Idiosyncratic volatility and stock returns: evidence from Colombia

Abstract. The purpose of this paper is to examine the association between idiosyncratic volatility and stock returns in Colombia from 2004 to 2013. Our methodology entails both assessing the performance of portfolio strategies that rely on one- or two-way sorts, and conducting errors-in-variables-free panel regressions. We are unable to document a relationship between idiosyncratic risk and stock returns in the sample period. In all, unsystematic risk is not a priced factor in Colombia in line with predictions of the CAPM and Fama et al. (1993) models and recent literature in the U.S. market. From a practical perspective, investors in Colombia's stock market were not able to profit by assuming higher levels of diversifiable risk in their portfolios.

Introduction and literature review

Since Fama et al. (1973) pioneer work that showed that idiosyncratic volatility (IVOL) is not a priced factor in the U.S. (in line with predictions of the CAPM model of Sharpe (1964) and Fama et al. (1993) three-factor model) several studies have attempted to understand the role of IVOL (if any) in explaining one-period ahead returns. Thus far previous findings are mixed pointing to a negative, positive, or a non-existent association between IVOL and future returns. Ang et al. (2009) show evidence of a negative (perhaps puzzling) relationship between lagged idiosyncratic volatility and future excess returns using monthly data for a sample of stocks from developed countries. This finding is similar to one reported by the same authors for the U.S. (see Ang et al. (2006)). Peterson et al. (2011) also find a negative relationship between lagged (or realized) IVOL and returns (for all months except January) in the U.S. Furthermore, Chen L. H. et al. (2012) document that the negative (and significant) alpha for a value-weighted portfolio, long on high past IVOL and short on low IVOL common stocks, tends to be quite ubiquitous. The negative spread is present for a subsample of both large and small stocks as well as for subgroups of stocks determined by prices ranges (e.g., the negative alpha is shown to be highly significant for portfolios of stocks with prices that range from $5 to $10 USD). In addition, they find that the indirect relationship between idiosyncratic

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volatility and returns is significant even after controlling for the effect of past (monthly) returns into current month returns. In the same venue, Guo et al. (2010) find that, controlling for size (usually small stocks show higher IVOL than large stocks); portfolios of high IVOL stocks underperform in risk-adjusted terms portfolios of low IVOL stocks. Furthermore, they show that in pricing regressions a factor related to idiosyncratic risk (returns of a portfolio long in low IVOL stocks and short in high IVOL stocks) appears, in the cross section, positively related to stock returns.

Two recent papers provide possible explanations for the negative association (or IVOL anomaly) between IVOL and returns. Han B. et al. (2013) show that retail investors tend to hold high IVOL stocks (usually overpriced) due to the speculative features (e.g., high idiosyncratic skewness and low price) of these assets. High retail trading proportion stocks in turn, tend to significantly underperform stocks that are predominantly traded by institutional investors. In all, the proportion of retail investing appears related to the puzzling negative association between IVOL and return. Meanwhile Avramov et al. (2013) document that several pricing anomalies (and in particular, the IVOL anomaly) are more salient in the worst credit-rated stocks. In particular, the short side of the IVOL strategy tends to profit around price decreases following credit rating downgrades. When Avramov et al (2013) exclude low-rated stocks or periods around downgrades the profitability of the IVOL long-short portfolio vanishes. Thus, financial distress appears as an important driver of the IVOL anomaly.

For emerging markets, the issue of the pricing ability of IVOL has unfortunately attracted less attention. Two studies that also find a negative association between past IVOL and returns are those of Lee et al. (2012) and Nartea et al. (2013). Lee et al. (2012) document a negative relationship between lagged IVOL and expected short-run returns for stocks listed in the Hong Kong Exchange. They claim (based on Shleifer et al. (1997)) that low idiosyncratic

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risk stocks are more profitable since arbitrageurs, being risk-averse in the short run, usually tilt their portfolios to low volatility shares causing an upswing in trading volume and prices for this particular type of stock. Nartea et al. (2013) report a negative relationship between risk-adjusted returns and IVOL (measured as in Ang et al. (2006 and 2009)) in China. This negative association might be related to a behavioral tendency of Chinese investors (many of them retail investors) who are prone to overpay for high volatility or speculative stocks that ultimately underperform.

A different set of studies reports a direct, perhaps more intuitive, relation between IVOL and one-step ahead returns. Malkiel et al. (2004) document a positive association between stock returns and past IVOL using Fama et al. (1973) portfolio formation methodology. Interestingly, they show that this association is stronger than the one between returns and beta (or size). In addition, Fu (2009) shows evidence of a positive relationship between expected IVOL (proxied by a one-step forecast from an EGARCH model) and expected (monthly) returns. Fu's (2009) results starkly contrast with findings in Ang et al. (2009). He criticizes the use of past or realized IVOL as a proxy for expected IVOL and shows that the negative relationship between returns and idiosyncratic volatility (Ang et al (2009)) is related to the return reversal of high idiosyncratic volatility (and especially high past returns) stocks. Once past returns are controlled for, the negative relationship between average returns and lagged IVOL breaks.

Also in the U.S. market, Huang et al. (2010) find a positive relation between monthly returns and IVOL (estimated with a rolling window of thirty months of returns and using an exponential GARCH model). The positive relationship between expected returns and idiosyncratic volatility can be understood based on Merton (1987) model that shows that undiversified investors will ask for a premium to hold high IVOL stocks. In consequence, these high IVOL stocks will bring about higher expected returns. Vozlyublennaia (2012)

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documents an overall positive and significant relationship between returns and lagged IVOL (see table 3 of her paper). She is able to determine which characteristics are more conducive of a positive correlation between returns and IVOL. In particular, large companies with low leverage, and high share turnover and cash are more likely to show a positive association between IVOL and returns.

Recently, Eiling (2013) presents evidence of a positive risk-adjusted spread between high and low IVOL stocks and argues that the premium is related to human capital. She claims that conventional pricing models by omitting factors (that end up in the residual) associated to industry-specific human capital (proxied by the growth rate in wages of several representative industries) distortion the role of IVOL in explaining returns. In all, a significant portion (e.g., up to 36%) of the IVOL premium appears to be related to a compensation for bearing nontradable human capital risk instead of company specific risk (in fact, high IVOL portfolios showed a positive and significant exposure to human capital factors and vice versa).

On the other hand, some of the literature supports the idea that IVOL is not significantly associated with future stock returns. For example, Bali et al. (2008) are not able to find a significant (and consistent) relationship between IVOL and average returns (or Fama et al. (1993) three factor alphas). Even though they report a negative and significant relationship between IVOL and average returns under certain portfolio configurations, the association disappears when they omit the smallest, lowest priced, and least liquid stocks. Fink et al. (2012) show that IVOL (out-of-sample) forecasts using returns' information up to time t-1 (i.e., using the information that in practice is available to a portfolio manager) are not informative of future (one-month ahead) returns. Controlling for liquidity effects, Han Y. et al. (2011) find that a hedge portfolio long on high IVOL (or residual IVOL calculated after purging the effect on IVOL of both the bid-ask spread and the percentage of zero returns)

stocks and short on low IVOL (or residual IVOL) stocks delivers a zero alpha after controlling for market, size, distress, and momentum effects. Furthermore, Jiang et al. (2009) show that controlling for future earning shocks the association between returns and IVOL disappears. In all, their evidence points to the fact that IVOL predicts returns through information on future earnings.

In addition, Chen Z. et al. (2012) argue that the negative relationship documented by Ang et al. (2006 and 2009) between IVOL and returns is a byproduct of an omitted risk factor (since the residual captures the effect on an omitted variable). As a first step to find this omitted factor, they decompose total market variance into average (value-weighted) stock variance and average correlation. Empirically they show that the omitted factor relates only to the pricing of average variance. Importantly, when both average variance and IVOL are included in a pricing model, only the former variable has a significant role in explaining excess returns.

We contribute to the literature by expanding the evidence on the IVOL and one-month ahead return association. More specifically, we examine the explanatory power of realized IVOL in foretelling future returns. We analyse an emerging market in which little or no evidence on the subject has been presented before in a period in which Colombia's stock market has witnessed an important increase in the volume of transactions. According to the World Federation of Exchanges, the market capitalization of listed shares increased 682% from January 2005 to December 2013. Moreover, the value of shares traded almost doubled in the same period. In addition, the Colombian stock market is for about three years a partner of the integrated trading venture between Chile, Colombia, and Peru stock exchanges (better known by its Spanish acronym: MILA or Latin American Integrated Market). MILA, the second largest market in Latin America and the Caribbean after Brazil, offers investors in the region wider diversification opportunities. Nonetheless, the Colombian stock exchange is far from being a

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liquid and deep market and it may well resemble the setup of Merton (1987) model in which investors are unable to diversify perfectly and may require compensation (in terms of higher returns) for bearing some company-specific risk.

In this paper, we begin by exploring the association between realized IVOL (estimated as the standard deviation of the residual of the Fama et al. (1993) model using daily data) and monthly returns. We first notice that high IVOL stocks usually are small and illiquid stocks. Examining the performance of a portfolio strategy that is long on high IVOL stocks and short on low IVOL stocks in Colombia, we find that IVOL does not carry a significant (and direct) ability to forecast in-sample returns. The alpha of the long-short IVOL portfolio is not statistically significant implying that investors were unable to profit from a non-systematic risk pricing anomaly during the sample period.

We then explore, whether controlling for several systematic risk factors and firm or stock attributes commonly suggested in the literature, affects the association between monthly returns and realized IVOL. Adopting Brennan et al. (1998) errors-in-variables-free panel regression methodology, we reconfirm that realized IVOL is unrelated to future (one-step ahead) returns. After controlling for systematic risk factors, and size, past return, and liquidity effects, the coefficient of realized IVOL is statistically insignificant in a regression that explains monthly returns.

We conclude (in line with findings of Bali et al. (2008), Jiang et al. (2009), Han Y. et al. (2011), Chen Z. et al. (2012), and Fink et al. (2012) in the U.S.) that IVOL has a non-significant ability to forecast future returns both within a univariate (using one-way sorted portfolios) and a multivariate context in Colombia. A battery of robustness tests lends further credence to our results.

2. Data

2.1 Sample

We use daily prices in U.S. dollars, adjusted for dividends and splits, of all Colombian stocks included in Bloomberg. The estimation period spans from November 2004 to December 2013 for a sample of listed and delisted stocks. We apply two filters to our sample. We exclude stocks with less than one year (250 days) of trading data (as in Asness et al. (2009)), and delete stocks with gaps or unreported information of price data of up to a month. In all, our sample includes information of 31 securities.

We also gather information on the number of outstanding and traded shares for our sample of Colombian stocks. Moreover, to obtain Fama et al. (1993) factors, we proxy the SMB ("small minus big") factor as the return difference between the MSCI small cap index (Bloomberg ticker: MSLUCOLN) and the MSCI large cap index for the country (Bloomberg ticker: MLCUCOLN). In a similar way, we proxy the returns for a HML ("high minus low") portfolio as the return difference between MSCI value and growth indices for Colombia (Bloomberg tickers: MVUECO and MGUECO).

Following Ang et al. (2006 and 2009), we estimate IVOL for a month as the standard deviation (σ) of the residuals of the Fama et al. (1993) pricing model. Every month we estimate for each stock i the following regression with daily (i.e., intra-monthly) data:

$$R_t - Rf_t = \alpha_i + b_i(Rm_t - Rf_t) + s_i Rsmb_t + h_i Rhml_t + e_t \qquad (1)$$

Where R_t and Rf_t are the daily return (R) for stock i and the risk free rate for a daily horizon respectively. We term the difference between the two as excess returns for stock i (in the left hand side of equation (1)). Rm_t is the return on the market index while $Rsmb_t$ is the return of the SMB portfolio. $Rhml_t$ stands for "high minus low" book-to market portfolio returns and e for the residual. To prevent biases arising from infrequent trading (Dimson (1979)), we expand the right hand side of equation (1) with one-period lagged values of Rm_t, $Rsmb_t$, and $Rhml_t$. We then convert the daily IVOL estimate (σ_e) to monthly by multiplying by the square root of the number of trading days in a month.

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2.2 Descriptive statistics

Table 1[1] includes descriptive statistics of our variables. Focusing on our set of independent variables, the mean value of monthly IVOL is 5.9% (or roughly 20% per annum), which is lower than the value reported by Ang et al. (2009) for a sample of developed countries. Mean alpha is positive (but close to zero) while the loading on the market and a size factor are on average positive. Nonetheless, the average loading on a distress factor turned out negative (either its mean or median value).

The last three lines of Table 1 show descriptive statistics of our control variables. The median firm has a market capitalization of $4.8 billion but firm size fluctuates considerably as the 10 and 90 percentiles of the distribution assert. We also control for past returns (as in Han Y. et al. 2011) using six-month momentum returns. This control variable (in t) is the return from month -2 to month -6. For example, we use the period from January to May to estimate a six-month momentum return for July. The typical firm had an average of 6.5% six-month momentum returns. In addition, we control for liquidity by using Amihud's (2002) illiquidity measure. We take the average over the whole month of the absolute daily return over the dollar traded volume (and multiply this ratio by 10,000 for presentation purposes). It is evident that our illiquidity variable shows a considerable degree of kurtosis.

3. Idiosyncratic volatility and stock returns: portfolio analysis

In this section we study whether lagged idiosyncratic risk is priced. The lack of diversification opportunities in Colombia given the low number of stocks and industrial sectors represented in the stock market may drive investors to require a premium for holding unsystematic risk.

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[1] Some tables are omitted to conserve space.

To assess the effect of diversifiable risk into stocks returns, we begin by classifying each month the available stocks into two portfolios. The first portfolio (P1) comprises stocks with IVOL below the median IVOL of all stocks in the month while the second (P2) comprises stocks with above median IVOL. Each stock is assigned an investment weight proportional to its market capitalization during the previous month. In addition to value-weighted portfolios, we also use equally weighted portfolios to gain a clearer perspective on the impact of IVOL on stock returns.

After the ranking and portfolio construction process, we track the monthly returns of the two portfolios in the next period (holding or evaluation period) we formed the portfolios. This ranking and evaluation procedure is repeated until the end of the sample. As a result, we obtain two stacked time-series of monthly returns for our IVOL portfolios. With the time series of portfolio returns, we estimate alphas (or intercepts) from the Fama et al. (1993) model (see equation (1))) using Newey et al. (1987) standard errors. As a robustness check, we also use two- and three-month ranking and evaluation periods.

Alphas for the two portfolios (j= 1, 2) and for a long-short portfolio become our measures of interest to examine whether bearing higher IVOL commands higher risk-adjusted returns. The long-short (or spread) portfolio invests in high IVOL stocks, and takes a short position in low IVOL stocks. We will focus on the sign and significance of the spread to conclude about the role of unsystematic risk on stock returns. A positive and significant alpha for the long-short portfolio would be then evidence that investors bearing more IVOL are actually compensated with higher returns after accounting for risk.

Table 3 shows our results for our IVOL portfolios. Panel A shows that low IVOL portfolios yield positive and significant alphas. High IVOL portfolios alphas are significant only at a monthly and quarterly interval. In a stark contrast to findings of Ang et al. (2006 and 2009) for the U.S. and some developed markets, the alphas to our zero investment cost portfolios

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(P2-P1) in Colombia are not statistically significant. Our results of a zero abnormal return to an arbitrage portfolio based on past IVOL agree with recent findings of Han Y. et al. (2011), and Fink et al. (2012) in the U.S. market.

Table 3. Alphas of lagged IVOL portfolios

Panel A. Value-weighted portfolios

	P1	P2	P2-P1
One month	0.010***	0.007**	-0.003
	[0.000]	[0.015]	[0.533]
Two months	0.007**	0.006	-0.000
	[0.011]	[0.208]	[0.981]
Three months	0.005**	0.010*	0.006
	[0.049]	[0.064]	[0.352]

Note: P1 (portfolio 1) includes the stocks with the lowest IVOL while P2 includes stocks with the highest IVOL. p-values for two-sided tests of zero alpha using Newey et al. (1987) standard errors are reported in brackets below alpha estimates. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

4. Idiosyncratic volatility and stock returns: regression analysis

Our portfolio analysis (univariate in nature) has a major drawback since we can only assess the impact of one variable (IVOL) into another variable (returns) without controlling for the effect of other variables which are likely to affect stock performance. To amend this problem we retort to regression analysis with our panel of monthly data. We follow Brennan et al. (1998) errors-in-variables-free methodology that comprises two steps. In the first step we calculate risk-adjusted returns (R_t^*) for each month t as the difference between realized (excess) returns in the month and expected returns using the coefficients related to systematic risk factors estimated from equation (1). Risk-adjusted returns are then equal to:

$$R_t^* = R_t - Rf_t - \hat{b}(Rm_t - Rf_t) - \hat{s}Rsmb_t - \hat{h}Rhml_t \qquad (2)$$

We use a conditional approach to get our coefficient estimates $\hat{b}, \hat{s},$ and $\hat{h}$ to apply in equation (2). We use a fixed-length rolling window of 24 months (a stock must trade for at least 80% of the months in the window) to retrieve coefficient estimates from equation (1). In particular, we use data from excess returns and returns on the market, size, and distress factors from

November, 2004 to October, 2006 to estimate regression coefficients and obtain expected returns for November, 2006. We repeat this process for each month (t) and stock (i) in the sample to obtain $R_{i,t}^*$.

In the second step, and in the spirit of Fama et al. (1973) approach, we run the following cross-sectional regression in each month:

$$R_i^* = \gamma_0 + \gamma_1 IVOL_{i,t-1} + \gamma_2 Cap_{i,t-1} + \gamma_3 Momentum_{i,t-1} + \gamma_4 Amihud_{t-1} + \varepsilon_i \qquad (3)$$

Instead of OLS (ordinary least squares) regressions that assign the same weight on either small or large cap stocks, we perform GLS (generalized least squares) regressions assuming uncorrelated errors and weights equal to the inverse of the market cap of the firm. This weighting scheme reduces the influence of small stocks in the excess returns and IVOL relationship. Ang et al. (2009) argues that these value-weighted regressions mirror value-weighted portfolios, while the standard (OLS) regressions resemble equally-weighted portfolios.

We use three control variables (motivated by the previous literature and data availability). These three variables control for firm attributes. We use the (one-month) lagged value of the natural logarithm of market cap to account for the fact that according to the international literature small companies usually experience higher returns than large firms. We also control for past returns (as in Han Y. et al. 2011) using six-month momentum returns. This control variable (in t) is the return from month -2 to month -6. For example, we use the period from January to May to estimate a six-month momentum return which in turn serves as a right hand side variable for excess returns in July. Han Y. et al. (2011) argue that disregarding microstructure or liquidity-related effects (like the bid-ask bounce) inflates or deflates the estimates of IVOL and subsequently bias the sensitivity of expected returns to IVOL. To cancel out these microstructure effects they estimate IVOL using bid-ask midpoint closing prices instead of closing prices and find that lagged IVOL is not a priced factor. Given data

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availability, we are able to indirectly (and roughly) control for these liquidity-induced effects by using the lagged (one-month) natural logarithm of the Amihud (illiquidity) measure.

The interest of the second step lies in obtaining the values of the γ coefficients that are usually interpreted as premia. γ_1 represents the premium for bearing unsystematic risk, while γ_2, γ_3, and γ_4 represent size, past returns, and liquidity premia respectively. Our main focus is on the sign and significance of γ_1 to conclude whether idiosyncratic risk is a determining factor of stock returns in Colombia.

Next, we average the γ coefficients across months. The mean values of the γ coefficients are used for inference purposes. To obtain p-values for our coefficients, we use coefficients' standard errors based on Newey et al. (1987) heteroskedasticity and autocorrelation consistent variance-covariance matrix. Nonetheless, our inferences are in a vast majority of cases similar when we estimate standard errors just as the (sample) standard deviation of the estimated γ (monthly) coefficients.

In Table 6 we use six specifications to analyze the relationship between lagged IVOL and stock returns. In the first three specifications we use excess returns as our dependent variable (and as a first benchmark) to study whether diversifiable risk commands higher returns. "Error-in-variables" problems (e.g., coefficient biases) would arise if we were to include in the second step of Brennan et al. (1998) panel regression methodology estimated coefficients ($\hat{b}$, $\hat{s}$, and $\hat{h}$) of the first step in equation (3) to control for non-diversifiable risk factors. In the last three models we use risk-adjusted returns as our left hand variable to account for systematic risk factors and to avoid "errors-in-variables" issues.

In the first model we use $IVOL_{t-1}$ as the sole explanatory variable. In line with our findings of panel A of Table 3, $IVOL_{t-1}$ is unrelated to excess returns of month t. The coefficient (-0.005) indicates that investors perceive a decrease of 0.5% in excess returns per 1% increase in a stock's idiosyncratic volatility. Nonetheless, the coefficient is not statistically significant.

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Specification 2 expands specification 1 by including size. In section 3 we found that small firms usually experience higher idiosyncratic volatility. Controlling for size, the coefficient of $IVOL_{t-1}$ remains statistically insignificant. We find a negative and significant coefficient for size implying a premium for small stocks. Thus, using unadjusted (excess) returns, we document a "size effect" in Colombia. The third model augments specification 2 by controlling by firm attributes which have been shown to affect returns. Past momentum returns appear unrelated to excess returns in line with evidence in Berggrun et al. (2011) who do not find a momentum effect in Colombia. The coefficient attached to illiquidity (proxied by Amihud's measure) does not attain statistical insignificant. In short, none of the coefficients attached to control variables (except for size) yielded significant values. Importantly, lagged IVOL remains in our third model unrelated to excess returns in month t.

We document an increase in the (average) adjusted R^2 as we expand the number of covariates. The final two rows of Table 6 report the number of months in which we conduct cross-sectional regressions and the average number of firms with available information in the monthly regressions.

The last three specifications of Table 6 employ the same covariates as in the first three specifications but modify the dependent variable. The coefficient on $IVOL_{t-1}$ continues to be insignificant in the last three specifications. Using risk-adjusted returns the premium for size now vanishes. Our remaining control variables (momentum and Amihud) keep their signs and lack of significance. In all, even after controlling for systematic risk factors and firm or stock attributes, we are unable to document a significant association between unsystematic risk and future excess returns.

In sum, using either an unconditional approach (as in section 3) or a conditional approach (as the one of this section), we are unable to verify that investors in Colombia profited from bearing higher idiosyncratic volatility levels in their portfolios. The risk-adjusted returns of

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low and high IVOL portfolios were basically the same and any premium from withstanding higher diversifiable risk was not distinguishably different from zero. Moreover, we find that the pricing model of equation (1) does an adequate job explaining stock returns. The intercepts in our regressions using risk-adjusted returns as our dependent variable turned out insignificant and none of the variables related to stock or firm characteristics (i.e., beyond systematic risk factors) achieved statistical significance.

We conclude (in line with findings of Bali et al. (2008), Jiang et al. (2009), Han Y. et al. (2011), Chen Z. et al. (2012), and Fink et al. (2012) in the U.S.) that IVOL has a non-significant ability to forecast future returns both within a univariate (using one-way sorted portfolios) and a multivariate context in Colombia.

Table 6. Panel regressions of stock returns on lagged idiosyncratic volatility

Dependent variable	Excess returns	Excess returns	Excess returns	Risk adjusted returns	Risk adjusted returns	Risk adjusted returns
Intercept	0.023**	0.025**	0.004	0.006	0.004	0.003
	[0.026]	[0.011]	[0.828]	[0.377]	[0.605]	[0.849]
$IVOL_{t-1}$	-0.005	-0.014	0.140	0.021	0.057	0.150
	[0.964]	[0.876]	[0.220]	[0.878]	[0.666]	[0.348]
Cap_{t-1}		-0.005*	-0.006**		-0.002	-0.002
		[0.065]	[0.020]		[0.334]	[0.393]
Momentum			-0.012			-0.022
			[0.406]			[0.544]
$Amihud_{t-1}$			-0.002			-0.001
			[0.347]			[0.684]
R^2	0.080	0.170	0.242	0.043	0.103	0.208
T.	108	108	103	86	86	86
N.	21	21	21	19	19	19

Note: Cap and momentum stand for market capitalization and six-month momentum returns respectively. T is the total number of monthly regressions. R^2 stands for the mean R-squared of the T monthly regressions. N is the average number of firms in the T cross-sectional regressions. p-values for two-sided tests of a zero regression coefficient using Newey et al. (1987) standard errors are reported in brackets below coefficient estimates. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

6. Conclusions

This paper analyses the association between stock returns and lagged IVOL for a sample of Colombian stocks in the 2004-2013 period. We examine whether shareholders require

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compensation (in terms of higher returns) for bearing some company-specific risk in a market (as in Merton (1987)) where investors are likely to be unable to diversify perfectly. We contribute to the current debate on the role of idiosyncratic risk in shaping expected stock returns, and by and large, on the extent and significance of pricing anomalies in an emerging stock market.

We first recreate a portfolio strategy that invests in high IVOL stocks and shorts low IVOL stocks. If investors get compensated for assuming higher unsystematic risk the alpha of this long-short portfolio should be positive and significant. However, we are not able to document a significant spread for this long-short portfolio implying that investors in Colombia were not able to profit by assuming diversifiable risk (in line with predictions of the CAPM or Fama et al. (1993) models where only systematic risk is priced). In one of our robustness checks we extend our portfolio strategy to two-way sorted portfolios. This approach allows us to control by one characteristic and then explore the association between IVOL and stock returns. Controlling for either size, past returns, or liquidity effects, we confirm the inability of lagged IVOL in forecasting future stock returns.

We then move to a multivariate setting using Brennan et al. (1998) panel regression methodology. Using both unadjusted (excess) or risk-adjusted returns, we do not find a significant coefficient attached to our idiosyncratic volatility proxy. IVOL is not statistically significant in univariate or bivariate regressions (that mirror our results for one- and two-way sorted portfolios) nor in more extensive regression models that control for systematic risk factors as well as size, return continuation, and illiquidity effects. In all, we are not able to document any idiosyncratic volatility effect in our sample since the association between lagged IVOL and current stock returns is non-existent in Colombia.

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