Is Idiosyncratic Volatility Priced in Bangladesh Stock Market?

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ABSTRACT

This paper uses three methods of idiosyncratic volatility to find whether or not firm-specific risk can explain returns of individual stock and portfolio returns in the Dhaka Stock Exchange (DSE), the larger of the two stock exchanges in Bangladesh. Results show that investors fail to diversify their portfolios and firm-specific risk cannot be totally driven away. Furthermore, we also find significant negative relationships between idiosyncratic volatility and returns for both portfolios and individual stocks. Firm characteristics such as volatility and size do not change the results. The study concludes that firm-specific volatility should be considered in the valuation models for the stocks listed in the DSE.

JEL Classification: G12; G14

Keywords: Dhaka Stock Exchange, Emerging stock market; Firm-specific risk; Frontier stock market

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INTRODUCTION

Previous studies document that firm-specific risk cannot predict the cross-section of stock returns (for example, Fama and MacBeth, 1973). After examining the standard deviation of portfolio returns, Campbell et al. (2001) find that a portfolio should have about 50 randomly selected stocks to achieve relatively complete diversification. In the case of under-diversification, investors may demand idiosyncratic risk to be priced. Findings of Blume and Friend (1975), Barber and Odean (2000), Benartzi and Thaler (2001), Campbell et al. (2001) and Goetzmann and Kumar (2008) imply that investors do not achieve efficient diversification for their portfolios since they hold only few assets. Consequently, it is impossible to eliminate idiosyncratic risk or volatility (hereafter, IV) and hence it may influence stock returns significantly. Kearney and Poti (2008) provide support in favor of this argument by reporting that 166 European stocks were required in 2003 to significantly reduce idiosyncratic risk. By contrast, only 35 stocks were needed in 1974 to reduce firm-specific risk. Likewise, Xu and Malkiel (2003) also find that more assets are required to achieve the desired level of portfolio diversification.

Campbell et al. (2001) also document a significant increase of IV in the past four decades. In two related studies, Xu and Malkiel (2003) and Wei and Zhang (2006) indicate that the ratio of idiosyncratic risk to total risk has been increasing over time. Merton (1987) suggests that investors ask for risk premium for holding poorly diversified portfolios. Thus, IV is expected to play a vital role in the risk-return relationship (Vozlyublennaia, 2013; Hsu and Huang, 2016).

Another important factor for the pricing of idiosyncratic risk is the presence of noise traders—especially, in emerging markets. These traders lack the skill to do fundamental analysis and tend to trade on impulse, irrational exuberance, fear and greed. Thus, they may not process firm-specific information properly, resulting in mispricing of stocks. When the market is dominated by noise traders, investors have to ask for risk premium for taking such risk. De Long et al. (1990) report that the unpredictability of noise traders' trading activities generates risk in the asset prices, which creates obstacles for rational arbitrageurs to bet against them. Dontoh et al. (2004) give evidence that noisy trading activities reduce the association between stock prices and relevant information such as earnings report. Thus, the relationship between idiosyncratic volatility and mispricing is positive because stock prices exhibit a propensity to deviate from fundamental value in the presence of noise trading and arbitrage costs.

Briefly, there is overwhelming evidence that under-diversified investors demand a return premium for taking idiosyncratic risk and the nature of such relationship may depend on the choice of volatility measures. Moreover, the robustness of the findings is an important issue. Chua et al. (2010) use unexpected idiosyncratic volatility to control for unexpected returns and report significant positive relationship between expected idiosyncratic volatility and expected returns. Their results are robust to various firm characteristics and different sample periods. However, Bali and Cakici (2008) argue that this relationship in the U.S. market depends on the choice of data frequencies, weighting schemes and volatility-based sorting.

Evidence found in developed markets may not be applicable in emerging or frontier markets because of the difference of behavior in these two types of markets. Some of the well-known features of emerging and frontier markets are the presence of (i) relatively high transaction costs, (ii) relaxed tax system, (iii) lack of transparency, (iv) illiquidity, (v) weak accounting practices, (vi) lack of governance and (vii) weak surveillance by capital market monitoring/regulatory authority. Lack of institutional infrastructure, political instability, corruption and weak legal environment are also impeding factors for the development of emerging markets (Kumari et al., 2017).

The behaviors of emerging markets are not alike. The diversity of emerging markets implies the need for the independent verification of IV-return relationship in individual markets. Angelides (2010), in a study that consists of 24 emerging markets, suggests that firm-specific and market risks jointly predict market returns since there is a negative (positive) relationship between firm-specific (market) risk and future returns. Bley and Saad (2012) report significant negative such relationship for Saudi Arabia, confirming the presence of such relationship even in the context of Arab emerging markets. Jiang et al. (2009) show that firm-specific volatility is influenced by the informational content of its future earnings. Moreover, this anomaly is stronger among the firms that have less-sophisticated investor base. This finding, obviously, indicates the possibility of strong impact of IV on emerging market returns as these markets are believed to have a noisy dissemination of information through less-informed, retail traders.

The relevant findings for developed markets and the recent strong performance and the peculiarity of emerging markets rekindle the interest of academics, investors, policy makers and media in the latter markets. This paper examines the relationship between idiosyncratic volatility and expected returns of portfolios and the cross-section of individual firms listed in Bangladesh stock market. This study may contribute to academics, regulators, policy makers and investors in many ways. Firstly, in the wake of increasing integration between emerging and mature markets, the study on idiosyncratic volatility attracts investors more than ever before. As Bangladesh market is highly dominated by retail traders, it can be an ideal market to test the impact of idiosyncratic volatility on stock returns considering the strong trading activities of noise traders. This contribution of the study can also be considered as a theoretical contribution to the literature on noise traders; more precisely, results can test the external validity of noise trading theory. Moreover, the implications of international studies involving many markets are not applicable universally due to the heterogeneity of markets. For example, all other things remaining same, a Latin American emerging market cannot be compared with a Middle-Eastern emerging market due to cultural differences. Thus, a single-country analysis is also important for investors. This study, therefore, helps to gain better understanding of the issue, which can then be applied to any market with high dominance of retail traders. Most of the frontier markets should fall in this category. Of course, relevant behavioral issues must be taken into account.

Secondly, this paper contributes to asset pricing literature in general by examining the robustness of findings on the IV-returns relationship with respect to the choice of risk measure. Since the related literature on the topic mainly focuses on the relationship using a particular methodology of volatility, results may not show the robustness to the choice of volatility measure. As shown in the next section, the use of two broad types of volatility series has shown different results for the developed markets. Hence, it is interesting to see how findings change with respect to the use of a particular type of IV. We use three different types of methodology for the construction of volatility series: (i) realized idiosyncratic volatility computed from daily residual returns; (ii) realized idiosyncratic volatility computed from past autocorrelation of returns; and (iii) expected idiosyncratic volatility computed from time-series returns. This study may inform us if the IV-return relationship is robust to the selection of estimation methods of idiosyncratic volatility. An unequivocal presence of the pricing of IV could be a matter of concern for policy makers since it implies less-than-efficient allocation of financial assets.

Thirdly, this study also contributes to the extant literature on Bangladesh stock market. This is probably the first comprehensive study to examine IV-return relationship in Bangladesh stock market. Bangladesh is a very promising stock market with a market capitalization of about US $50 billion (as of November 2017). Dhaka Stock Exchange—the largest bourse in the country—has been around since 1954. It can be considered as one of the few frontier markets in the world that have the potential to be upgraded to emerging status in near future. A frontier market is a less-known investment opportunity to global investors; thus, using a single method of volatility can be less reliable and the findings from the use of three methods of IV are interesting for investors. The participation of foreign investors is the key to the future success of Bangladesh market. This study should immensely help global portfolio managers to understand how IV should be treated in their asset valuation and portfolio selection.

Results of the study show that Bangladeshi investors cannot diversify their portfolios to the extent that firm-specific risk becomes negligible. Moreover, the returns of both portfolios and individual stocks exhibit an inverse relationship with idiosyncratic volatility. This result is robust to firm characteristics such as volatility and size. This study concludes that idiosyncratic volatility is an important risk factor and it should be considered in the valuation models for the stocks listed in the DSE.

Rest of the paper is organized as follows. Next section discusses the extant literature on IV. The third section describes the data and explains the methodology used in the study. Following section explains the empirical results obtained from using different idiosyncratic volatility measures. Final section concludes the paper.

REVIEW OF LITERATURE

As mentioned above, the relationship between IV and stock returns of developed markets has been observed in many previous studies (Vozlyublennaia, 2013; Hsu and Huang, 2016; Chua et al.,2010; Ang et al., 2006; Cotter et al., 2015; Bali and Cakici, 2008). As far as the impact of idiosyncratic volatility is concerned, empirical

literature on the relationship between such risk and returns recognizes two broad strands. The first one is based on the construction of expected volatility series using long time-series (monthly) return data whereas the second one is based on the construction of realized volatility series using short time-series (such as daily) return data. Research based on the first one reports significantly positive relationship between IV and expected return (Chichernea et al., 2015; Fu, 2009). The same with the second method reports negative relationship (Ang et al., 2006, 2009; Cotter et al., 2015). Interestingly, some of the studies such as Bali and Cakici (2008) and Boyer et al. (2010) use the second method but find insignificant relationship. Hence, the choice of volatility measure could be a decisive factor for the idiosyncratic risk-return relationship.

The influence of IV on returns is also evident in some of the studies on non-U.S. markets. Ang et al. (2009) confirm negative relationship between IV and expected returns for international developed markets. In a study on the G-7 countries, Guo and Savickas (2008) report a significant such relationship only for the U.S. and the U.K. markets. However, because of high integration between the developed stock markets, the U.S. idiosyncratic volatility negatively predicts international stock market returns. They also show that IV increased during the late 1990s and then went back to the pre-1990s level. While there are a handful of prior studies on the Australian market, there is a lack of agreement in their findings. For example, Gharghori et al. (2011) and Zhong and Gray (2016) find the usual negative IV-return relationship, whereas Bollen et al. (2008) and Liu and Di Iorio (2016) report a positive relationship.

Findings of Li et al. (2004), Morck et al. (2000) and Kearney and Poti (2008) observe a significant rise in IV in the most of the emerging markets during the 1990s. The degree of firm-specific information available in the emerging markets is lower than that in mature markets. Moreover, the availability of information also varies from one emerging market to another. Firm-specific information plays a significant role in contributing to the total variance of a company. In the absence of such information, financial analysts have to rely on the market as a whole (Bruner et al., 2003; Roggi et al., 2017).

Emerging markets also show the ability of IV to explain stock returns. In the absence of quality information in these markets, investors cannot completely rely on available information, resulting in over-dependence on firm-specific risk. India and China are the two most prominent emerging markets in the world at this moment. Nartea et al. (2013) present the evidence of a negative effect of IV on stock returns in China. Their finding contrasts with that of Nartea et al. (2011), who do not find any idiosyncratic volatility effect in the five largest Southeast Asian emerging markets (Singapore, Malaysia, Thailand, Philippines and Indonesia). Kumari et al. (2017) show how firm-specific characteristics can explain idiosyncratic volatility of non-financial firms in the Indian stock market. For the same market, Aziz and Ansari (2017) suggest a positive relationship between idiosyncratic volatility and future stock returns. They also show that this relationship is sensitive to firm characteristics such as firm size.

As the markets around the world reward the investors for the presence of idiosyncratic risk, some papers try to focus on the possible reasons for such phenomenon. Since the role of IV in explaining stock returns was accepted, the literature on the role of firm-specific characteristics that explains IV has been growing rapidly. Pastor and Veronesi (2003) show that the persistence of idiosyncratic risk changes during the life cycle of the firm. When firms are young and have volatile profitability, IV tends to have more impact on stock returns. Chen and Petkova (2012) note that IV depends on the use of estimated asset-pricing models. Portfolios with high (low) idiosyncratic risk based on the Fama-French (Fama and French,1993) model have positive (negative) contributions to innovations in average stock volatility and consequently lower (higher) expected returns. These findings are in line with those of Ang et al. (2006, 2009) and Berggrun et al. (2016). Argument for this finding is that stocks with high (low) IV lead to low (high) expected returns since average stock volatility has an inverse relationship with investment opportunities. Obviously, risk averse investors do not feel comfortable to invest when perceived risk is high.

Given that IV is an important contributor to arbitrage risk, Stambaugh et al. (2015) suggest that a negative IV-returns relationship should exist among the highly-overpriced stocks because short-selling becomes less (more) attractive for investors to correct overpricing of high (low) IV stocks. On the other hand, high arbitrage costs may discourage investors to have the requisite long positions to rectify underpricing, leading to a positive IV-return relation for underpriced stocks. They suggest that the combined effect of short-sale constraints and a reluctance of traders to have short positions results in relatively less capital being allocated to correct overpriced stocks. Thus, they hypothesize that the magnitude and persistence of the negative IV-return should lead to an

ultimate dominant outcome for overpriced stocks. In fact, this argument is able to explain some of the presences of idiosyncratic risk-return relationship in the emerging markets.

Aabo et al. (2017) investigate how market efficiency may have implications on firm-specific return volatility in the U.S. markets and their results indicate an important role of noise traders. They show that the level of market volatility determines the strength of association between absolute idiosyncratic volatility and mispricing. Using multiple markets, Morck et al. (2000) opine that strong property rights encourage informed arbitrage, which leads to more firm-specific information and high IV. Durnev et al. (2003) argue that relatively high idiosyncratic volatility is an indication of active trading by informed arbitragers, resulting in less spread between stock price and fundamental values. Furthermore, Jin and Myers (2006) in a comprehensive study on 40 countries provide evidence that if a firm is less transparent, insiders are able to capture more firm-specific risk.

Liu et al. (2019) find that there is a significantly positive relationship between idiosyncratic volatility and future returns in the Chinese market when Fama-French five-factor model (Fama and French, 1996) is used to estimate idiosyncratic volatility. Moreover, according to them, the power of idiosyncratic volatility depends on how this volatility measure is constructed. Using recent U.S. data, Qadan et al. (2019) show that the aggregate market volatility risk—captured by the VIX (an estimate of overall investor fear)—plays a significant role in the association between IV and stock returns. A rise (fall) in the VIX tends to be followed by a negative (positive) relationship between idiosyncratic volatility and risk-adjusted future returns. They are of the view that an increase in the investor fear may cast an increase in investors' risk aversion, encouraging them to balance their portfolios through more efficient diversification.

Umutlu (2019) examines the time-series nature of the relationship between aggregate global idiosyncratic volatility and market returns by considering various global proxies of aggregate idiosyncratic volatility. He finds an absence of relationship between the aggregate global idiosyncratic volatility and global market return. Obviously, his results indicate that international diversification is still effective in eliminating firm-specific risk.

Herding could be an important factor to affect idiosyncratic risk—especially in emerging and frontier markets. Vo and Phan (2019) investigate the impact of idiosyncratic volatility on the herd behavior of individual investors in Vietnam stock market. Their results indicate the presence of herding in this market. However, herding behavior displays clear patterns, which can be linked to the levels of idiosyncratic volatility. The results are robust under various timeframes around market crisis. Some studies also support the view that herd behavior influences market volatility and even leads to market instability (Scharfstein and Stein, 1990; Bikhchandani and Sharma, 2001; Spyrou, 2013; Guney et al., 2017). For the Japanese market, Chang and Dong (2006) show that institutional herding occurs for firms with high idiosyncratic volatility. This finding is also supported by Tan and Henker (2010) in their study on the Australian equity market.

RESEARCH DATA AND METHODOLOGY

Data

The sample of this study consists of daily stock return index data of 274 firms listed in Dhaka Stock Exchange (DSE), the largest stock exchange in Bangladesh. This study covers the period from January 2004 through December 2015. Returns are defined as the log difference of two daily (or monthly) consecutive stock return indexes times 100. We use both daily and monthly data. Data for stock return indexes and market capitalization are collected from DataStream[1].

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[1] We employ some caution while choosing and cleaning data for this study. In general, such caution is necessary whenever emerging market data are used. Since this study involves a single market, visual method is also applied to check data integrity. We had 448 firms reported in the raw file for return index for individual firms listed in the Dhaka Stock Exchange (DSE). There are some dead firms that have been excluded. In fact, DataStream mentions it in the firm heading (column) that the concerned firm has been delisted from the market at a certain point. We prefer cleaner data to the possibility of survivorship bias. Some columns of "#ERROR" are present, which have also been taken out. Any security besides equity is not considered. Any return over 200% in absolute value is ignored. Only in very few cases have we observed such outliers. Finally, if any stock is not traded for more than 24 months, it is dropped in order to avoid retention of stale information (and resultant autocorrelation). Finally, every stock must have returns data for at least 36 months to be eligible for inclusion in the sample because of two-step regression process of Fama-MacBeth (1973). Arguably, data for the period 2004-2015 can be considered more reliable than that for earlier periods. Visual observation as well as descriptive statistics show that data quality of DataStream, in general, have improved over time.

Computation of idiosyncratic volatility

Prior research provide evidence that the relationship between IV and returns maybe sensitive to the choice of idiosyncratic volatility measure. To overcome this, we employ three different measures of IV: first, realized monthly IV computed from the past daily autocorrelation of returns; second, realized monthly IV computed from daily residual returns; and third, expected (conditional) monthly IV computed from monthly time-series returns. Detailed methodology for the construction of IV is discussed below.

Realized idiosyncratic volatility computed from past autocorrelation of returns

To compute idiosyncratic volatility, we combine the methodologies used in French et al. (1987) and Goyal and Santa-Clara (2003) and estimate a 19-day rolling volatility for the market. We use 19-day period or window due to the less number of average trading days because of frequent Government holidays and political unrest in Bangladesh. Goyal and Santa-Clara (2003) estimate the monthly variance of stock i as follows:

$$V_{i,t} = \sum_{d=1}^{D_t} r_{i,d}^2 + 2 \sum_{d=2}^{D_t} r_{i,d} r_{i,d-1}, \tag{1}$$

where D_t is the number of trading days in month t and $r_{i,d}$ is the return of stock i on day d. The last term in equation (1) uses the methodology of French *et al.* (1987) to adjust for the autocorrelation in daily stock returns.

Realized idiosyncratic volatility computed from daily residual returns

Ang et al. (2006, 2009) estimate idiosyncratic volatility as the standard deviation of the residuals from the Fama and French three-factor model. Due to the lack of data on book value for a reasonable length we cannot compute high minus low (HML). Thus, we use the following modified (short) version of the Fama-French model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + \varepsilon_{it}, \tag{2a}$$

where t refers to approximately 19 trading days in a month. A firm's monthly idiosyncratic volatility is computed from the standard deviation of past 19 daily residual returns.

$$\sigma_{i,m}^2 = \frac{(\varepsilon_{i,t} - \bar{\varepsilon}_i)^2}{N-1} \tag{2b}$$

Expected idiosyncratic volatility computed from time-series returns

E-GARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) model given in equation (3a) and (3b) is used to compute expected (conditional) volatility. Since using the whole period to compute monthly expected volatility may provide biased estimates, we divide the whole period into two sub-periods and expected volatility series is constructed based on the returns characteristics in those two sub-periods. As mentioned earlier, the full Fama-French three-factor model cannot be used due to the lack of book value to market value data for the whole period of the study. Equation (2a) can be used as the mean equation in the following E-GARCH model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + \sigma_{it-1} + \varepsilon_{it} \quad and \tag{3a}$$

$$ln\sigma_{it}^2 = a_i + \sum_{l=1}^{p} b_{i,l} ln\sigma_{i,t-l}^2 + \sum_{k=1}^{q} c_{i,k} \left\{ \theta \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} + \gamma \left[\left| \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right| - \left(\frac{2}{\pi} \right)^{1/2} \right] \right\}, \tag{3b}$$

where σ_{it}^2 is the conditional volatility series based on p-period of residual variance and q-period of return innovations. We use E-GARCH (1,1) model for this study.

Fama-MacBeth (1973) regression for time-series cross-sectional regression

The IV series for individual stocks is used to conduct time-series and cross-sectional regressions. First, residual return series of every individual stock is regressed on respective volatility series. It gives monthly idiosyncratic volatility beta for each firm and then return is regressed on respective coefficients to find if "volatility" coefficients can explain cross-section of stock returns. Due to the short length of data, IV coefficients are

estimated using data of previous 24 months. This technique can show if IV can explain the cross-section of stock returns for Bangladesh market.

RESULTS AND DISCUSSION

Figure 1 shows the three measures of equally weighted volatility—realized volatility using French et al. (1987) and Goyal and Santa-Clara (2003) methodology (hereafter, *gsvol*), realized volatility using Ang et al. (2006, 2009) methodology (hereafter, *ahxzvol*) and expected volatility using E-GARCH models (hereafter, *egarchvol*) —employed in this study. All these volatility series are of monthly frequency. Overall, all of them follow similar path although expected volatility is usually stronger in magnitude than realized ones. Only for the period from June 2008 through June 2009, we see high expected volatility compared to realized volatility. In other periods (i.e., except for the period June 2008 through June 2009), the movements for all of them are much smoother as well as similar.
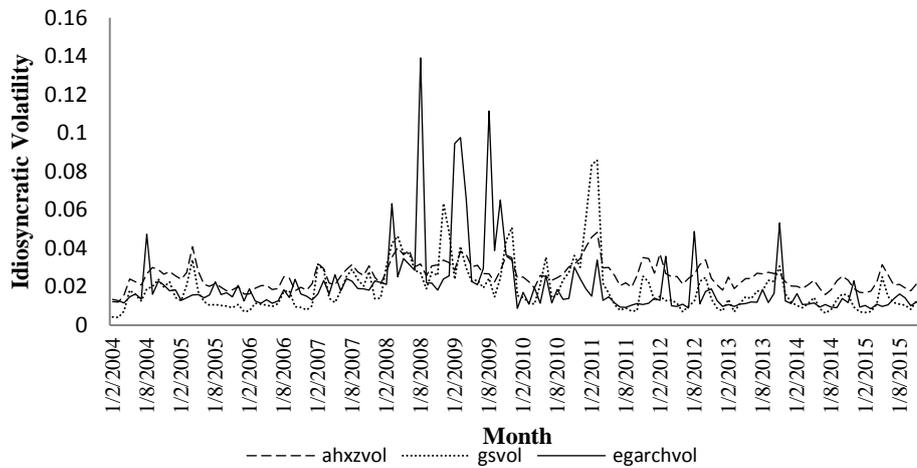

Figure 1 Monthly Idiosyncratic Volatility Series, 2004-15

Descriptive statistics of three idiosyncratic volatility series are given in table 1. Among the three volatility series, average monthly *gsvol* is the lowest and *ahxzvol* is the highest. Interestingly, *ahxzvol* has the lowest volatility (standard deviation) although its mean is the highest. The difference between *ahxzvol* and *gsvol* is somewhat striking as both of them represent realized volatility series. Low range of *ahxzvol* also suggests that the monthly values of this series are very close to its mean. As far as the distribution of these volatility series are concerned, they are positively skewed, meaning they are skewed to the right and there is presence of more observations in the left. High values of Jarque-Bera statistic imply that none of the volatility series is normally distributed.

Table 1 Descriptive Statistics of Monthly Idiosyncratic Volatility Series

	ahxzvol	*gsvol*	*egarchvol*
Mean	0.0256	0.0191	0.0209
Median	0.0252	0.0147	0.0152
Standard Deviation	0.0065	0.0134	0.0188
Sample Variance	0.0000	0.0002	0.0004
Kurtosis	0.7961	7.8165	16.9718
Skewness	0.7659	2.3833	3.7990
Jarque-Bera	28.83	137.00	1162.83
Range	0.0363	0.0819	0.1305
Minimum	0.0121	0.0040	0.0086
Maximum	0.0483	0.0859	0.1391
Obs. (months)	143	143	143

Note: This table provides the descriptive statistics of three different measures of idiosyncratic volatility: first, realized monthly IV computed from the past daily autocorrelation of returns (equation 1); second, realized monthly IV computed from daily residual returns (equations 2a and 2b); and third, expected (conditional) monthly IV computed from monthly time-series returns (equations 3a and 3b).

Table 2 provides the correlation between IVs, including their one-month lags. As far as the relationship between contemporaneous and lagged volatility is concerned, the correlation between *ahxzvol* and its lag is the highest (0.72) and that between *egarchvol* and its lag is the lowest (0.36). As both *ahxzvol* and *gsvol* are realized volatility, they seem to be highly correlated at 0.86. Correlation between both realized volatility and expected volatility series is about 0.34. Overall, findings reveal that all the volatility series used in the study are reasonably-correlated although they are formulated following different methodologies.

Table 2 Correlation among Volatility Series

	ahxzvol	ahxzvol lag	gsvol	gsvol lag	egarchvol	egarch lag
ahxzvol	1.0000					
ahxzvol lag	0.7241	1.0000				
gsvol	0.8575	0.6294	1.0000			
gsvol lag	0.6401	0.8609	0.6882	1.0000		
egarchvol	0.3424	0.2817	0.3370	0.2938	1.0000	
egarchvol lag	0.2926	0.3452	0.2517	0.3364	0.3618	1.0000

Note: This table provides the correlation between idiosyncratic volatility measures. There are three different measures of idiosyncratic volatility: first, realized monthly IV computed from the past daily autocorrelation of returns (equation 1); second, realized monthly IV computed from daily residual returns (equation 2a and 2b); and third, expected (conditional) monthly IV computed from monthly time-series returns (equation 3a and 3b).

Table 3 presents the results of regressions where individual stock returns are regressed on three individual idiosyncratic volatilities—*ahxzvol*, *gsvol* and *egarchvol*. Panel A uses *egarchvol* as the IV. Two models are used—one with lagged IV and other without lagged IV. These models have two stages of estimation. In the first stage, returns are regressed on IV and coefficients are collected and in the second stage, returns are regressed on coefficients. Results in panel A show that expected idiosyncratic volatility (*egarchvol*) strongly negatively explains the cross-section of contemporaneous returns.

De Long et al. (1991) suggests two effects of the increase of volatility on stock returns. The first is the direct effect of noise traders. These investors enter the market in wrong time and hence buy high and sell low, resulting in negative returns. This phenomenon is also known as "Friedman" effect. The second effect is called "create space" effect, which is also related to the presence of noise traders. In this case, noise traders increase market volatility through their variability of beliefs and consequently stock prices go down, resulting in an increase in stock returns. Overall impact depends on which effect dominates. Bangladesh market is highly dominated by uninformed individual investors who are expected to create noise. The significant negative coefficient of IV suggests the presence of "Friedman" effect. However, there is no relationship between lagged IV and cross-section of returns. In the second model in panel A, returns are regressed only on contemporaneous idiosyncratic volatility. In this case, even stronger negative impact of expected IV on cross-section of returns is observed.

Table 3 Fama-MacBeth Cross-sectional Idiosyncratic Volatility-Return Relationship

Variable	Mean	N	*t*-stat.
Panel A. Idiosyncratic Volatility Method (egarchvol): E-GARCH			
Intercept	0.0144	118	1.74[*]
Idiosyncratic Volatility	-0.0002	118	-2.55[**]
Lagged Idiosyncratic Volatility	0.0001	118	0.53
Intercept	0.0143	118	1.74[*]
Idiosyncratic Risk	-0.0003	118	-3.25[***]
Panel B. Idiosyncratic Volatility Method (gsvol): Goyal-Santa-Clara			
Intercept	0.0162	118	1.93[*]
Idiosyncratic Volatility	-0.0006	118	-2.35[**]
Lagged Idiosyncratic Volatility	0.0006	118	-1.34
Intercept	0.0152	118	1.80[*]
Idiosyncratic Volatility	-0.0004	118	-1.82[*]
Panel C. Idiosyncratic Volatility Method (ahxzvol): Ang, Hodrick, Xing and Zhang			
Intercept	0.0154	118	1.88[*]
Idiosyncratic Volatility	-0.0003	118	-1.11
Lagged Idiosyncratic Volatility	-0.0007	118	-1.81[*]
Intercept	0.0148	118	1.79[*]
Idiosyncratic Volatility	-0.0002	118	-0.97

Note: [*], [**], and [***] indicate significance at 10%, 5%, and 1% level, respectively. In this table Fama-MacBeth (1973) regressions are used to find the effect of idiosyncratic volatility on the cross-section of individual stock returns. This methodology is described in equations 4(a)-4(f). This table uses three different measures of idiosyncratic volatility: first, realized monthly IV computed from the past daily autocorrelation of returns (equation 1); second, realized monthly IV computed from daily residual returns (equation 2a and 2b); and third, expected (conditional) monthly IV computed from monthly time-series returns (equation 3a and 3b).

Panel B uses *gsvol* as the IV. Results are to some extent similar to that in Panel A. It also shows a strong negative impact of IV on the cross-section of expected returns. Unlike *egarchvol*, the impact of *gsvol* becomes weak when lagged volatility is not considered. The presence of "Friedman" effect is further evident when *gsvol* is used as the proxy for idiosyncratic volatility.

When *ahxzvol*—the other realized idiosyncratic volatility is used, results become weak. Although contemporaneous IV does not influence returns, lagged volatility negatively predicts returns with 10% significance level. When only contemporaneous volatility is considered in the model, there exists no relationship between returns and volatility. In all these three panels, the intercept term is significant at 10% level. The presence of weakly significant intercept terms implies the presence of returns attributed to the firms themselves, which are not explained by risk factors used in the study.

It is plausible that high volatility firms behave differently from low volatility firms do. For example, when sentiment is low or when risk averseness increases, investors may avoid risky firms and prefer to invest in low-volatility firms. Therefore, volatility is an important issue to detect the IV-return relationship. For this purpose, firms are sorted based on past volatility. Then, portfolios are constructed and their returns are computed. Portfolios are reconstructed in January every year and then followed through December of the respective year. That is, we are now examining how volatility-sorted portfolio returns react to idiosyncratic risk changes.

In the case of sorting based on the expected volatility (table 4, panel A), all the portfolios show significantly negative influence of IV on returns. This effect is particularly strong for medium and high volatility portfolios. Panel B and C use realized volatility and provide results similar to what we have found in panel A. Panel B shows significantly negative relationship between returns and IV for all the volatility-sorted portfolios based on Goyal-Santa-Clara method. In the previous table, we have considered individual firms and we have found idiosyncratic volatility could be important. In this table, portfolio returns are used and hence the idiosyncratic volatility is supposed to be diversified away. Therefore, the presence of inverse IV-return relationship is an interesting as well as important finding.

The strong significant negative relationship between IV and portfolio returns further corroborates the negative relationship found in table 3. Results for the volatility-sorted portfolios show that R^2 is the highest for high volatility portfolio, indicating relatively stronger power of IV to explain the returns of riskier firms. As before, volatility-sorted portfolios also show the presence of "Friedman" effect in the Bangladesh market. However, in this case (panel C), intercept terms of all the portfolios are strongly significant, implying the presence of firm-specific returns for all the portfolios, which are not sensitive to firm-specific and market risk. Interestingly, the IV-returns relationship is not that much different across portfolios with different volatility level. Our take on this is that low-volatility firms should have better information dissemination ability and possibly investors have more consensus about their return generation and hence the low-volatility portfolio should be less-sensitive to idiosyncratic risk. Hence, this finding confirms our initial guess.

Table 4 Effect of Idiosyncratic Volatility on Volatility-sorted Portfolio Returns

Variables/R^2	Low	t-stat.	Medium	t-stat.	High	t-stat.
Panel A. Sorting based on E-GARCH method						
Intercept	0.0045	1.96**	0.0053	3.16***	0.0026	3.06***
Idiosyncratic Volatility	-1.4219	-2.34**	-1.4669	-3.86***	-0.7674	-5.31***
R^2	0.04		0.09		0.17	
Panel B. Sorting based on Goyal-Santa-Clara method						
Intercept	0.1157	1.85*	0.1032	1.56	0.0668	0.93
Idiosyncratic Volatility	-0.0078	-4.52***	-0.0081	-4.63***	-0.0072	-5.15***
R^2	0.13		0.13		0.16	
Panel C. Sorting based on Ang, Hodrick, Xing and Zhang method						
Intercept	0.0030	3.05***	0.0032	2.98***	0.0029	2.56**
Idiosyncratic Volatility	-0.3909	-3.99***	-0.3817	-4.19***	-0.3843	-4.48***
R^2	0.10		0.11		0.12	

Note: *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively. This table uses three different measures of idiosyncratic volatility: first, realized monthly IV computed from the past daily autocorrelation of returns (equation 1); second, realized monthly IV computed from daily residual returns (equation 2a and 2b); and third, expected (conditional) monthly IV computed from monthly time-series returns (equation 3a and 3b). Volatility-sorted portfolios are reconstructed at the beginning of every year. Portfolios are constructed based on the IV of individual firms.

Just like the volatility of firms, size could play a role in the IV-returns relationship too. Especially, in a frontier market such as Bangladesh, large firms are different from the rest mainly due to the scarcity of transparent and reliable firms. Information asymmetry is a problem due to lax financial reporting system, weak monitoring by regulatory authority, media coverage and lack of professional advice from finance experts. This kind of common feature of emerging and frontier markets generally pushes investors toward relatively-safer large firms. In this perspective, table 5 examines if the IV-returns relationship can be explained by the size of firms. Estimations in panel A uses E-GARCH model to construct expected volatility series. Significantly negative impact of IV on the returns of small and large portfolios is observed. Panel B shows that portfolio returns—regardless of size—are negatively related to idiosyncratic volatility at 1% level of significance.

Table 5 Effect of Idiosyncratic Volatility on Size-sorted Portfolio Returns

Variables/R^2	Small	t-stat.	Medium	t-stat.	Large	t-stat.
Panel A. Volatility series based on E-GARCH method						
Intercept	0.0097	3.05***	-0.0004	-0.22	0.0049	1.94*
Idiosyncratic Volatility	-2.8817	-3.20***	-0.1509	-0.34	-1.7740	-2.39**
R^2	0.07		0.00		0.04	
Panel B. Volatility series based on Goyal-Santa-Clara method						
Intercept	0.1761	-2.67***	0.0671	-0.85	0.0163	-0.24
Idiosyncratic Volatility	-0.0116	-6.05***	-0.0057	-3.89***	-0.0063	-3.30***
R^2	0.21		0.10		0.07	
Panel C. Volatility series based on Ang, Hodrick, Xing and Zhang method						
Intercept	0.004	3.75***	0.0025	2.01**	0.0021	2.12**
Idiosyncratic Volatility	-0.4817	-4.84***	-0.3141	-3.42***	-0.3621	-3.73***
R^2	0.14		0.08		0.09	

Note: *, **, and *** indicate significance at 10%, 5%, and 1% level, respectively. This table uses three different measures of idiosyncratic volatility: first, realized monthly IV computed from the past daily autocorrelation of returns (equation 1); second, realized monthly IV computed from daily residual returns (equation 2a and 2b); and third, expected (conditional) monthly IV computed from monthly time-series returns (equation 3a and 3b). Size-sorted (based on market value of individual firms) portfolios are reconstructed at the beginning of every year.

The most intriguing finding is that small-size portfolio returns are significantly explained by both itself and idiosyncratic volatility. This result makes sense because there should be more information asymmetry for small firms, which may mislead investors to diversify idiosyncratic risk, contributing to the tendency of the market to price firm-specific risk. Moreover, significant intercept term for small firms suggests that both firm-specific and market risk cannot explain all the returns of the size portfolios. Results in panel C do not change that much from previous panels. The stronger ability of the IV to explain returns of small firms is again evident. Thus, there is a significant impact of IV on small-size portfolio returns—no matter what method of volatility is used. As suggested by R^2s between the two realized volatility models, it seems that earlier method captures the returns of size portfolios better.

CONCLUSIONS

In this study we utilize three methods of idiosyncratic volatility to investigate whether or not idiosyncratic volatility (firm-specific risk) can explain returns of individual stock and portfolio returns in Bangladesh stock market. We find that investors fail to diversify their portfolios so that firm-specific risk can be totally diversified away. Furthermore, we also find negative contemporaneous relationship between idiosyncratic volatility and returns both for portfolios and individual stocks. Results remain unchanged regardless of the methodologies used to measure idiosyncratic volatility.

Our results are reasonably robust to firm characteristics such as volatility and size. In a frontier market such as Bangladesh where uninformed, retail investors dominate trading, it is not a surprising result—especially when we have the evidence of pricing of idiosyncratic volatility even in the developed markets. Overall, idiosyncratic volatility is negatively related to stock returns, a phenomenon, which indicates the presence of "Friedman" effect. That is, noise traders enter the market in wrong time by buying high and selling low, resulting in negative returns.

The presence of impact of firm-specific risk on stock returns indicates sub-optimal asset allocations in investors' portfolios. Policy makers should encourage more institutional participation in Bangladesh market through various financial motivations such as tax relief. More participation by institutional investors will automatically reduce such phenomenon due to their better ability to diversify risk.

Finally, we conclude that firm-specific risk is priced in Bangladesh stock market. Investors will be better off if they consider firm-specific risk in their asset pricing models. Without further studies on other frontier and emerging markets, results of this study cannot be generalized because our results may be related to some unknown peculiarity of the Bangladesh investment environment. Obviously, future research may shed more light on how other frontier markets behave with respect to firm-specific risk-return relationship.

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