 2012 for the fiscal year ending in $t + 1$. We impose a six-month gap between financial year-end statements, on 31 March of each year, but we use the portfolio formation at 1 September of each year. A five-month time lag (at the minimum) is maintained between the financial year-end and the formation of test assets, or between the disclosure of accounting information and its availability to the market, to avoid the look-ahead bias, and this approach helps us accommodate this lag. Next, we use independent sorts to allocate firms of two size groups and three BM groups. We use the median value of size to split the sample into two groups – big stocks (B) and small stocks (S). Similarly, independent of size, the bottom 30 per cent (low), middle 40 per cent (medium), and top 30 per cent (high) percentiles of BM serve as breakpoints for three BM groups. Low BM stocks are below the 30th percentile; medium BM stocks are in the middle 40 per cent and high BM stocks are above the 70th percentile.

4.1. Construction of systematic risk factors

We deploy five daily market-wide systematic risk factors. The Mkt is measured as the daily market excess risk-adjusted returns over the risk-free interest rate. The SMB, HML, WML, and LIQ represent, respectively, daily size, value, momentum, and liquidity factors. We follow the standard literature to construct Mkt, SMB, HML, WML, and LIQ. Next, we form six value-weighted portfolios – S/L (small-low), S/M (small-medium), S/H (small-high), B/L (big-low), B/M (big-medium), and B/H (big-high) as the intersection of the two size and three BM groups; and calculate the corresponding daily value-weighted portfolio returns from September of the year t to the August of year $t + 1$. For instance, the firms in portfolio S/L are simultaneously among the 50 per cent in the lowest market

[1] We selected NSE-listed non-financial firms for two reasons. The NSE, which was set up in 1994, has become the leader in the market because of microstructure changes like demutualization of exchanges, dematerialization of securities, the introduction of derivative products, use of information technology, and improvement in trading practices. Hence, the NSE has become a harbinger of growth of Indian securities market. Secondly, since its inception, NSE witnessed rapidly growing market capitalization, trading volume, liquidity, and turnover. The value-weighted S & P CNX Nifty equity index is a proxy for the market return. The CNX Nifty is a well-diversified 50-stock index that accounts for 23 sectors of the economy. It is used for a variety of purposes such as benchmarking fund portfolios, index-based derivatives, and index funds.

[2] The calendar year ends on 31 August.

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

	Mkt	SMB	HML	WML	LIQ
Panel A: Descriptive statistics					
Mean	−0.22852	0.004594	0.006412	−0.44724	−0.15621
Median	−0.23092	−0.03706	0.012854	−0.43589	−0.07545
Maximum	−0.03656	6.831049	4.199281	4.995598	4.995598
Minimum	−0.47288	−4.82737	−6.08933	−5.9397	−5.9397
Std. Dev.	0.064949	1.080744	0.772201	0.958709	0.872556
Skewness	−0.14517	0.591953	−0.31519	−0.03159	−0.63691
Kurtosis	2.782711	6.516696	7.430862	6.327695	8.656622
JB Test	23.20663	2429.617	3534.446	1954.725	5932.526
Probability	0.000009	0	0	0	0
Panel B: Correlation matrix					
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

Note: This table shows descriptive statistics in (Panel A) and cross correlations in (Panel B) for the systematic factor loadings: market risk premium (Mkt), size factor (SMB), the value factor (HML) liquidity factor (LIQ) and the momentum factor (WML). We calculate the Mkt as the returns difference between the S & P CNX Nifty index and the risk-free rate. We calculate SMB and HML as in FF (1993) and WML as in Carhart (1997). SMB (*i.e.*, small minus big), HML (*i.e.*, high minus low) and WML goes long in past winners and short in past losers and LIQ (*i.e.*, low liquid minus high liquid).

* Significance at 5% level.

capitalization and among the 30 per cent of firms with the lowest BM. The SMB factor is measured each day as the simple value-weighted average of the returns on the three small stock portfolios minus the returns on the three big stock portfolios. Likewise, HML is a hedge portfolio that we construct as the difference in returns of the two high BM portfolios and the returns of the two low BM portfolios. Further, following Jegadeesh and Titman (1993) and Carhart (1997), we calculate the momentum of stock at 1 September of month t as the cumulative past returns from month $t - 12$ to $t - 2$. For each month t, we rank all the stocks based on their past 11 months returns, lagged one month but use daily momentum values. Therefore, the lag imposition on stock returns would be from $t - 250$ to $t - 22$. The one-month lag is imposed to avoid short-term reversals and the bid-ask spread effect. To measure the WML, we construct six value-weighted portfolios with the interaction of the two size and three return momentum groups, *i.e.*, S/W (small-winners), S/N (small-neutral), S/L (small-losers), B/W (big-winners), B/N (big-neutral), and B/L (big-losers). WML is simply the value-weighted average of the returns on the two winner stock portfolios minus the returns on the two loser stock portfolios.

Further, liquidity is the annual average of the daily turnover ratio, *i.e.*, value shares traded to the value of shares outstanding at the end of August 31 of every year y (Amihud, 2002; Chan and Faff, 2005). Following Chan and Faff (2005) and Keene and Peterson (2007), we construct the LIQ. We form four daily value-weighted portfolios with the combined interaction of the two size and two LIQ based portfolios, *i.e.*, S/HL (small-high liquid), S/LL (small-low liquid), B/HL (big-high liquid), and B/LL (big-low liquid). LIQ is the difference between the daily average returns on the two low liquid stock portfolios and the average on the two high liquid stock portfolios. In the construction process, consistent with the standard literature, we consider one year of portfolio holding period, and every year portfolios are rebalanced on 1 September to calculate the value-weighted returns for all factor loadings from the beginning of September of year t to 31 August of year $t + 1$.

The mean returns are positive for SMB and HML but negative for Mkt and WML (Table 1). The descriptive statistics show that the premium of WML is the most pronounced, with average returns of 0.44 per cent per day. The average size and value premiums are also positively significant. The average Mkt is negative but insignificant. The statistics confirm the presence of size, value, liquidity, and momentum premiums in the Indian stock market. Overall, the correlations between these five market-wide risk factors are quite low, and suggest their significance in determining the expected stock return (Panel B, Table 1). Low and insignificant correlations between Mkt with other risk factors implies the importance of the multi-factor asset-pricing model for determining the expected return of the stock. Consistent with the finding of Liu (2006), liquidity factor is negatively correlated with Mkt; this result supports the proposition that investors require a high liquidity premium as a compensation for the systematic liquidity risk.

We present the cross-sectional average time series coefficients of five systematic risk factors of unconditional models in Table 2 and of conditional models in Table 3. For each year, we develop a linear liquidity-augmented five-factor model and estimate the conditional EGARCH model in which the conditional mean equation is specified as liquidity-augmented five-factor model.

4.2. Firm-specific returns predictors

In addition to the factors discussed in the literature, we introduce size, value, and momentum variables, and some value variables (such as growth indicators, profit margin, growth opportunities of firms and, finally, trading turnover and liquidity) to determine Ivol. In this regard, firm-specific characteristics and their impact on returns and volatility pose a practical difficulty because of the criterion of selecting firm-specific factors for predicting cross-sectional returns and volatility.

Further, if many factors (such as firm characteristics) are added in prediction of stock returns – without understanding correlation

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}
1997	−3.34 (−4.21)	0.97 (2.00)	2.22 (2.00)	3.23 (2.45)	0.96 (1.87)	−4.02 (−3.00)
1998	0.80 (1.46)	1.90 (1.70)	−1.87 (−1.70)	2.32 (2.01)	0.80 (1.67)	2.87 (2.01)
1999	1.98 (2.67)	0.80 (1.89)	1.15 (1.89)	−3.76 (4.01)	−3.23 (−5.21)	1.87 (2.00)
2000	3.56 (5.00)	0.87 (1.85)	1.30 (1.64)	−2.21 (2.31)	−2.34 (2.01)	0.60 (1.59)
2001	1.04 (3.53)	1.01 (3.22)	0.99 (2.01)	1.34 (3.22)	0.84 (2.79)	0.77 (1.55)
2002	0.65 (1.76)	0.80 (2.00)	0.82 (2.00)	1.02 (2.87)	−1.23 (3.02)	−1.01 (1.45)
2003	0.76 (1.80)	−0.65 (1.60)	1.02 (3.23)	−1.23 (−3.98)	0.45 (1.23)	0.50 (1.54)
2004	2.01 (4.23)	0.76 (1.56)	0.54 (1.65)	−0.76 (−1.65)	−2.01 (−5.23)	0.40 (0.90)
2005	−0.90 (−2.23)	−2.23 (−5.56)	0.56 (1.65)	0.68 (1.70)	1.00 (2.34)	0.98 (2.02)
2006	2.25 (6.21)	0.51 (1.76)	−0.87 (−2.02)	0.34 (1.01)	2.40 (2.03)	−3.23 (−5.32)
2007	0.54 (0.97)	0.60 (1.78)	1.70 (3.11)	−1.24 (−3.23)	0.90 (2.34)	0.81 (2.11)
2008	−3.23 (−4.90)	−0.65 (−1.80)	0.72 (1.99)	0.80 (2.21)	3.21 (4.87)	1.08 (3.01)
2009	−0.90 (−2.21)	0.87 (2.11)	−2.91 (−4.21)	0.32 (0.98)	0.41 (0.98)	1.03 (3.23)
2010	0.95 (2.10)	1.00 (1.31)	1.30 (3.98)	2.87 (5.32)	−0.56 (−1.87)	−0.45 (−1.34)
2011	3.09 (4.98)	3.33 (5.22)	0.55 (1.19)	0.65 (1.65)	0.92 (2.10)	−0.87 (−1.78)
2012	2.01 (4.21)	−0.56 (−1.09)	1.01 (2.90)	0.65 (1.78)	3.65 (6.23)	2.21 (3.21)
2013	−2.10 (−3.21)	1.90 (3.00)	−0.92 (−1.87)	3.21 (6.21)	4.23 (6.69)	1.87 (2.23)

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

and the covariance structure among variables – it is not possible to predict cross-sectional returns meaningfully (Subrahmanyam, 2010). To eliminate the problem of many control variables, we identify 21 relevant firm-specific variables based on stock return predictors, value variables, profitability, tangibility, and liquidity. The choice of factors conforms with the extant literature.

We categorize variables by characteristics.

1. Returns predictors: market capitalization, the BM.
2. Value indicators of firms: earnings-to-price ratio (PE), CF/P, dividend yield (DivY), and sales growth (SG).
3. Measures of earnings quality: accounting accruals (ACC) and net operating assets (NOA).
4. Measures related to a firm's past returns: short-term momentum (MM) (*i.e.*, the past 12 months cumulative returns) and long-term reversal (LngR) (*i.e.*, past three years stock returns).
5. Measures of firm's tangible and intangible investments, including the capital expenditure (CAPEX), research and development expenditure (R & D), and advertising expenditure.
6. Firm's liquidity measure (LQ).
7. Proxies that measure the leverage risk of the firm: book leverage (Bliv), market leverage (Mliv), financial leverage (long-term debt/total assets).

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}
1997	2.20 (5.32)	0.54 (1.08)	−2.34 (3.56)	0.09 (0.98)	0.34 (1.01)	2.13 (3.67)
1998	0.45 (1.08)	4.87 (7.72)	1.90 (3.34)	1.87 (2.78)	−0.51 (−1.45)	0.89 (1.87)
1999	−2.98 (−4.32)	0.45 (0.99)	−0.87 (−1.20)	2.34 (4.44)	2.01 (3.33)	−2.13 (−4.52)
2000	0.98 (2.12)	1.45 (2.34)	2.10 (3.24)	−3.21 (−5.23)	0.87 (1.90)	1.01 (2.01)
2001	0.86 (2.01)	1.50 (3.12)	0.67 (2.45)	−1.90 (−2.22)	−0.81 (−1.68)	−3.21 (−6.21)
2002	4.76 (7.34)	2.22 (4.43)	0.40 (1.65)	2.01 (3.98)	1.33 (2.10)	0.80 (1.80)
2003	2.34 (4.56)	−0.09 (−0.29)	−0.08 (−0.23)	1.10 (2.23)	2.07 (3.24)	1.98 (2.76)
2004	1.30 (4.22)	0.78 (1.55)	0.65 (1.54)	−0.90 (−1.90)	1.09 (2.14)	4.22 (8.09)
2005	1.23 (2.21)	6.38 (8.98)	0.09 (0.30)	0.38 (1.56)	−0.08 (−0.34)	−0.22 (−0.87)
2006	0.98 (1.87)	0.23 (0.90)	0.99 (1.79)	0.56 (1.34)	0.77 (1.65)	0.54 (1.26)
2007	0.45 (1.02)	1.15 (2.00)	2.87 (3.18)	2.98 (5.23)	2.01 (5.34)	2.32 (4.22)
2008	0.60 (1.34)	−1.87 (−2.87)	3.56 (6.78)	3.29 (5.90)	1.00 (2.43)	−1.11 (−2.02)
2009	0.75 (1.98)	2.00 (3.87)	4.23 (8.98)	2.01 (3.21)	−0.80 (−2.01)	0.76 (1.89)
2010	−2.34 (−4.21)	3.23 (6.89)	1.20 (2.02)	1.12 (2.32)	0.40 (1.00)	1.90 (3.23)
2011	−3.65 (−6.67)	1.87 (2.23)	0.76 (1.77)	−0.04 (−0.23)	0.61 (1.24)	1.80 (3.76)
2012	0.34 (1.11)	1.12 (1.98)	−0.24 (−0.96)	0.24 (0.99)	0.80 (1.34)	2.22 (6.22)
2013	0.76 (1.34)	−0.65 (−1.34)	−0.81 (−1.76)	1.11 (2.34)	0.23 (0.98)	−0.34 (−1.01)

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

8. Proxies that represent the firms' growth in size and profit margin: assets growth (AG), ROA, ROE and growth rate of gross profit margin (GFM).

We construct 21 firm-specific predictor variables. A description of these variables follows.

1. Firm size (SZ) is natural logarithm of the market value of equity, which is the firm's market price multiplied by the common shares outstanding (Fama and French, 1992, 1993).
2. BM is the book value of the equity to its market capitalization.
3. EP is the ratio of net earnings, *i.e.*, profit after tax.
4. CF/P ratio is the sum of earnings before extraordinary items and depreciation to the market capitalization.
5. DivY is the ratio of the dividend paid by the firm.
6. SG is the sales revenue for the fiscal year ending in the calendar year $t-1$ over the sales revenue from the fiscal year-end in year $t-2$.
7. ACC is the noncash component of earnings, the change in non-cash current assets less the change in current liabilities. We exclude debt in current liabilities and income tax payable and less depreciation, during the fiscal year-end $t-1$, and scaled by the average total assets at the beginning and end of the fiscal year (Sloan, 1996).
8. Following Hirshleifer et al. (2004), we estimate NOA as the difference between operating assets and operating liabilities for the fiscal year ending in calendar year $t-1$, scaled by the average total assets at the beginning and end of that fiscal year.[3]
9. MM is the cumulative return of a stock in $t-12$ through $t-2$ t. We skip one month between portfolio formation and holding period to avoid the effects of the bid-ask spread, price pressure, and any lagged reaction.
10. LngR of a stock in the month t is measured each month by sorting stocks on past cumulative returns from month $t-36$ to $t-7$.
11. CAPEX is measured as a firm's capital expenditure over average total assets at the beginning and end of that fiscal year in calendar year $t-1$ and $t-12$.
12. We take RD as the ratio of R & D expenditure to market capitalization.
13. Advertising expenditure is the ratio of advertising expenditure to market capitalization.
14. LQ is the annual average of monthly turnover ratio *i.e.*, the number of shares traded to the number of shares outstanding.
15. Bliv is total assets divided by book equity of the fiscal year ending in the year t divided by the market value of equity.
16. Mliv is computed as total assets in the fiscal year ending in year t divided by the market value of equity. This approach of leverage measurement differs from the standard norm in corporate finance, in which higher leverage implies a higher proportion of asset risk (Chen and Zhang, 2010).
17. Financial leverage is the ratio of long-term debts over total assets for each firm. AG is the percentage change in total assets from the fiscal year ending in calendar year $t-2$.
18. ROA of a firm is profit after tax divided by total assets.
19. ROE is measured as profit after tax divided by a firm's total equity.
20. Consistent with Abarbanell and Bushee (1998), GPM is the difference between net sales and cost of goods sold divided by net sales.
21. ΔGPM is the percentage change in GPM from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$.

The descriptive statistics presented in Table 4 show that predictors of firm-specific variables (except CF/P) are positively skewed at the thicker upper tail of the distribution than at the lower tail. The kurtosis for both market portfolios is positive, which suggests that the distribution is leptokurtic or fat-tailed. The selected variables are non-normally distributed.

4.3. Identification of firm variables with return variations

Our objective is to identify the maximum possible firm-specific predictors and firm-specific determinants of Ivol. To identify the variables, we first examine the return-predictive performance of 21 variables using the decile portfolio approach. In September of each year t, we rank stocks into decile portfolios based on each predictor employing the year $t-1$ financial statement data. Following the approach of Chen et al. (2010) and Artmann et al. (2012), we form 10 equally weighted decile portfolios for all the 21 firm predictors to find out which firm-specific variables explain the cross-sectional variation of returns for the subsequent one-year return. For each firm-specific characteristic at the beginning of September of calendar year t, we form 10 portfolios based on the decile breakpoints. For example, for firm SZ, D10 stocks contain the largest firms with the largest past returns, and D1 contains the decile of the smallest firms with low returns, and so forth (Table 5). The conservative five-month lag is imposed to ensure that accounting data is made available to investors in March, the end of the financial year of calendar year t. We hold the position of portfolios from year t to year $t+1$ for 12 months, and portfolios are rebalanced at the beginning of September of every year t. The portfolios formed on characteristics like MM and LngR are rearranged every month.

We furnish the average returns of portfolios formed on 21 firm-specific predictors in Table 5. We find that the mean difference values of SZ, BM, CF/P, MM, LQ, and ROA are significant predictors, and that the statistics show that these six firm-specific factors

[3] Each variable is computed for the fiscal year-end March to the market capitalization at the end of August of the year.

Table 4
Descriptive statistics of the firm-specific variables predictors.

	Mean	Median	Standard deviation	Skewness	Kurtosis
SZ	21.761	21.58	1.972	0.481	4.360
BM	2.334	1.381	5.792	17.41	54.23
E/P	0.087	1.345	4.236	7.897	50.13
CF/P	0.006	0.030	2.068	−6.838	95.01
DivY	0.654	0.765	1.245	3.765	12.54
SG	0.345	0.006	0.123	2.345	4.653
ACC	0.005	0.026	1.245	0.234	6.652
NOA	0.543	0.013	0.987	2.976	8.233
MM	0.123	0.008	0.765	3.097	4.877
LngR	0.235	0.008	0.145	3.064	5.508
CAPEX	0.765	1.654	2.065	1.873	20.655
R & D	0.007	0.999	3.009	0.994	79.544
Adv.	1.245	0.654	0.006	0.874	45.885
LQ	1.456	0.123	0.002	0.534	4.679
Bliv	0.986	0.003	0.123	0.113	6.870
Mliv	0.543	0.009	1.256	8.374	3.982
Fliv	0.240	0.245	0.006	7.545	4.003
AG	0.010	0.124	0.002	6.025	5.214
ROA	0.020	0.765	0.008	0.237	3.675
ROE	0.165	0.875	0.234	2.348	4.764
GFM	2.356	0.198	0.129	1.231	5.503

Note: This table presents the time-series averages of the cross-sectional averaged statistics of firm-specific predictors for India for the sample period 1996–2013. The equal weighted average is used to compute cross-sectional averages.

Table 5
Average returns for decile sorted portfolios on firm-specific predictors.

Firm-specific predictors	Mean returns of decile portfolios formed on the firm-specific predictors										Return spread between 10-1 and 10-5 portfolios	
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	(D10-D5)	(D10-D1)
SZ	3.07	2.56	1.86	3.54	3.02	2.75	1.04	1.99	2.00	1.32	−1.70 (−2.45)	−1.75 −(2.21)
BM	1.45	1.49	1.02	2.06	0.56	2.74	1.05	1.99	2.33	2.76	2.20 (3.00)	1.31 (1.87)
E/P	2.96	2.01	2.87	2.21	2.34	1.75	1.44	2.80	2.97	2.84	−0.12 (0.34)	0.50 (0.26)
CF/P	1.09	1.98	1.76	2.01	0.62	2.10	2.66	1.98	2.01	2.80	2.18 (2.76)	1.71 (1.99)
DivY	1.98	2.54	2.12	1.54	2.23	1.24	2.21	2.87	2.66	2.54	0.31 (0.03)	0.56 (0.23)
SG	2.99	2.34	1.87	2.65	2.09	2.98	2.11	2.14	2.08	2.52	0.43 (0.45)	−0.47 (0.35)
ACC	1.11	1.42	1.83	1.35	2.27	1.85	1.96	2.10	1.77	2.38	0.11 (0.23)	1.27 (1.80)
NOA	2.83	1.74	1.88	1.97	2.22	2.38	0.56	0.89	2.32	2.45	0.23 (0.23)	−0.38 (0.26)
MM	0.33	1.33	0.47	2.37	0.34	2.02	1.20	1.23	2.01	2.92	2.58 (3.00)	2.59 (2.98)
LngR	2.87	2.56	2.11	2.03	2.76	2.67	1.76	1.85	1.10	2.32	−0.44 (0.34)	−0.55 (0.28)
CAPEX	1.83	1.13	1.74	2.16	2.67	3.00	2.89	2.11	3.00	2.87	0.20 (0.20)	1.04 (1.50)
R & D	2.22	2.03	2.76	2.19	1.87	1.96	1.43	2.75	1.10	2.80	0.93 (0.67)	0.58 (0.50)
Adv.	2.22	1.67	2.45	3.89	2.90	2.00	2.54	2.13	2.80	2.75	−0.15 (0.21)	0.53 (0.43)
LQ	2.03	2.97	2.67	2.34	1.65	2.66	1.90	1.11	2.00	3.76	2.11 (1.99)	1.73 (2.65)
Bliv	1.00	2.18	0.11	0.67	1.87	1.25	2.00	1.26	1.12	0.54	−1.33 (1.52)	−0.46 (0.32)
Mliv	2.20	1.20	2.78	1.09	1.87	2.86	2.40	1.70	2.20	2.10	0.23 (0.30)	−0.10 (0.24)
Fliv	1.90	1.78	2.05	2.18	2.76	2.65	2.10	1.10	1.89	2.04	−0.72 (1.00)	0.14 (0.05)
AG	2.00	1.87	1.76	1.54	2.00	1.56	1.78	2.12	2.30	2.34	0.34 (0.46)	0.34 (0.45)
ROA	0.35	2.01	2.20	2.22	1.12	2.87	2.76	2.65	2.90	3.34	2.22 (3.65)	2.99 (3.87)
ROE	2.87	2.86	2.30	2.65	3.89	3.10	2.98	2.99	2.19	2.89	−1.00 (0.87)	0.02 (0.15)
ΔGFM	1.67	1.87	1.65	2.01	2.10	2.65	2.85	2.65	2.87	1.08	−1.02 (0.29)	−0.59 (0.22)

Note: The table reports returns to decile portfolios sorted on firm specific predictors. The mean monthly returns on 21 firm specific characteristics are presented. D1 shows the smallest decile portfolio's average returns and D10 shows the highest decile portfolio's average returns. For instance, size (SZ) D1 represents the smallest stock returns portfolio average and size (SZ) D10 represents the biggest firm's portfolio average returns. D10-D1 and D10-D5 shows the portfolio average spread between two portfolios.

significantly predict stock performance for the subsequent year. More specifically, we find that small-size sorted portfolios outperform big-size sorted portfolios by −2.45 and −2.21 per cent per month at 5 per cent level of significance. The top BM-sorted portfolio outperforms the bottom BM-sorted portfolio at 3 per cent and 1.87 per cent per month. Similarly, we find that the CF/P, MM, LQ and ROA variables returns spread are statistically significant and play a significant role in determining future stock returns and variations in returns (Table 5). It implies that stock returns and volatility of future expected returns in the Indian market are determined by these firm-specific characteristics. For instance, the statistical significance of the MM spread of high past stock returns

Table 6
Mean descriptive statistics of unconditional idiosyncratic volatility of the stock returns across the years for 516 firms.

Years	Mean	Median	Standard deviation	Kurtosis	Skewness
1997	1.002	1.002	0.000	2.080	0.227
1998	1.003	1.003	0.001	2.145	0.743
1999	1.002	1.002	0.001	10.250	1.566
2000	1.002	1.002	0.001	9.592	4.221
2001	1.002	1.002	0.001	3.142	0.929
2002	1.004	1.003	0.001	3.344	0.995
2003	1.003	1.003	0.002	11.258	2.130
2004	1.003	1.003	0.002	11.273	2.083
2005	1.002	1.002	0.001	5.115	1.151
2006	1.004	1.004	0.001	−0.453	0.086
2007	1.002	1.002	0.001	11.558	0.633
2008	1.002	1.002	0.001	12.727	1.119
2009	1.003	1.003	0.001	0.408	0.456
2010	1.002	1.002	0.001	3.973	0.131
2011	1.002	1.002	0.001	8.972	1.647
2012	1.002	1.001	0.001	2.156	0.810
2013	1.004	1.003	0.003	5.674	1.651
Average	**1.002**	**1.002**	**0.001**	**6.071**	**1.210**

Note: We summarize the time series statistics of individual firms' idiosyncratic volatilities. We first compute the time series of Ivol for each stock and then the mean statistics across all the firms. Stocks are traded on the NSE India during September 1996 to August 2013. The Ivol is estimated as follows: In each year, excess daily returns of each stocks are regressed on the daily five factors model augmented with Carhart four factors are: Mkt, SMB, HML, WML and LIQ. The (yearly) Ivol of the stock is the product of the standard deviation of the regression residuals.

portfolio and low past stock returns portfolio reveal that firms with high past returns out-perform firms with low past returns over the preceding 12 months. Except SZ, BM, CF/P, MM, LQ, and ROA, we find no other firm-specific characteristics that explain stock return variation and, therefore, the variation in returns (Table 5). Our findings are consistent with the cross-sectional analysis of Chen et al. (2010) for the stock market in China, but it is difficult to justify theoretically, why certain firm-specific fundamentals have statistically significant predictive power and others do not. There may be two reasons: First, return predictors in EMs are less heterogeneously distributed than in developed markets. Since risk level depends on firm-specific fundamentals, the cross-sectional dispersion in stock returns associated with such variables will be small, if there is no significant cross-sectional dispersion in a return-predictive variable or lack of homogeneity in the firm variables (Chen et al., 2010). Second, stock prices in EMs must be less informative than in developed markets in which the synchronicity is high.

5. Empirical results and discussion

5.1. Estimation of unconditional and conditional volatility

Tables 6 and 7 present the cross-sectional averages of time series statistics of the unconditional and conditional Ivol of stock returns. Across firms, the time series mean average of unconditional Ivol is 1.002 and of conditional Ivol is 3.726. The mean standard deviations across stocks are 0.001 and 4.317, respectively, for unconditional and conditional Ivol. The values in the tables show that unconditional Ivol is steady, but conditional volatility fluctuates across the years and does not follow a particular trend. The plots of average trends of unconditional and conditional volatility show persistence in Ivol over the period, and suggest that the Ivol is priced in the Indian stock market (Figs. 1 and 2). Hence, excess risk premium is required on the idiosyncratic component of the portfolio.

5.2. Determinants of idiosyncratic volatility of stock returns

The statistics in Panel A of Table 8 show a wide difference between high and low values of unconditional Ivol (IvolU), conditional Ivol (IvolC), SZ, BM, MM, LQ, CF/P and ROA. The skewness is positive for all variables except MM and CF/P, which indicate that these are at the thicker upper tail of the distribution. The kurtosis coefficient values for selected variables are positive and suggest that the distribution is leptokurtic. Further, the statistics in Panel B suggest variables are uncorrelated and problem of multicollinearity among variables do not exist.. We estimate panel regression to examine the relationship between Ivol in conditional and unconditional specifications with firm-specific characteristics. In this regard, our study is the first to utilize five systematic risk factors to estimate unconditional and conditional Ivol. In the second step, when we estimate regression between Ivol and firm-specific factors individually, these factors should show insignificant values, because their dynamics were already captured in the first step. However, if the individual variables become significant to explain dynamic Ivol, it explicitly implies the significance of firm-specific factors (SZ, BM, MM, LQ, CF/P, and ROA) across securities as determinants and predictors of future Ivol.

We estimate the fixed and random effect models and present the results in Table 9. The Hausman (1978), F, LR, and LM tests suggest that the fixed effect models are appropriate for unconditional and conditional Ivol with firm-specific characteristics. The panel regressions suggest that SZ, BM, MM, LQ, CF/P, and ROA are significant in determining Ivol in the unconditional and

Table 7
Mean descriptive statistics of conditional idiosyncratic volatility of the stock returns across the years.

Years	Mean	Median	Standard deviation	Kurtosis	Skewness
1997	3.642	3.391	1.303	6.640	1.842
1998	4.779	3.595	8.889	367.01	17.91
1999	5.990	3.898	15.584	49.381	20.53
2000	6.055	4.139	19.181	478.81	21.50
2001	5.543	3.736	5.208	6.807	2.524
2002	5.032	3.679	5.214	29.381	4.313
2003	3.211	2.637	3.450	87.197	7.254
2004	3.219	3.002	2.212	9.956	2.211
2005	2.617	2.534	1.420	7.244	1.056
2006	2.886	2.947	1.281	45.519	3.447
2007	2.501	2.466	0.973	3.402	0.108
2008	3.507	3.590	1.099	3.507	−0.853
2009	3.925	3.973	1.342	50.98	3.288
2010	2.723	2.530	2.782	96.129	18.757
2011	2.487	2.277	1.001	16.339	2.256
2012	2.542	2.368	1.067	6.792	1.658
2013	2.688	2.412	1.396	20.212	3.156
Average	**3.726**	**3.127**	**4.317**	**75.60**	**6.526**

Note: We summarize the time series statistics of individual firms' idiosyncratic volatilities. We first compute the time series of Ivol for each stock and then the mean statistics across all the firms. Stocks are traded on the NSE India during September 1996 to August 2013. The Ivol is estimated as follows: Each year, excess daily returns of each individual stock are regressed on the daily five factors model augmented with Carhart four factors are: Mkt, SMB, HML, WML and LIQ. The (yearly) Ivol of the stock is the product of the standard deviation of the regression residuals in each year.

conditional framework. Characteristics such as SZ and BM and CF/P are significant at the conventional significance level in an unconditional framework, whereas SZ, MM, and LQ are significant in a conditional framework. The signs of coefficients of all variables are in line with the evidence in the literature (*e.g.*, Brown and Kapadia, 2007; Cao et al., 2008).

Our evidence of an inverse relationship between SZ and Ivol suggests that smaller and young firms are highly prone to Ivol. These findings are consistent with the prior literature and support the empirical relationship between SZ and volatility (Malkiel and Xu, 2003; Brown and Kapadia, 2007; Vozlyublennaia, 2013). In the same line, we find a positive relationship between BM and Ivol. The signs of BM coefficients in the literature are controversial. The higher BM indicates that these stocks are less likely to be growth stocks, and should have lower risk in markets and, therefore, suggest a negative relationship between BM and Ivol. The negative sign implies a positive relationship between BM and Ivol because, BM is inversely related with the market price of the security. This occurs when investors and speculators find stocks attractive; such stocks should have higher risk. In this study, BM is positively related to Ivol, and this finding is consistent with the extant literature. Further, the firms' MM is positively linked to Ivol in a conditional framework, which suggests lower volatility in past winner stocks. Investment decisions are more centered to past cumulative returns individually. In this line, a firm's momentum acts as a predictor of its future volatility.

Similarly, the LQ of the stock is positively associated with Ivol. High liquidity implies high risk, and *vice versa*. The literal interpretation is that liquid stocks are more prone to risk. This evidence is in line with Brown and Kapadia (2007) and Vozlyublennaia (2013). Our analysis also shows a negative relationship between CF/P ratio and future Ivol. Theoretically, the present value of future cash flows determines the firm's future volatility and present value in the market. The lower present value of future cash flows is

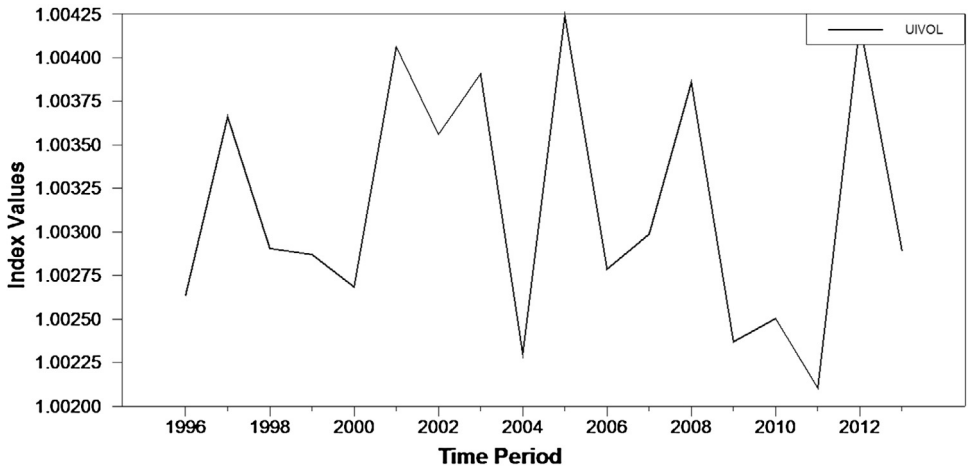

Fig. 1. Yearly cross-sectional averages of unconditional idiosyncratic volatility of stock returns for 516 firms.

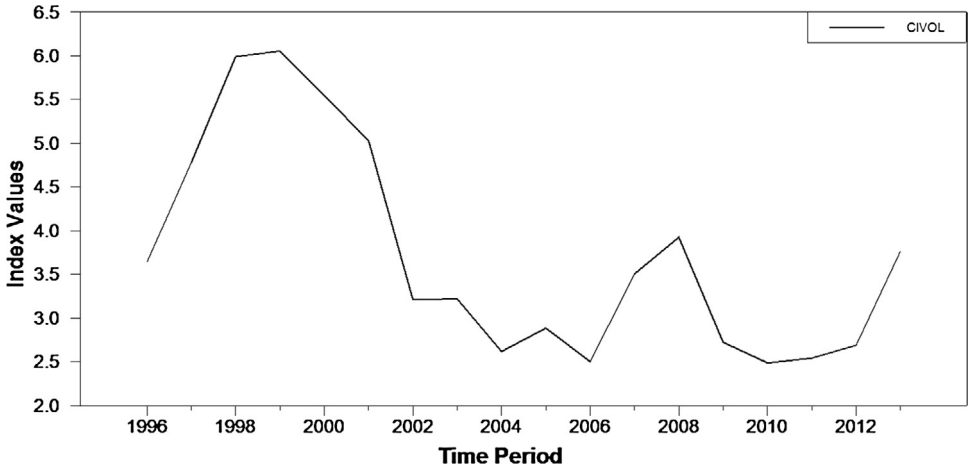

Fig. 2. Yearly cross-sectional averages of conditional idiosyncratic volatility of stock returns for firms.

highly associated with higher volatility, and *vice versa*. Moreover, our panel regression results suggest that a given security is likely to have high Ivol if it is associated with the smaller size company, higher LQ, low MM, high BM, and low CF/P.

Similarly, the LQ of the stock is positively associated with Ivol. High liquidity implies high risk, and *vice versa*. The literal interpretation is that liquid stocks are more prone to risk. This evidence is in line with Brown and Kapadia (2007) and Vozlyublennaia (2013). Our analysis also shows a negative relationship between CF/P ratio and future Ivol. Theoretically, the present value of future cash flows determines the firm's future volatility and present value in the market. The lower present value of future cash flows is highly associated with higher volatility, and *vice versa*. Moreover, our panel regression results suggest that a given security is likely to have high Ivol if it is associated with the smaller size company, higher LQ, low MM, high BM, and low CF/P. From the practical perspective, and from the investors' viewpoint, if the idiosyncratic risk is mis-estimated by the limited information hypothesis of Merton (1987), these company fundamentals constitute a good indicator of the future dynamics of volatility. If these company fundamentals are significant indicators as the differences in cross-sectional Ivol, these firm-specific characteristics can be used to decide which stock should be added to a portfolio. Moreover, if company-specific characteristics are good predictors of the dynamics of the future trend of Ivol for securities, these factors can be used to forecast the risk of an existing portfolio of securities over the period. Firm-specific fundamentals always have a significant role in portfolio formation, investment decisions, and future trends of securities.

Table 8
Pooled descriptive and correlation matrix of the panel data set of the variables.

Panel A: Descriptive statistics

	IvolU	IvolC	Size	BM	MM	LQ	CF/P	ROA
Mean	1.0031	2.0023	21.840	2.123	−0.344	0.0009	0.011	3.6978
Max	1.0264	5.0345	33.737	20.27	7.29	0.066	6.294	19.84
Min	0.994549	0.9934	14.564	0	−2.19	1.39E−06	−2.535	−13.64
St. Dev.	0.001924	2.0934	3.047	4.086	8.766	0.0034	6.964	1.663
Skewness	1.898123	1.2345	0.641	10.027	−0.028	9.993	−12.480	1.981
Kurtosis	14.35533	9.2367	3.449	7.079	51.423	33.815	13.290	25.623

Panel B: Pairwise correlations

	Size	BM	MM	LQ	CF/P	ROA
Size	1					
BM	0.002	1				
MM	−0.023	0.014	1			
LQ	0.001	−0.103	0.045	1		
CF/P	0.006	−0.002	0.230	0.021	1	
ROA	−0.089	0.106	0.020	−0.005	−0.006	1

Note: This table reports the descriptive statistics of the stocks traded on NSE India during September 1996 to August 2013. IvolU and IvolC stand for the unconditional and conditional pooled samples of Ivol respectively. The size is the product of monthly closing price and the number of outstanding shares in the month of September each year. Book-to-market equity (BM) is the fiscal year-end book value of common equity divided by the calendar year-end market value of equity. The Ivol is estimated as follows. Each year, excess daily returns of each individual stock are regressed on the Carhart's four factors: Mkt, SMB, and HML, WML and LIQ. The (yearly) Ivol of the stock is the product of the standard deviation of the regression residuals. CIVOL is the one-year-ahead expected Ivol estimated from EGARCH model. Turn is the average turnover. Variables with skewness greater than 3.00 are reported as the natural logarithm.

Table 9
Fixed effect estimates of determinants of unconditional and conditional idiosyncratic volatility.

Independent variables	Unconditional idiosyncratic volatility Fixed effect	Conditional idiosyncratic volatility Fixed effect
Constant	963.55 (0.00)	45.46 (0.00)
Size	−3.56* (0.00)	−4.67* (0.00)
BM	1.83** (0.06)	0.65 (0.76)
MM	0.09 (0.93)	6.87* (0.00)
LQ	−1.10 (0.27)	4.89* (0.00)
CF/P	−1.69*** (0.10)	1.23 (0.99)
ROA	1.16 (0.24)	0.98 (0.95)
F-test, *F*(6,8249)	4.25 (0.00)	5.25 (0.00)
Restricted *F*-test	11.36 (0.00)	12.76 (0.00)
Hausman-test [χ^2(5)]	32.69 (0.00)	25.00 (0.00)
LR TEST [x^2(516)]	543.66 (0.00)	654.87 (0.00)
LM test	15.67 (0.00)	23.10 (0.00)
R^2	0.343 (0.00)	0.056 (0.00)

Note: Sample period consists of 17 years observations for 516 firms from September 1996 to August 2013. *F*-test is reported for the overall fitness of the fixed effect model over the random effect model. Hausman (1978) test determines the appropriateness of fixed or random panel model. Likelihood Ratio (LR) test identifies the presence of individual firm specific effects in the data set. Lagrange Multiplier (LR) test shows the acceptability of panel data models over the classical linear regression models.
*, **, *** denotes significance at 1%, 5% and 10% respectively.

6. Summary and conclusions

We analyze the empirical relationship between Ivol and firm-specific characteristics for cross-sectional securities in India. We use the decile portfolio approach through the average return spread between high and low decile portfolios. Out of 21 stock returns predictors, we show that SZ, BM, MM, LQ, CF/P, and ROA are significant in terms of the returns spread.

We find SZ, BM, and CF/P ratio as significant factors that explain the volatility in the unconditional Ivol specification. However, in the conditional Ivol, we find that SZ, MM, and LQ are the determinants of volatility. The empirical findings suggest that firm-specific fundamentals are significant determinants of unsystematic risk, and support the theory of an under-diversified portfolio. The present findings suggest usefulness of company characteristics in investment analysis.

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