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High idiosyncratic volatility and low returns: International and further U.S. evidence ☆

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ABSTRACT

Stocks with recent past high idiosyncratic volatility have low future average returns around the world. Across 23 developed markets, the difference in average returns between the extreme quintile portfolios sorted on idiosyncratic volatility is −1.31% per month, after controlling for world market, size, and value factors. The effect is individually significant in each G7 country. In the United States, we rule out explanations based on trading frictions, information dissemination, and higher moments. There is strong covariation in the low returns to high-idiosyncratic-volatility stocks across countries, suggesting that broad, not easily diversifiable factors lie behind this phenomenon.

1. Introduction

In a recent paper, Ang, Hodrick, Xing, and Zhang (2006) (AHXZ hereafter) show that volatility of the market return is a priced cross-sectional risk factor. After demonstrating this fact, AHXZ sort firms on the basis of their idiosyncratic stock return volatility, measured relative to the Fama and French (1993) model. They reason that the idiosyncratic errors of a misspecified factor model could contain the influence of missing factors, and hence, by sorting on idiosyncratic volatility, they might develop a set of portfolios that would be mispriced by the Fama and French (1993) model but that might be correctly priced by the new aggregate volatility risk factor. AHXZ find that U.S. stocks with high lagged idiosyncratic volatility earn very low future average returns, and these assets are indeed mispriced by the Fama-French model.

The AHXZ results are surprising for two reasons. First, the difference in average returns across stocks with low and high idiosyncratic volatility is large. In particular, the average return on the first quintile portfolio of stocks with the lowest idiosyncratic volatility exceeds the average return on the fifth quintile portfolio of stocks with the

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highest idiosyncratic volatility by over 1% per month. Second, AHXZ demonstrate that their findings cannot be explained either by exposure to aggregate volatility risk or by other existing asset pricing models. AHXZ's findings are particularly puzzling for financial theories that link idiosyncratic volatility to expected returns. While idiosyncratic volatility is not priced in a correctly specified factor model, in environments with frictions and incomplete information the idiosyncratic volatility of a stock may be linked to its expected return. For example, Merton (1987) shows that in the presence of market frictions where investors have limited access to information, stocks with high idiosyncratic volatility have high expected returns because investors cannot fully diversify away firm-specific risk. But AHXZ find the exact opposite relation.

This paper contains three main contributions. Our first goal is to see if the anomalous relation between lagged idiosyncratic volatility and future average returns in U.S. data exists in other markets. As with any empirical results, there is a danger that AHXZ's finding is dependent only on a particular small sample. AHXZ's results could be datasnooping, as argued by Lo and MacKinlay (1990).[1] If a relation between lagged idiosyncratic volatility and future average returns exists in international markets, it is more likely that there is an underlying economic source behind the phenomenon. Thus, we examine whether stock returns in international markets sorted on idiosyncratic volatility conform to the same pattern observed in the U.S. cross section.

We present evidence that the negative relation between lagged idiosyncratic volatility and future average returns is observed across a broad sample of international developed markets. In particular, for each of the largest seven (G7) equity markets (Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom), stocks with high idiosyncratic volatility tend to have low average returns. The negative idiosyncratic volatility–average return relation is strongly statistically significant in each of these countries and is also observed in the larger sample of 23 developed markets. From these strong international results, it is hard to explain the low returns to high-idiosyncratic-volatility stocks as a small-sample problem.

Our second, and perhaps most interesting, contribution is that the negative spread in returns between stocks with high and low idiosyncratic volatility in international markets strongly co-moves with the difference in returns between U.S. stocks with high and low idiosyncratic volatilities. The large commonality in co-movement shared by the spread in returns between stocks with high and low idiosyncratic volatility across countries suggests that broad, not easily diversifiable factors lie behind this effect. However, we do not claim that the low average returns to stocks with high idiosyncratic volatility represent a priced risk factor because we do not yet have a theoretical framework to understand why agents have high demand for high-idiosyncratic-volatility stocks, causing these stocks to have low expected returns.

Finally, in detailed analysis of the U.S. market where more data are available, we rule out explanations based on market frictions, information dissemination, and option pricing. We consider the effects of transaction costs by using the incidence of zero returns proposed by Lesmond, Ogden, and Trzcinka (1999). To characterize the severity of market frictions, we control for Hou and Moskowitz's (2005) delay with which a stock's price responds to information. Since the extent of analyst coverage and institutional ownership are important determinants for trading volume (Chordia, Huh, and Subrahmanyam, 2007) and can proxy for the proportion of informed agents (Brennan and Subrahmanyam, 1995), we investigate whether the idiosyncratic volatility effect persists after controlling for both of these variables. We also investigate the relation to the amount of private information in trading activity (Easley, Hvidkjaer, and O'Hara, 2002) and to skewness (Barberis and Huang, 2005). An alternative explanation suggested by Johnson (2004) is that the idiosyncratic volatility effect is due to idiosyncratic volatility interacting with leverage, motivated from the fact that equity is a call option on a firm's underlying assets. None of these explanations can entirely account for the high idiosyncratic volatility and low average returns relation.

In our analysis, we investigate the relation between future returns and past idiosyncratic volatility. Thus, the idiosyncratic volatility effect that we document in both U.S. and international markets is not necessarily a relation that involves expected volatility (Fu, 2005; Spiegel and Wang, 2005), which is unobservable and must be estimated. In contrast, past idiosyncratic volatility is an observable, easily calculated stock characteristic. Since idiosyncratic volatility is persistent, we expect that our lagged measure is correlated with future idiosyncratic volatility that agents might assess in determining expected returns. Thus, we also examine the contemporaneous relation between expected future idiosyncratic volatility and realized returns. Our investigation indicates that a strong negative relation between lagged idiosyncratic volatility and future returns remains even after controlling for the information that past idiosyncratic volatility provides about future idiosyncratic volatility.

Our results are related to a literature that investigates whether idiosyncratic volatility can predict future aggregate market returns (see, e.g., Goyal and Santa-Clara, 2003; Bali et al., 2005; Wei and Zhang, 2005; Guo and Savickas, 2007). Goyal and Santa-Clara (2003) find that average idiosyncratic volatility predicts aggregate market excess returns.[2] However, our focus is on the

[1] AHXZ's results could also have just been wrong, but the AHXZ results for U.S. stocks have been independently confirmed by Brown and Ferreira (2003), Jiang, Xu, and Yao (2005), Huang, Liu, Rhee, and Zhang (2006), Zhang (2006), and Bali and Cakici (2008).

[2] According to an ICAPM, a factor which predicts stock returns in the cross section should also predict aggregate market returns (see Campbell, 1993). However, if returns are tied to firm characteristics rather than factor loadings as advocated by Daniel and Titman (1997), then because idiosyncratic volatility is a firm characteristic, a relation between idiosyncratic volatility and returns at the firm level does not imply a relation between average idiosyncratic volatility and market returns at the aggregate level.

cross-sectional, as opposed to the aggregate time series, relation between firm-level idiosyncratic volatility and expected returns. Other authors, like Campbell, Lettau, Malkiel, and Xu (2001), Bekaert, Hodrick, and Zhang (2005), and Brandt, Brav, and Graham (2005) have examined trends in average idiosyncratic volatility, but they do not link idiosyncratic volatility to cross-sectional returns.

Idiosyncratic volatility has been used to proxy for various economic effects. For example, building on Miller (1977), idiosyncratic volatility has been used as an instrument to measure differences in opinion (see, e.g., Baker, Coval, and Stein, 2007). We do not investigate the success of idiosyncratic volatility to proxy for different economic effects, and AHXZ show that differences in opinion measured by analyst dispersion (see Diether, Malloy, and Scherbina, 2002) cannot account for the idiosyncratic volatility effect. Our focus is on how idiosyncratic volatility itself is related to expected returns in the cross-section of international stock returns. Similarly, idiosyncratic volatility could be related to other economic factors, like liquidity risk (see, e.g., Spiegel and Wang, 2005). Hence, we specifically control for the effect of other risk loadings or risk characteristics in our analysis of idiosyncratic volatility.

The remainder of the paper is organized as follows. Section 2 describes how we measure the idiosyncratic volatility of a stock and discusses the international stock return data. Section 3 explains our cross-sectional version of the Fama and MacBeth (1973) methodology. Section 4 shows that the negative relation between idiosyncratic volatility and future returns is observed across the world, while Section 5 examines how the difference in returns between foreign stocks with high and low idiosyncratic volatilities covaries with the analogous difference in U.S. stock returns. In Section 6, we examine in detail some potential economic explanations for the effect using U.S. data. We rule out market frictions, asymmetric information, skewness, and an interaction with leverage as complete explanations for the idiosyncratic volatility phenomenon. Section 7 concludes.

2. Measuring idiosyncratic volatility

This section discusses how we measure the idiosyncratic volatility of a firm using local, regional, and global versions of the Fama-French (1993) three-factor model. It also introduces the international data. In most of our analysis, we work with returns and factors expressed in U.S. dollars, and we compute excess stock returns using U.S. T-bill rates. For robustness, we also report the relation between idiosyncratic volatility measured in local currency and excess returns expressed in local currency terms.

2.1. F -F

In each country, we specify a local version of the Fama-French model (L-FF hereafter) with three factors: a local market excess return factor, a local size factor, and a local value factor. When we analyze only U.S. stocks, our L-FF model is just the standard model of Fama and French (1993). The construction of the L-FF models for other countries is similar, and we follow Fama and French (1993, 1998). The market factor for country , *MK* , is computed as the value-weighted excess return of the local market portfolio over the one-month U.S. T-bill rate. Within each country , MKT using daily U.S. dollar excess returns of stock over the past month and expressing all of the W-FF factors in U.S. dollars.

2.4. D

Our stock return data comprise daily returns on firms from 23 developed markets. We select these countries because they constitute the universe of the MSCI Developed Country Index. We study both local-currency and U.S. dollar-denominated returns, but we compute excess returns using the U.S. one-month T-bill rate. Individual stock returns for the United States are obtained from CRSP, and other U.S. firm-level data are from COMPUSTAT. International stock return data are from Datastream. For the international data, the sample period is January 1980 to December 2003, except for Finland, Greece, New Zealand, Portugal, Spain, and Sweden, which begin in the mid-1980s. In all non-U.S. countries, we exclude very small firms by eliminating the 5% of firms with the lowest market capitalizations. For the more detailed analysis using U.S. data, the sample period is July 1963 to December 2003.

Panel A of Table 1 presents summary statistics for the stock returns and other data across countries. We provide time-series means for the average firm size and book-to-market ratio, and the average number of firms. There is moderate variation in firm characteristics across countries. The average firm size ranges from $182 million in Greece to $1,632 million in the Netherlands. In comparison, the size of the average U.S. firm is $975 million. Japanese firms tend to have the lowest book-to-market ratios (at 0.70), whereas Belgian firms have the highest

Table 1
Summary statistics of international data

	Starting year	Book-to-market	Size	Number of firms	Number of months	Total volatility (%)	Idiosyncratic volatility (%)	
							W-FF	R-FF
Panel A: Individual country returns								
G7 *υ*								
Canada	1980	0.98	628	380	280	44	40	40
France	1980	1.05	847	384	280	37	33	32
Germany	1980	0.71	951	443	280	32	28	27
Italy	1980	0.90	1286	118	280	35	31	30
Japan	1980	0.70	1568	1453	280	39	33	31
U.K.	1980	0.91	818	1077	280	30	26	25
U.S.	1980	0.81	975	5441	280	57	51	51†
O								
Australia	1980	0.97	626	292	280	41	37	37
Austria	1980	1.30	183	58	280	27	24	23
Belgium	1980	1.40	504	79	280	29	26	25
Denmark	1980	1.18	230	131	280	29	26	25
Finland	1986	0.74	662	87	201	42	38	37
Greece	1987	0.78	182	172	189	47	43	42
Hong Kong	1980	1.29	784	242	280	44	40	40
Ireland	1980	1.13	467	39	280	38	35	34
Netherlands	1980	1.22	1632	116	280	31	27	26
New Zealand	1985	0.99	390	46	213	39	36	35
Norway	1980	0.82	282	81	280	42	38	37
Portugal	1987	1.24	419	58	189	35	31	30
Singapore	1980	0.94	358	122	280	38	34	34
Spain	1986	0.96	1589	105	203	33	29	28
Sweden	1982	0.98	510	165	261	43	39	38
Switzerland	1980	1.11	1049	174	278	31	27	26

Panel B: Global and regional factors

	World		N. America		Europe		Asia	
	Mean (%)	Stdev. (%)	Mean (%)	Stdev. (%)	Mean (%)	Stdev. (%)	Mean (%)	Stdev. (%)
MK	0.55	4.37	0.66	4.61	0.63	4.94	0.45	6.54
MB	0.17	3.41	−0.08	4.72	0.23	3.04	0.53	4.74
HML	0.42	2.27	0.15	3.01	0.57	2.09	0.72	3.98

All returns are denominated in U.S. dollars and are at a monthly frequency. In Panel A, the sample for each country begins in January of the year stated in the "Starting year" column and ends in December 2003. The columns "Book-to-market" and "Size" report average firm characteristics within each country of book-to-market ratios and market capitalization in U.S. dollars of the average number of firms reported in the column "Number of firms." The column (at 1.40). Note that the average number of U.S. firms, 5,441, dwarfs the number of firms in any other market. The next largest equity market is Japan, which has an average of 1,453 firms. Because of the dominant number of U.S. firms, we are careful in our empirical work to disentangle the effect of the U.S. on any result involving data pooled across markets.

In Panel A, we report summary statistics for three different average volatility measures, which are all annualized by multiplying by $\sqrt{250}$. The first measure is total volatility, which is computed as the volatility of daily raw returns over the previous month. Theand third measures are idiosyncratic volatility computed with respect to the R-FF model (Eq. (2)) and the W-FF model (Eq. (3)). All three volatility measures are highly correlated with each other, with the correlations all above 95% in each country. The United Kingdom has the lowest idiosyncratic volatility (26% per annum with respect to W-FF), compared to the average W-FF idiosyncratic volatility across countries of 41% per annum. There is also quite a wide range in the dispersion of idiosyncratic volatility across markets. For the United States, the interquartile range (the difference between the 75th and 25th percentiles) of W-FF idiosyncratic volatility is $61.1\% - 25.0\% = 36.1\%$, compared to an average interquartile range of $38.4\% - 18.5\% = 19.9\%$ for the other 22 countries. Stock-level volatility is only weakly correlated with aggregate volatility in each country. In the United States, the average correlation of L-FF idiosyncratic volatility with aggregate market volatility using monthly data, where both measures are computed using daily returns over the month, is only 16.5%. While Campbell, Lettau, Malkiel, and Xu (2001) report a time trend in idiosyncratic volatility over the late 1990s, Brandt, Brav, and Graham (2005) report that there is no time trend extending the sample into the 2000s. Bekaert, Hodrick, and Zhang (2005) find similar results in international markets.

In Panel B of Table 1, we report monthly means and standard deviations of R-FF and W-FF factors, all expressed in U.S. dollars. The mean of the *MB* factor for North America is slightly negative, at −0.08% per month, indicating that small firms have not outperformed large firms in the United States over the post-1980 sample, in contrast to the results first reported by Banz (1981). The evidence for the size effect is stronger in the post-1980 sample for Europe and Asia, where the regional *MB* factors have positive means. Value strategies have also performed better in overseas markets than in the United States, with high book-to-market stocks significantly underperforming low book-to-market stocks during the late 1990s bull market in the United States. The value premium is particularly strong in Asia, where the mean regional *HML* factor is 0.72% per month. In comparison, the mean of the world *HML* factor is 0.42% per month.

3. The cross-sectional regression methodology

We examine the relation between total volatility and idiosyncratic volatility with respect to the L-FF, R-FF, and W-FF models using a series of two-stage Fama and MacBeth (1973) regressions. In the first stage, for every month, we regress the cross-sectional firm excess returns onto idiosyncratic volatility together with various risk factor loadings, some firm characteristics, and other control variables. In the second stage, we use the time series of the regression coefficients and test whether the average coefficient on the lagged idiosyncratic volatility measure is significantly different from zero. To take into account serial correlation in the coefficient estimates, we compute Newey-West (1987) standard errors with four lags in the second stage.

The Fama-MacBeth cross-sectional regressions take the form

$$(\, , \; +1) = \; + \gamma \; (\; -1, \;) + \; '_{\beta} \beta (\, , \; +1) + \; ' \; (\;) + \varepsilon (\; +1), \tag{4}$$

where $(\, , +1)$ is stock 's excess return from month to $+1$, $(-1,)$ is stock 's idiosyncratic volatility computed using daily data over the previous month from -1 to , $\beta(, +1)$ is a vector of risk factor loadings over the month to $+1$, and $( )$ is a vector of firm characteristics observable at time . We use the notation $(-1,)$ and $(, +1)$ to emphasize the timing of the statistics that are computed using data from month -1 to and over month to $+1$, respectively. The cross-sectional regressions for a particular country and month use all available firm-level data for that country and month.

We are especially interested in the coefficient γ on idiosyncratic volatility, which should be zero under the null hypothesis of a correctly specified factor model. Each month, we run the regression in Eq. (4) with returns measured in percentage terms and use annualized volatility numbers as dependent variables. Because our volatility measures are known at the beginning of the month, $(-1,)$ is a measurable statistic at time . Following Shanken (1992), Eq. (4) controls for exposures to risk factors by including contemporaneous factor loadings estimated over the current month, $\beta(, +1)$, but we obtain almost identical results if we use past factor loadings, $\beta(-1,)$. These results are available upon request.

We use contemporaneous factor loadings because a factor model explains high average returns over a time period with contemporaneous high covariation in factor exposure over the same period if the factor commands a positive risk premium. Using contemporaneous factor loadings is similar to the Fama-MacBeth regressions run by Black, Jensen, and Scholes (1972), Fama and French (1992), and Jagannathan and Wang (1996), among others. We use firm factor loadings from the W-FF model using MK^{W}, MB^{W}, and HML^{W} as factors, where the W-FF regression (3) is run using daily returns over the month from to $+1$. For the United States, we also consider contemporaneous L-FF factor loadings from Eq. (1) computed using daily data over the month from to $+1$.

Daniel and Titman (1997) report that factor loadings might not account for all variation in expected returns compared to firm-level characteristics. Hence, we also include other firm characteristics in the vector $( )$ in the

Fama-MacBeth regression. All of these characteristics are known at time . The firm characteristics include log size, book-to-market ratios, and a Jegadeesh and Titman (1993) momentum characteristic measured by lagged returns over the previous six months. All of these firm characteristics are measured in U.S. dollars. We also include country-specific dummies as fixed effects.

We investigate the relation between idiosyncratic volatility and expected returns by examining the sign and statistical significance of the mean value of γ, the coefficient on the volatility statistic in Eq. (4). Another approach taken by AHXZ to measure the relation between average returns and idiosyncratic volatility is to form portfolios ranked on idiosyncratic volatility and then examine holding-period returns of these portfolios. AHXZ consider controlling for other effects using a series of double-sorted portfolios, but they do not consider Fama-MacBeth regressions.

While the Fama-MacBeth regressions capture variation in cross-sectional expected returns, residual variation and components of returns related to other factors also enter portfolio returns. One advantage of cross-sectional regressions is that they allow for controls for multiple factor loadings and characteristics in a setting that retains power, whereas creating portfolios that have dispersion on more than two dimensions generally results in some portfolios with only a few stocks and, consequently a lot of noise. This is especially true for countries with only a small number of listed stocks. In our analysis of portfolio returns, we will form portfolios aggregated across geographic areas to ensure that we have a reasonable number of stocks in our portfolios.

4. Idiosyncratic volatility and expected returns in international markets

We begin our analysis by examining the relation between lagged idiosyncratic volatility and future stock returns across the world. Section 4.1 examines the G7 countries in detail, while Section 4.2 considers all 23 countries.

4.1. F , u

Table 2 reports results of the Fama-MacBeth (1973) regressions in Eq. (4) using stock returns within each of the G7 countries. The regressions in Panel A of Table 2 use excess stock returns denominated in U.S. dollars. Panel B repeats the cross-sectional regressions using local-currency-denominated excess returns. All regressions are run using monthly data. Because of data requirements on lagged firm characteristics, the dependent variable returns of the regressions span September 1980 to December 2003, but data on the independent variables, particularly book values and past returns, begin from January 1980.

The first result in Table 2 is that a strong negative relation between lagged idiosyncratic volatility and average future excess returns exists in each of the non-U.S. G7 countries. For the United States, the estimated coefficient on W-FF idiosyncratic volatility is -2.01, with a robust -statistic of -6.67. After the United States, the negative lagged idiosyncratic volatility–expected return relation is statistically strongest for Japan, which has a point estimate of -1.96 with a robust -statistic of -5.18. The coefficient on W-FF idiosyncratic volatility ranges from -0.87 for the United Kingdom to less than -2.00 for Germany. In all cases, the coefficients are statistically significant at the 95% level, with the smallest magnitude of the -statistic of -2.10 occurring for Italy.

Second, in contrast to the strong predictive power of lagged idiosyncratic volatility, the coefficients on factor loadings and characteristics are often insignificant. In fact, Table 2 shows that two of the coefficients on MB^W have the wrong sign from those predicted by Fama and French (1993). This is partly because the small-stock effect and the value premium in the post-1980 sample are relatively weak, and possibly because betas contain significant measurement error. The book-to-market and lagged return characteristics generally have greater statistical significance than the coefficients on the factor betas, consistent with the findings of Daniel and Titman (1997). Examining the coefficients on the characteristics, we find is a statistically significant size effect in Canada and the United States, and five of the seven book-to-market effects are statistically significant. The relatively weak evidence of momentum in international stock returns presumably arises because we take relatively large firms for which the momentum effect is weaker compared to small firms (see Rouwenhorst, 1998; Hong, Lim, and Stein, 2000).

To interpret the magnitude of the coefficient on volatility, we measure the cross-sectional distribution of volatility. Panel A of Table 2 reports the 25th percentile and the 75th percentile of W-FF idiosyncratic volatility in each country. Using these percentiles, we can translate the coefficients on L-FF idiosyncratic volatility into an economic effect by asking the following question: if a firm were to move from the 25th to the 75th idiosyncratic volatility percentile while its other characteristics were held constant, what is the predicted decrease in that firm's expected return? The U.S. coefficient of -2.01 translates to a decrease in expected returns of $|-2.01| \times (0.611 - 0.250) = 0.73\%$ per month. These are economically very large differences in average excess returns. Of course, this increase in idiosyncratic volatility is large, and news that caused such a change would probably also be associated with changes in other firm characteristics.

While the German and Japanese coefficients on idiosyncratic volatility of -2.00 and -1.96 are similar to the -2.01 coefficient for the United States, the range of idiosyncratic volatility in the United States is much larger than in the other large, developed countries. This makes the idiosyncratic volatility effect stronger in the United States, but it still remains large in economic terms for the other countries. The interquartile range of W-FF idiosyncratic volatility for the non-U.S. G7 countries is around 0.19, which is about half the average interquartile range in the United States of 0.36. Thus, although the coefficients on W-FF idiosyncratic volatility are similar, the magnitude of the idiosyncratic volatility effect is approximately half of the U.S. effect because the United States tends to have stocks with a much wider dispersion of idiosyncratic volatility. The last row of Panel A illustrates this, where across the non-U.S. G7 countries, moving from the 25th percentile to the 75th percentile produces a reduction in expected returns of around 0.15–0.30% per month in magnitude, which is less than half of the expected 0.73% per month decrease using only U.S. firms.

in local currency to compute contemporaneous factor loadings in Eq. (3). The results (available upon request) are almost unchanged if R-FF or L-FF factors denominated in local currency are used. The coefficients on L-FF idiosyncratic volatility are similar to the coefficients on W-FF idiosyncratic volatility in Panel A. All the coefficients on L-FF idiosyncratic volatility are highly statistically significant. The biggest change occurs for France, where the magnitude of the idiosyncratic volatility coefficient decreases from −1.44 in USD returns to −1.06 in local returns. For Canada, Italy, Japan, and the United Kingdom, the volatility coefficients increase in magnitude using L-FF idiosyncratic volatility.

In summary, similar to the finding in AHXZ for the United States, we find that a strong negative relation between expected returns and past idiosyncratic volatility also exists in the other large, developed markets. The economic effect is strongest in the United States, not because the coefficient on idiosyncratic volatility is much more negative in the United States but because the range of idiosyncratic volatility is more dispersed in the United States than in other countries. The strong relation between idiosyncratic volatility and average returns in international data sets a high bar for any potential explanation.

For example, Jiang, Xu, and Yao (2005) recently argue that investors are not in a rational expectations environment and must learn about firms' earnings. They argue that firms with past high idiosyncratic volatility tend to have more negative future unexpected earnings surprises, leading to their low future returns. Given that non-U.S. financial reporting and accounting standards are generally less rigorous than in the U.S., the scope for greater dispersion in future unexpected earnings in non-U.S. countries seems larger. This seems particularly true for negative unexpected earnings surprises, which would imply a more negative relation between idiosyncratic volatility and expected returns in other countries. Our international results show that this is not the case.

Another potential explanation is that the negative relation between idiosyncratic volatility and returns persists due to lack of overall liquidity. Yet the United States has the most liquid markets of the G7, and it has the largest negative reward to holding stocks with high idiosyncratic liquidity. Therefore, the data seem inconsistent with this hypothesis.

4.2. u u

4.2.1. F -M B (1973)

Table 3 extends our analysis to incorporate all 23 developed countries. We report Fama-MacBeth coefficients for Europe and Asia, the G7 (with and without the United States), and all countries (with and without the United States). To control for cross-country differences, or fixed effects, we include seven country dummies. The first six dummies correspond to non-U.S. countries in the G7 (Canada, France, Germany, Italy, Japan, and the United Kingdom), and the last dummy corresponds to all other developed countries. Thus, this approach implicitly treats the United States as a benchmark and measures cross-country differences relative to the U.S. market. In all the regressions, the country dummies are statistically insignificant, indicating that there are only modest country-specific effects after controlling for factor loadings and firm characteristics.[3]

The first two columns of Table 3 show that high-idiosyncratic-volatility stocks in Europe and Asia also have low expected returns. The coefficients on idiosyncratic volatility are −0.67 and −1.18 for Europe and Asia, respectively, and are somewhat smaller in magnitude than the U.S. coefficient of −2.01. These coefficients are highly statistically significant. The third and fourth columns pool together all the G7 countries and separately consider the effect of excluding the United States. Across all the G7 countries, the coefficient on W-FF idiosyncratic volatility is −1.75, with a very negative robust -statistic of −6.40. By construction, this coefficient is an average of the individual G7 country coefficients in Table 2. Clearly, the effect of low expected returns to stocks with high idiosyncratic volatility is very strong across the largest developed markets. However, Table 3 makes clear that the U.S. effect dominates, since the coefficient on idiosyncratic volatility falls to −1.07 when U.S. firms are excluded. This coefficient has a -statistic of −4.14.

The final two columns of Table 3 pool the data across all 23 developed countries. Pooled across all countries, the coefficient on idiosyncratic volatility is −1.54 and highly significant. Because the interquartile range of W-FF idiosyncratic volatility is $50.5\% - 20.3\% = 30.2\%$ per annum over all countries, there is a large economic decrease of $|-1.54| \times (0.505 - 0.203) = 0.47\%$ per month in moving from the 25th to the 75th percentile of W-FF idiosyncratic volatility. When the United States is excluded, the coefficient on idiosyncratic volatility falls in absolute magnitude to −0.60 from −1.54, but this is still significant with a robust -statistic of −2.32. Thus, while the idiosyncratic volatility effect is concentrated in the United States, it is still strongly observed across the world.

4.2.2. u u

One potential concern about the use of cross-sectional regressions is that each stock is treated equally in a standard Fama-MacBeth setting. Thus, even though we exclude very small stocks in each country, a standard Fama-MacBeth regression places the same weight on a very large firm as on a small firm. Placing greater weight on small firms could generate noise, and although it measures the effect of a typical firm, it might not reflect the effect of an average dollar. To allay these concerns, we report value-weighted Fama-MacBeth regressions in Table 4, where each return is weighted by the firm's market capitalization in U.S. dollars at the start of the month. In the first stage, we perform GLS regressions with

[3] We have also included a dummy to represent the technology, media, and telecommunications sectors following Brooks and Del Negro (2005), with very little effect on our results. Ending the sample in 1997 also does not affect our results. In fact, the coefficients on idiosyncratic volatility are slightly larger in absolute magnitude in the 1981–1997 sample compared to the whole sample.

a weighting matrix that is diagonal, with the inverse of the firms' market capitalization along the diagonal. These value-weighted Fama-MacBeth regressions are analogous to creating value-weighted portfolios, whereas the standard Fama-MacBeth regressions are analogous to creating equal-weighted portfolios.

Table 4 reports that the coefficients on idiosyncratic volatility increase in magnitude moving from equal-weighted to value-weighted Fama-MacBeth regressions. The coefficients also have correspondingly stronger statistical significance. For example, for the U.S. coefficient on idiosyncratic volatility, the value-weighted coefficient is −2.24 in Table 4 compared to the equal-weighted coefficient of −2.01 from Table 2, and the -statistic goes from −6.67 to −7.00. This result is also documented by Bali and Cakici (2008) for the United States only, but Table 4 shows that the same effect holds true for all international markets. Similarly, the coefficient on idiosyncratic volatility for Asia (the G7 countries) is −1.27 (−1.97) when using market capitalization weights in Table 4, which are higher in magnitude than the equal-weighted idiosyncratic volatility coefficient

Table 4
Weighted Fama-MacBeth (1973) regressions

	Geographic areas			G7 countries		All countries	
	U.S.	Europe	Asia	G7	G7 Ex. U.S.	All	All Ex. U.S.
Constant	1.796	0.752	1.203	1.459	0.886	1.362	0.846
	[3.93]	[1.92]	[1.91]	[3.92]	[2.11]	[3.79]	[2.06]
W-FF idiosyncratic volatility	−2.243	−0.893	−1.267	−1.974	−1.287	−1.750	−0.846
	[−7.00]	[−3.17]	[−3.38]	[−6.89]	[−4.90]	[−6.41]	[−3.26]
$\beta(MK\ ^{W})$	0.368	0.121	0.170	0.351	0.320	0.297	0.224
	[3.95]	[1.03]	[1.67]	[3.88]	[3.35]	[3.23]	[2.33]
$\beta(\ MB^{W})$	−0.086	0.016	−0.016	−0.084	−0.046	−0.077	−0.055
	[−1.84]	[0.24]	[−0.22]	[−1.85]	[−0.84]	[−1.67]	[−1.00]
$\beta(HML^{W})$	−0.041	−0.058	−0.025	−0.035	−0.056	−0.027	−0.035
	[−1.16]	[−1.17]	[−0.37]	[−0.88]	[−0.94]	[−0.71]	[−0.64]
Size	−0.141	−0.067	−0.151	−0.102	−0.088	−0.092	−0.087
	[−2.98]	[−1.86]	[−2.52]	[−2.80]	[−2.32]	[−2.69]	[−2.46]
Book-to-market	0.241	0.206	0.542	0.270	0.298	0.247	0.255
	[3.20]	[5.34]	[3.56]	[5.18]	[5.21]	[6.02]	[5.78]
Lagged return	0.001	0.010	−0.006	0.002	0.003	0.003	0.004
	[0.61]	[3.83]	[−1.39]	[0.71]	[1.06]	[1.17]	[1.59]
Dummy Canada				−0.153	0.169	−0.150	0.122
				[−0.79]	[0.59]	[−0.77]	[0.43]
Dummy France		0.250		−0.089	0.258	−0.052	0.260
		[0.80]		[−0.24]	[0.81]	[−0.14]	[0.81]
Dummy Germany		−0.149		−0.554	−0.166	−0.527	−0.170
		[−0.48]		[−1.56]	[−0.51]	[−1.48]	[−0.51]
Dummy Italy		0.456		0.188	0.561	0.219	0.550
		[0.94]		[0.36]	[1.14]	[0.42]	[1.13]
Dummy Japan				−0.256	−0.131	−0.256	−0.120
				[−0.53]	[−0.31]	[−0.53]	[−0.29]
Dummy U.K.				−0.316		−0.285	
				[−1.01]		[−0.91]	
Dummy other country		0.061				−0.170	0.121
		[0.27]				[−0.58]	[0.56]
Adjusted ^{2}	0.053	0.123	0.120	0.126	0.181	0.120	0.158

The table reports Fama-MacBeth (1973) regressions (Eq. (4)) for all 23 countries, where each firm is weighted by the firm's market capitalization in U.S. dollars at the start of the month. The regressions are split into geographic areas (U.S., Europe, and Asia), the G7 (with and without the U.S.), and all countries (with and without the U.S.). We regress next-month excess firm returns on a constant; idiosyncratic volatility over the past month with respect to the W-FF model in Eq. (3); contemporaneous factor loadings, $\beta(MK\ ^{W})$, $\beta(\ MB^{W})$, and $\beta(HML^{W})$ with respect to the W-FF model; and firm characteristics at the beginning of the month. "Size" is the log market capitalization of the firm at the beginning of the month, "Book-to-market" is the book-to-market ratio available six months prior, and "Lagged return" is the firm return over the previous six months. The cross-sectional regressions are run with separate dummy variables taking the value one if the firm is in Canada, France, Germany, Italy, Japan, the United Kingdom, or another non-U.S. country, and zero otherwise. We report robust -statistics in square brackets below each coefficient. The row "Adjusted ^{2}" reports the average of the cross-sectional adjusted ^{2}'s. Each cross-sectional regression is run separately for each geographic area or group of countries using U.S. dollar-denominated firm excess returns. The sample period is from January 1980 to December 2003, with returns for most countries commencing in 1980, but some smaller countries start in the mid-1980s (see Table 1).

Since volatility is well known to be persistent (e.g., Engle, 1982), we expect that past idiosyncratic volatility should still have predictive power when longer sample periods are used to compute idiosyncratic volatility. Table 5 confirms that this is the case.

Table 5 is similar to Table 3, except that instead of computing idiosyncratic volatility over the past month ((− 1,)), we compute idiosyncratic volatility using daily returns over the past 3, 6, or 12 months, denoted by (− 3,), (− 6,), and (− 12,), respectively. This is done relative to the W-FF model of Eq. (3) with all volatilities expressed in annualized terms. We report the results for the United States, all countries, and all countries excluding the United States.

In all the regressions in Table 5, the coefficients on W-FF idiosyncratic volatility using different formation periods are all negative and highly statistically significant. Not surprisingly, as the formation period increases, the magnitude of the coefficients on idiosyncratic volatility decreases. For the United States, the coefficients decrease from −2.46 at a three-month formation period to −2.09 using six months and −1.27 using the past year. For comparison, the Table 3 coefficient is −2.01 for (− 1,), so using the past three months of daily returns actually makes the idiosyncratic volatility effect stronger. These patterns are also repeated for all countries as well as for all countries excluding the United States. Like the results in previous tables, the magnitude of the coefficients decreases when U.S. stocks are excluded, but the effects are still significant.

Volatility does vary over time, but it is not the time-series persistence of stock volatilities that is driving the results in Table 5. Rather, over a month to three months, the relative rankings of stocks sorted by idiosyncratic

Table 5
Effect of different formation periods to compute idiosyncratic volatility

Formation period	U.S.			All countries			All excluding U.S.		
	(−3,)	(−6,)	(−12,)	(−3,)	(−6,)	(−12,)	(−3,)	(−6,)	(−12,)
Constant	2.104	1.879	1.125	1.703	1.576	1.054	1.008	0.990	0.864
	[5.00]	[4.39]	[2.57]	[4.93]	[4.70]	[3.09]	[2.57]	[2.49]	[2.20]
W-FF idiosyncratic volatility	−2.461	−2.091	−1.273	−2.050	−1.765	−1.188	−0.930	−0.685	−0.605
	[−5.68]	[−4.35]	[−2.60]	[−6.05]	[−5.02]	[−3.32]	[−2.93]	[−2.07]	[−1.98]
$\beta(MK^{W})$	0.388	0.364	0.346	0.322	0.302	0.289	0.249	0.256	0.253
	[4.80]	[4.59]	[4.35]	[4.07]	[3.82]	[3.64]	[2.89]	[2.99]	[2.88]
$\beta(MB^{W})$	−0.052	−0.055	−0.046	−0.052	−0.056	−0.051	−0.041	−0.043	−0.032
	[−1.30]	[−1.37]	[−1.17]	[−1.24]	[−1.31]	[−1.16]	[−0.72]	[−0.75]	[−0.55]
$\beta(HML^{W})$	−0.057	−0.055	−0.055	−0.052	−0.049	−0.050	−0.048	−0.044	−0.048
	[−1.93]	[−1.87]	[−1.83]	[−1.72]	[−1.60]	[−1.62]	[−0.95]	[−0.88]	[−0.89]
Size	−0.190	−0.170	−0.095	−0.138	−0.129	−0.080	−0.123	−0.121	−0.106
	[−4.09]	[−3.60]	[−2.05]	[−3.99]	[−3.74]	[−2.35]	[−3.66]	[−3.56]	[−2.95]
Book-to-market	0.276	0.305	0.411	0.265	0.280	0.387	0.250	0.247	0.352
	[3.92]	[4.12]	[4.17]	[6.92]	[6.99]	[6.98]	[6.08]	[6.06]	[6.93]
Lagged return	−0.001	−0.001	−0.001	0.002	0.002	0.001	0.005	0.005	0.004
	[−0.28]	[−0.22]	[−0.19]	[0.76]	[0.80]	[0.57]	[1.86]	[1.77]	[1.15]
Dummy Canada				−0.085	−0.057	−0.062	0.249	0.201	0.150
				[−0.40]	[−0.27]	[−0.29]	[0.83]	[0.67]	[0.50]
Dummy France				−0.029	0.070	0.131	0.338	0.375	0.345
				[−0.07]	[0.18]	[0.36]	[1.03]	[1.16]	[1.08]
Dummy Germany				−0.565	−0.476	−0.374	−0.145	−0.130	−0.140
				[−1.53]	[−1.31]	[−1.02]	[−0.44]	[−0.39]	[−0.41]
Dummy Italy				0.112	0.001	0.114	0.412	0.230	0.359
				[0.22]	[0.00]	[0.22]	[0.88]	[0.50]	[0.76]
Dummy Japan				−0.171	−0.186	−0.162	−0.001	−0.057	−0.070
				[−0.33]	[−0.36]	[−0.31]	[−0.00]	[−0.13]	[−0.16]
Dummy U.K.				−0.379	−0.309	−0.186			
				[−1.13]	[−0.92]	[−0.56]			
Dummy other country				−0.154	−0.131	−0.104	0.198	0.163	0.115
				[−0.49]	[−0.42]	[−0.33]	[0.89]	[0.73]	[0.50]
Adjusted ^{2}	0.048	0.048	0.050	0.101	0.101	0.105	0.145	0.143	0.149

N : The table reports Fama-MacBeth (1973) regressions (Eq. (4)) for all 23 countries. The regressions are split into three groups: United States, all countries, and all countries excluding the United States. We regress next-month excess firm returns on a constant; idiosyncratic volatility computed using daily returns over the past 3, 6, or 12 months with respect to the W-FF model in Eq. (3) all expressed in annualized terms, which are denoted as denoted by (−3,), (−6,), and (−12,), respectively; contemporaneous factor loadings, $\beta(MK^{W})$, $\beta(MB^{W})$, and $\beta(HML^{W})$ with respect to the W-FF model; and firm characteristics at the beginning of the month. "Size" is the log market capitalization of the firm at the beginning of the month, "Book-to-market" is the book-to-market ratio available six months prior, and "Lagged return" is the firm return over the previous six months. The cross-sectional regressions are run with separate dummy variables taking the value one if the firm is in Canada, France, Germany, Italy, Japan, the United Kingdom, or another non-U.S. country, and zero otherwise. We report robust -statistics in square brackets below each coefficient. The row "Adjusted ^{2}" reports the average of the cross-sectional adjusted ^{2}'s. Each cross-sectional regression is run separately for each geographic area or group of countries using U.S. dollar-denominated firm excess returns. The sample period is from January 1980 to December 2003, with returns for most countries commencing in 1980, but some smaller countries start in the mid-1980s (see Table 1).

volatility remain roughly the same because of the strong cross-sectional persistence of idiosyncratic volatility. For all cases in Table 5 the results are slightly stronger using three-month formation periods rather than one month, perhaps because using three months of data allows for more accurate estimates of idiosyncratic volatility. However, rankings of idiosyncratic volatility do change across longer sample periods, causing the effects of the six- and 12-month ranking periods to produce less significant and weaker results.

4.2.4. u

Across all 23 developed markets, stocks with high idiosyncratic volatility tend to have low expected returns. The effect is most pronounced in the United States. It is economically and statistically significant across the individual G7 countries, and it is also observed when data are pooled across all 23 developed countries. The negative idiosyncratic volatility and expected return relation is robust to controlling for factor loadings and firm characteristics using equal-weighted or value-weighted cross-sectional regressions and to considering different formation periods up to the past year for computing idiosyncratic volatility.

5. International portfolio returns

The presence of an idiosyncratic volatility effect in a large cross-section of countries raises the issue of whether these effects exhibit any covariation. To investigate this we create idiosyncratic volatility portfolios across regions and across all 23 countries.

5.1.

To create international idiosyncratic volatility portfolios, we first sort firms within each individual country into quintile portfolios ranked on W-FF idiosyncratic volatility using daily excess returns over the previous month as in Eq. (3). For small countries, each quintile portfolio could contain very few firms, so we focus on creating volatility portfolios across regions. We create regional quintile W-FF idiosyncratic portfolios by forming value-weighted sums of the country quintile portfolios, where the weights are the U.S. dollar market capitalizations of the corresponding quintile portfolio of each country. The quintile portfolios are rebalanced every month, expressed in U.S. dollars, and cover the same period of returns as the Fama-MacBeth (1973) regressions in Section 4 (September 1980 to December 2003).

Table 6 lists the returns of the international quintile W-FF idiosyncratic volatility portfolios. Panel A reports

Table 6
International idiosyncratic volatility portfolios

	Geographic areas		G7 countries		All countries	
	Europe	Asia	G7	G7 Ex. U.S.	All	All Ex. U.S.
Panel A: W-FF alphas						
1 Low	0.172	−0.063	0.153	−0.011	0.163	0.040
	[0.95]	[−0.24]	[2.19]	[−0.06]	[2.40]	[0.25]
2	0.084	−0.086	0.065	−0.059	0.069	−0.026
	[0.44]	[−0.30]	[1.16]	[−0.31]	[1.35]	[−0.16]
3	−0.021	0.055	0.027	−0.040	0.031	−0.011
	[−0.11]	[0.19]	[0.34]	[−0.23]	[0.45]	[−0.07]
4	−0.263	−0.187	−0.433	−0.290	−0.416	−0.280
	[−1.26]	[−0.58]	[−3.26]	[−1.46]	[−3.44]	[−1.61]
5 High	−0.551	−0.592	−1.201	−0.663	−1.144	−0.629
	[−2.19]	[−1.59]	[−6.10]	[−2.83]	[−6.39]	[−3.08]
5–1	−0.723	−0.529	−1.353	−0.651	−1.307	−0.670
	[−3.01]	[−1.84]	[−5.46]	[−2.77]	[−5.68]	[−3.16]
Panel B: Raw average returns						
5–1	−0.412	−0.270	−0.927	−0.388	−0.893	−0.396
	[−1.50]	[−0.83]	[−2.55]	[−1.36]	[−2.62]	[−1.49]

For every month, within each country, we first sort firms into quintile portfolios according to the W-FF idiosyncratic volatility measure in Eq. (3) using daily firm returns over the previous month. We aggregate the country quintile portfolios into regional portfolios, reported in the table for geographic areas (Europe and Asia), the G7 countries (with and without the U.,-1096([)[

W-FF alphas using the full sample of monthly returns for each regional quintile portfolio. These alphas are the estimates of the α^W coefficient in Eq. (3), where the regression is estimated at a monthly frequency using each portfolio's full series of returns in excess of the one-month U.S. T-bill yield. We also report the W-FF alpha of the trading strategy 5–1 that goes long the highest volatility quintile and short the quintile of stocks with the lowest idiosyncratic volatilities. This trading strategy produces a W-FF alpha of −0.72% per month in Europe with a robust -statistic of −3.01. In Asia, the trading strategy is less profitable, but it still has a large W-FF alpha of −0.53% per month, with a -statistic of −1.84.

For Asia, the difference between the modestly strong results for the tradable portfolios in Table 6 and the large, significantly negative Fama-MacBeth coefficient on the previous month's W-FF idiosyncratic volatility in Tables 3 and 4 arises because the significant Fama-MacBeth coefficient does not take into account the smaller range of idiosyncratic volatility in Asia. We could obtain a higher dispersion of idiosyncratic volatility across portfolios by creating more extreme portfolios—for example, by forming decile portfolios. The average annualized W-FF idiosyncratic volatilities for the Asian first and fifth quintile portfolios are 17.1% and 62.1%, respectively, compared to 16.7% and 92.0% per annum for portfolios formed over the same sample period using only U.S. stocks. Despite the smaller range of idiosyncratic volatility in Asian stocks, the 5–1 W-FF alpha for Asia is still economically large, at −0.53% per month. When decile portfolios ranked on idiosyncratic volatility are formed in Asia, the 10–1 difference in the extreme decile portfolio W-FF alphas is 0.79%, with a -statistic of −2.23.

Panel A of Table 6 also reports W-FF alphas for idiosyncratic volatility portfolios formed across the G7 countries and across all 23 countries, with and without U.S. stocks. The returns to the 5–1 strategy are considerably more negative when the United States is included. Without the United States, the 5–1 W-FF alpha is −0.65% per month across the G7 countries and −0.67% per month across all countries. Both of these alphas are significant with -values less than 1%, indicating that there are potentially large trading returns possible in going long (short) stocks with low (high) idiosyncratic volatility in international markets.

For completeness, we also report differences in raw returns between the first and fifth world idiosyncratic volatility portfolios in Panel B of Table 6. Note that raw returns are not risk-adjusted, unlike the W-FF alphas in Panel A, and hence they provide only a rough guide for a naïve implementation of a trading strategy based on sorting stocks by idiosyncratic volatility which does not take into account exposure to risk factors. Thus, the numbers must be carefully economically interpreted. The 5–1 differences in raw returns are economically large and, consistent with the W-FF alphas in Panel A, the effect in the United States dominates. For example, the average raw 5–1 return difference is −0.89% per month across all 23 countries, but the difference shrinks in magnitude to −0.40% when U.S. stocks are removed. Even without the United States, this difference in raw returns is still economically large, but only when the United States is included are the differences in raw returns statistically significant.

5.2. I -

This section investigates the degree of international co-movement in returns of stocks with high idiosyncratic volatilities. We construct 5–1 strategies that go long (short) the quintile portfolio containing firms with the highest (lowest) idiosyncratic volatility in various regions. Since stocks with high (low) idiosyncratic volatility have low (high) expected returns, these 5–1 strategies earn negative returns on average. All of these strategies are denominated in U.S. dollars and are rebalanced at a monthly frequency over January 1980 to December 2003. We denote the 5–1 strategy in the United States as OL^{US}.

Panel A of Table 7 reports the results of time-series regressions using the W-FF model where the W-FF alpha in Eq. (3) represents a tradable return not explained by existing risk factors. The alphas reported in Panel A

Table 7
International co-movement in idiosyncratic volatility portfolios

	Alpha	MK^{W}	MB^{W}	HML^{W}	OL^{US}	Adjusted ^{2}
Panel A: Using the W-FF model						
U.S. (OL^{US})	−1.952	0.733	1.307	−0.311		0.51
	[−5.59]	[8.56]	[13.1]	[−1.88]		
Europe	−0.723	0.456	0.433	0.004		0.29
	[−3.01]	[7.72]	[6.32]	[0.04]		
Asia	−0.529	0.339	0.699	−0.087		0.28
	[−1.84]	[4.82]	[8.54]	[−0.64]		
G7	−1.353	0.622	1.028	−0.220		0.57
	[−5.46]	[10.2]	[14.6]	[−1.88]		
G7 excluding U.S.	−0.651	0.432	0.618	−0.087		0.37
	[−2.77]	[7.49]	[9.23]	[−0.79]		
All	−1.307	0.596	0.966	−0.189		0.58
	[−5.69]	[10.6]	[14.8]	[−1.75]		
All excluding U.S.	−0.670	0.428	0.597	−0.050		0.41
	[−3.16]	[8.24]	[9.89]	[−0.50]		
Panel B: Using only OL^{US}						
Europe	0.134				0.370	0.42
	[0.63]				[14.1]	
Asia	0.130				0.271	0.16
	[0.43]				[7.29]	
G7	0.121				0.723	0.90
	[1.04]				[50.6]	
G7 excluding U.S.	0.176				0.362	0.37
	[0.77]				[12.8]	
All	0.081				0.673	0.89
	[0.71]				[47.6]	
All excluding U.S.	0.148				0.348	0.40
	[0.71]				[13.6]	
Panel C: Using W-FF and OL^{US}						
Europe	−0.104	0.223	0.018	0.103	0.317	0.44
	[−0.46]	[3.78]	[0.23]	[1.01]	[8.61]	
Asia	−0.475	0.319	0.662	−0.078	0.028	0.27
	[−1.57]	[4.02]	[6.35]	[−0.57]	[0.56]	
G7	−0.115	0.157	0.199	−0.023	0.635	0.91
	[−0.98]	[5.12]	[4.92]	[−0.43]	[33.1]	
G7 excluding U.S.	−0.245	0.279	0.346	−0.023	0.208	0.43
	[−1.04]	[4.52]	[4.25]	[−0.21]	[5.40]	
All	−0.176	0.171	0.208	−0.009	0.580	0.91
	[−1.53]	[5.69]	[5.25]	[−0.18]	[30.9]	
All excluding U.S.	−0.283	0.283	0.338	0.012	0.198	0.47
	[−1.34]	[5.11]	[4.63]	[0.13]	[5.73]	

N : For every month, within each country, we sort firms into quintile portfolios according to the W-FF idiosyncratic volatility measure (see Eq. (3)) using daily firm returns over the previous month. We aggregate the country quintile portfolios into regional quintile portfolios, for geographic areas (Europe and Asia), the G7 countries (with and without the U.S.), and across all 23 developed markets (with and without the U.S.). Each regional W-FF idiosyncratic volatility quintile portfolio is a value-weighted sum of the country quintile portfolios, with the weights being the market capitalization of the corresponding quintile portfolios in each country. Within each region, we create a "5–1" strategy that goes long the highest idiosyncratic volatility quintile and short the quintile portfolio with the highest idiosyncratic volatility stocks. For the U.S., we denote this 5–1 strategy as OL^{US}. The table reports the estimates of regressions from the full sample monthly returns of the 5–1 regional strategies onto a constant, the three W-FF factors, and the OL^{US} returns. We report robust -statistics in square brackets below each coefficient. The sample period is from September 1980 to December 2003.

correspond to the 5–1 alphas reported in Table 6. These regressions serve as a base case for investigating how the international 5–1 idiosyncratic volatility strategies are related to the 5–1 strategy in the United States, OL^{US}, in Panels B and C. In our discussion, we focus on the geographic areas excluding the United States, since, by construction, we can always partly explain regional returns that include the United States with U.S. returns. Nevertheless, we include all the regions in Table 7 for completeness.

Panel B shows that there are large and significant co-movements between the idiosyncratic volatility portfolio returns in international markets and in the United States. If the 5–1 idiosyncratic volatility portfolio returns are regressed only on a constant and OL^{US}, the alphas are all statistically insignificant. The OL^{US} loadings range from 0.27 for Asia to 0.36 for the G7 countries excluding the U.S. market. All of these OL^{US} loadings are highly statistically significant, with the lowest absolute -statistic occurring for Asia at 7.29.

Controlling for the W-FF factors in Panel C also does not generally remove the explanatory power of the OL^{US} returns for the international idiosyncratic volatility trading strategies. For Europe, the loading of 0.32 on OL^{US} is similar to the 0.37 loading without W-FF factors. The coefficient on OL^{US} for the G7 excluding the United States falls slightly from 0.72 to 0.63, while the corresponding loading for all countries excluding the United States decreases from 0.67 to 0.58 when the W-FF factors are added. These coefficients are still highly significant with -statistics above 5.4. Only in the case of Asia is the loading on OL^{US} small, at 0.03, after adding the W-FF factors.

In summary, there are remarkably similar returns across the international idiosyncratic volatility portfolios. Trading strategies that go long stocks with high idiosyncratic volatility and go short low-idiosyncratic-volatility stocks in foreign markets have large exposures to the same idiosyncratic volatility trading strategy using only U.S. stocks. After controlling for the exposure to the United States, there are no excess returns. Without controlling for U.S. exposure, however, the low returns to high-idiosyncratic-volatility stocks cannot be explained by standard risk factors. This high degree of covariation suggests that what is driving the very low returns to high-idiosyncratic-volatility stocks around the world cannot be easily diversified away and is dominated by U.S. effects.

6. A more detailed look at the United States

Sections 4 and 5 show that around the world, stocks with high idiosyncratic volatility have low returns. The effect is strongest in the United States, and we observe significant covariation between the returns of high-idiosyncratic-volatility stocks in non-U.S. countries with the returns of high-idiosyncratic-volatility stocks in the United States. This warrants a detailed look at the effect in U.S. data, where a relatively large number of firms allows for greater power in investigating the cross-sectional determinants of the effect. The U.S. market also has more detailed data on trading costs and other market frictions than other countries to facilitate the analysis.

AHXZ show that the U.S. idiosyncratic volatility effect is robust to controlling for standard risk and firm characteristics such as size, value, liquidity, and co-skewness. They find that exposure to aggregate market volatility risk measured by VIX cannot explain the effect.[4] Simple microstructure measures, volume, turnover, and bid–ask spreads also cannot explain the phenomenon. Dispersion in analysts' forecasts is also not an explanation. AHXZ report that the idiosyncratic volatility effect is robust to controlling for momentum strategies using one-, six-, and 12-month past returns, and they show that the idiosyncratic volatility effect persists for holding periods of up to at least one year.

In Section 6.1 we outline other potential economic explanations based on the costs of trading and information dissemination. We go beyond AHXZ in using better measures of transaction costs; in particular, we use a recently developed measure for assessing the amount of private information in trades. We also examine economic stories regarding how different types of investor clienteles might analyze and process information. Stocks with different idiosyncratic volatility could have different exposures to these risk factors. We also consider the effects of investor preferences for skewness. Examining these economic sources of risk is important because past research has established them to be important determinants of other CAPM anomalies.

Section 6.2 shows that the low returns to high-idiosyncratic-volatility stocks survive after controlling for these explanations. In Section 6.3, we construct investable portfolios based on idiosyncratic volatility while controlling for other relevant variables. Section 6.4 focuses on how lagged idiosyncratic volatility is related to expected future volatility and examines whether an option hypothesis proposed by Johnson (2004) can explain our findings.

6.1.

6.1.1.

Easley and O'Hara (2004) argue that expected stock returns differ because of differences in the amount of private information embedded in the trades of those stocks. Specifically, stocks with more private information command higher expected returns. To measure the degree of private information contained in the trading activity of each stock, Easley, Hvidkjaer, and O'Hara (2002) construct a measure of private information, denoted PIN. They show that stocks with high PINs have significantly higher

[4] AHXZ also include market volatility and liquidity risk factors in their analysis of U.S. data, and neither factor explains the returns to portfolios sorted on past idiosyncratic volatility. Because these factors are difficult to measure with international data, we did not include them in this paper. Adrian and Rosenberg (2007) argue that the U.S. market volatility risk factor can be split into short-run and long-run components. Neither of these risk factors explains the anomalous low returns of stocks with high idiosyncratic volatility. These results are available upon request.

expected returns than stocks with low PINs. It is possible that stocks with low (high) idiosyncratic volatility are stocks whose trades contain very high (low) amounts of private information. This situation would explain the relatively high returns on low-volatility stocks and low returns on high-volatility stocks. One drawback of the PIN measure is that it is constructed using intraday trades, which restricts the sample to post-1984.

6.1.2.

Lesmond, Ogden, and Trzcinka (1999) construct a measure of transaction costs using the proportion of daily returns equal to zero each month. They demonstrate that this measure is highly correlated with spread and commission estimates of transaction costs. A major advantage of their measure is that it only requires daily returns, allowing the use of long time series. We examine if the volatility effect is concentrated in stocks with the highest transaction costs where arbitrage is difficult.

6.1.3. A

Stocks with few analysts might incorporate new information into prices more slowly. Hou and Moskowitz (2005) hypothesize that if investors value fast information

Table 8
Control variables for the U.S

	I	II	III	IV	V	VI	VII
Panel A: L-FF idiosyncratic volatility							
Constant	1.101	4.003	4.074	1.926	1.923	3.326	4.964
	[1.45]	[6.69]	[5.21]	[2.81]	[3.08]	[6.27]	[3.98]
L-FF idiosyncratic volatility	−1.117	−1.023	−1.767	−0.789	−0.759	−0.937	−1.813
	[−3.24]	[−4.76]	[−5.02]	[−2.31]	[−2.96]	[−4.17]	[−4.27]
$\beta(MK^{L})$							

are actually insignificantly different from zero, and some carry the wrong sign. For example, if expected returns increase with transaction costs as measured by the Lesmond, Ogden, and Trzcinka (1999) proportion of zero returns, we would expect a positive coefficient, but the estimate is −0.46, which indicates that average firm excess returns decrease as transaction costs increase. To take account of potential nonlinearities in transaction costs, we also augment regression II with the square of the proportion of zero returns; this has a coefficient of almost zero and does not change any results.

Looking individually at regressions I–VI, we observe that the coefficient on L-FF idiosyncratic volatility is smallest in magnitude in regression IV, which controls for institutional ownership, with an L-FF idiosyncratic volatility coefficient of −0.79. However, power is of concern in this specification. Regression IV uses relatively few firms (on average only 776), and these firms tend to be relatively large. Even for these firms, however, the −0.79 volatility coefficient is significant with a robust -statistic of −2.31. In regression IV, the coefficient on the institutional ownership variable is close to zero and statistically insignificant. The only individually significant control variable is skewness in regression VI, and here, consistent with the argument of Barberis and Huang (2005), we find that the more positively skewed are individual returns, the lower is the expected return. The idiosyncratic volatility coefficient of −0.94 remains highly significant with a robust -statistic of −4.17.

Regression VII controls for all variables over July 1981 to June 2000. In this regression, the percentage of zero returns and analyst coverage are significant variables, but the coefficients have the wrong signs compared to the theoretical predictions. The institutional ownership, delay, and past skewness variables have insignificant explanatory power. The coefficient on L-FF idiosyncratic volatility is −1.81, with a robust -statistic of −4.27. This is similar to the −2.01 coefficient on L-FF idiosyncratic volatility in Table 2 using the 1980–2003 sample. Given the results in Table 8, it is unlikely that any of these variables can explain the idiosyncratic volatility effect.

Panels B and C of Table 8 investigate whether using different measures of volatility substantially changes inferences about the effects. For each regression specification, we use the same variables as Panel A except we substitute either lagged total volatility or lagged W-FF idiosyncratic volatility for L-FF idiosyncratic volatility. The Fama-MacBeth coefficients on the other variables are not reported to save space. Panels B and C show that using total volatility or W-FF idiosyncratic volatility produces very similar results across all the regressions. In particular, for regression VII using the largest set of controls, the coefficients on total volatility and W-FF idiosyncratic volatility are −1.73 and −1.87, respectively, compared to −1.81 in Panel A for L-FF idiosyncratic volatility.

6.3. I

In this section, we form portfolios based on L-FF idiosyncratic volatility and examine actual holding-period returns. For each month, we sort firms into quintile portfolios based on L-FF idiosyncratic volatility at the beginning of the month, computed as in Eq. (1) using daily returns over the previous month, and we rebalance the portfolios each month. Each quintile portfolio is value weighted using weights at the beginning of the month. After the resulting quintile portfolio returns are formed in excess of the one-month U.S. T-bill return, we compute L-FF alphas by running Eq. (2) at a monthly frequency over the whole sample. Since the L-FF factors are traded factors, the L-FF alpha represents an investable return.

The first row of Table 9 under "No Controls" reports the results of this procedure after sorting firms into L-FF idiosyncratic quintile portfolios over the whole U.S. sample, with the returns spanning August 1963 to December 2003. The table reports L-FF alphas of each quintile portfolio with the column "5–1" reporting the difference in L-FF alphas between a trading strategy that goes long stocks in the highest-idiosyncratic-volatility quintile and short stocks in the lowest-idiosyncratic-volatility quintile. The "no control" row reports the AHXZ result. The 5–1 difference in L-FF alphas is −1.29% per month with a robust -statistic of −6.71. For comparison, the difference in raw average returns between the first and fifth volatility quintile portfolios is a large −0.97% per month and is highly statistically significant.

Table 9
L-FF alphas of U.S. portfolios sorted on idiosyncratic volatility

	Ranking on idiosyncratic volatility					5–1	Ave. no. of stocks	Sample
	1 Low	2	3	4	5 High			
No controls	0.103	0.027	0.067	−0.398	−1.186	−1.290	956	Aug 63–Dec 03
	[2.15]	[0.56]	[1.00]	[−3.84]	[−7.12]	[−6.71]		
PIN	0.054	−0.107	−0.081	−0.276	−0.950	−1.004	185	Jan 84–Dec 01
	[0.54]	[−0.98]	[−0.67]	[−2.22]	[−5.59]	[−4.56]		
Proportion of zero returns	−0.014	−0.045	−0.039	−0.379	−1.116	−1.101	956	Aug 63–Dec 03
	[−0.31]	[−0.82]	[−0.61]	[−4.96]	[−8.71]	[−7.35]		
Analyst coverage	0.658	0.910	0.831	0.733	−0.029	−0.687	114	Jul 76–Jun 01
	[3.14]	[3.56]	[2.92]	[2.33]	[−0.07]	[−2.13]		
Institutional ownership	0.065	0.093	0.096	−0.117	−1.087	−1.152	95	Jul 81–Jun 00
	[0.54]	[0.91]	[0.69]	[−0.87]	[−5.89]	[−4.73]		
Delay	0.064	0.196	0.034	0.016	−0.603	−0.667	241	Jul 65–Dec 01
	[0.92]	[2.79]	[0.45]	[0.16]	[−4.73]	[−4.28]		
Skewness	0.047	0.042	−0.019	−0.306	−1.156	−1.204	956	Aug 63–Dec 03
	[1.02]	[0.84]	[−0.31]	[−3.35]	[−6.94]	[−6.23]		

The table reports L-FF alphas (see Eq. (1)) for only U.S. stocks for forming portfolios ranked on L-FF idiosyncratic volatility at the beginning of each month

In the remaining rows of Table 9, we form portfolios that control for the various risk characteristics (PIN, the proportion of zero returns, analyst coverage, institutional ownership, delay, and skewness). We first sort stocks into quintiles based on the control variable, and then, within each quintile, we sort stocks based on L-FF idiosyncratic volatility. The five idiosyncratic volatility portfolios are then averaged over each of the five characteristic portfolios, and the results are idiosyncratic volatility quintile portfolios that control for the characteristic. All these portfolios are also value weighted. Note that this procedure only controls for a single characteristic at a time, but the computation of the expost L-FF alpha also controls for the *MK* , *MB*, and *HML* factor loadings.

Controlling for the various characteristics slightly reduces the idiosyncratic volatility effect, but not by much, and none of the characteristics can overturn the low returns to high-idiosyncratic-volatility stocks. Some of these controls also result in a large drop in the average number of firms in each portfolio. The differences in L-FF alphas after controlling for PIN, the proportion of zero returns, institutional ownership, and skewness for the 5–1 strategy are very similar to the "no control" returns. The PIN and proportion of zero return controls do almost nothing to change the "no control" strategy L-FF alpha of -1.29% per month – to -1.00% and -1.10% per month, respectively. Similarly, institutional ownership and skewness have almost no effect.

The variables that have the largest effect in shrinking the difference in the returns between stocks with high and low idiosyncratic volatility are analyst coverage and the Hou and Moskowitz (2005) delay measure. Controlling for analyst coverage shrinks the L-FF alpha of the 5–1 trading strategy to -0.69% per month, while controlling for delay shrinks it to -0.67% per month. The robust -statistics for both effects are still significantly above the 95% confidence level, and both effects remain economically large. Thus, analyst coverage and delay help the most to explain, but by no means remove, the low returns to stocks with high idiosyncratic volatility.

In summary, portfolios in the United States formed on idiosyncratic volatility exhibit large differences in returns between stocks with high and low idiosyncratic volatilities. These differences are robust in portfolios that control for the degree of informed trading, transaction costs, analyst coverage, institutional ownership, price responsiveness to information, and skewness.

6.4. A

So far, we have measured idiosyncratic volatility as a lagged firm characteristic. Naturally, since idiosyncratic volatility is persistent (see below), it is related to future volatility, and some component of lagged idiosyncratic volatility could be instrumenting expected volatility. Expected volatility could be related to future returns differently than lagged volatility. Indeed, Fu (2005) and Spiegel and Wang (2005) find a positive relation between conditional idiosyncratic volatility estimated using monthly frequency data and expected returns. Alternatively, lagged volatility could be negatively related to future returns because equity is a call option on the firm's underlying assets, as suggested by Johnson (2004). In this section, we investigate this option interpretation, which involves a leverage effect interacting with idiosyncratic volatility.

Black and Scholes (1973) are the first to interpret equity as a call option on the firm's underlying assets. Johnson takes this framework and, following Merton (1974), derives that the return of a stock, d / , in excess of a constant risk-free rate, , is given by

$$\mathrm{d}\;/\; - \;\mathrm{d}\; = (\;\Delta\;/\;)\mathrm{d}\; + (\;_{a}\Delta\;/\;)\mathrm{d}\;, \qquad (5)$$

where is the risk premium on the unlevered stock, is the price of an unlevered claim on the firm's assets, $_a$ is the firm's underlying asset volatility, Δ is a standard option delta, $\Delta = \partial\;/\partial$, and d is a Brownian motion term. The total stock volatility, , comprises both underlying asset volatility, $_a$, as well as the variance of uncertainty of the current value of the firm's assets, . The latter can be proxied by the dispersion of analysts' earnings forecasts, as Johnson investigates, or perhaps by idiosyncratic volatility, as we examine below.

Johnson notes that Δ is decreasing in the volatility of the stock return, as is $\partial\Delta/\partial\; < 0$ in a standard Black-Scholes (1973) model. Thus, according to Johnson's option interpretation, leverage causes the expected stock return to decrease as idiosyncratic volatility increases, since the sign of the partial derivative $\partial\Delta/\partial$ is negative. Furthermore, as leverage increases, the strength of the negative association between returns and idiosyncratic volatility increases.

This interpretation raises several issues. First, Johnson originally applies his result to the negative relation between stock returns and the dispersion of analysts' forecasts documented by Diether, Malloy, and Scherbina (2002). We would expect—and indeed we find—that the dispersion of beliefs is positively correlated with idiosyncratic volatility; the dispersion of analysts' forecasts as constructed by Diether, Malloy, and Scherbina has a cross-sectional correlation of 0.201 with lagged idiosyncratic volatility. Thus, Johnson's interpretation of the cross-sectional dispersion of beliefs could also apply to cross-sectional idiosyncratic volatility.

Second, a richer option model need not produce a negative relation between volatility and expected returns. In particular, models with mean-reverting stochastic volatility can produce cases where Δ is an increasing function of volatility (see comments by Ledoit, Santa-Clara, and Yan, 2002). For example, in results available from the authors, a Heston (1993) model produces an upward-sloping Δ as a function of for an out-of-the-money call option. The out-of-the-money region would not be relevant in a simple model of equity as a call option because in this region the face value of debt is greater than the asset value of the firm, so the firm would be bankrupt. This suggests that in more sophisticated models with endogenous default, the relation between Δ and volatility could change sign as the firm approaches the default boundary. However, this does not make the simple Johnson (2004) explanation invalid.

Third, lagged volatility is not the appropriate parameter that enters the option pricing model. The parameter of interest is conditional volatility, which is the expectation of quadratic variation over the next period. Since idiosyncratic volatility is persistent, any estimate of conditional volatility will be correlated with lagged idiosyncratic volatility. In the next section, we try to disentangle the predictive relation of lagged idiosyncratic volatility and returns versus the relation between conditional estimates of future volatility and firm returns. We also investigate the cross-sectional relation between stock returns and realized, rather than lagged, idiosyncratic volatility.

6.4.1. I

To investigate the leverage interaction effect, we first examine the coefficient on lagged volatility in Eq. (4) controlling for leverage and an interaction term between leverage and lagged volatility. We define leverage following Johnson (2004) as the book value of debt over the sum of the book value of debt and the market value of equity. Johnson's model suggests that controlling for leverage should remove the statistical significance of the coefficient on lagged volatility, and the coefficient on the interaction between leverage and volatility should be negative.

Table 10 reports the coefficients on lagged idiosyncratic volatility, leverage, and the interaction term of leverage and idiosyncratic volatility after controlling for *MK* , *MB*, and *HML* contemporaneous factor loadings and size, book-to-market, and past return characteristics. Idiosyncratic volatility has a coefficient of −1.14 with a -statistic of −4.45. Regression I reports that the coefficient on idiosyncratic volatility without the leverage and interaction controls (but retaining the *MK* , *MB*, and *HML* factor loadings and size, book-to-market, and past return characteristics) is −0.94, with a -statistic of −2.24. Thus, controlling for leverage does not decrease the idiosyncratic volatility effect, but instead slightly strengthens its effect. Leverage carries a negative coefficient of −0.92 and the interaction term has a positive coefficient of 1.59. Both these coefficients are highly significant at the 95% level. These are opposite to the signs predicted by Johnson, where the negative return to high-idiosyncratic-volatility stocks should be greater in firms with higher leverage.

In Table 11, we examine the relation between leverage and lagged idiosyncratic volatility in more detail. We first sort firms into quintile portfolios according to leverage and then, within each leverage quintile, we sort stocks on (− 1,) in columns. Panel A reports the results listing L-FF alphas of each of these 25 portfolios. The last column labeled "5–1" is the long-short portfolio that goes long the highest (− 1,) portfolio and goes short the lowest (− 1,) portfolio within each leverage quintile. If an option interpretation is correct, then the most negative L-FF alphas should be observed in the portfolios with the highest leverage. We observe the opposite pattern. The greatest spread between high- and low-idiosyncratic-volatility stocks is −1.59% per month in the portfolios with the lowest leverage. If we use predicted idiosyncratic volatility instead of lagged idiosyncratic volatility, we still

Table 10
Idiosyncratic volatility and leverage

	I	II
Constant	2.463	2.697
	[9.23]	[8.88]
L-FF idiosyncratic volatility	−0.935	−1.135

do not find the 5–1 spread to be most pronounced for stocks with the highest volatility. In the last row, we construct idiosyncratic volatility portfolios that control for leverage, similar to those constructed in Table 9 by averaging over the five leverage portfolios. Controlling for leverage does not remove the idiosyncratic volatility effect.

6.4.2. I

Idiosyncratic volatility exhibits strong cross-sectional persistence and is highly correlated with conditional volatility. We now disentangle the effect of lagged idiosyncratic volatility from predicted future volatility. We construct cross-sectional forecasts of future idiosyncratic volatility, E [(, + 1)], by running a cross-sectional regression of (, + 1) on firm characteristics at time . We use lagged idiosyncratic volatility, size, the book-to-market ratio, past six-month returns, stock return skewness, and turnover as characteristics. Skewness is measured using daily returns over the previous month, and turnover is defined as the trading volume over the

Table 11
Relation between idiosyncratic volatility and leverage

	Ranking on (− 1,)					
	1 Low	2	3	4	5 High	5–1
1 Low leverage	0.530	0.320	0.235	−0.348	−1.061	−1.592
	[3.84]	[2.43]	[1.36]	[−1.78]	[−4.02]	[−5.62]
2	0.269	0.327	0.156	−0.058	−1.066	−1.335
	[3.09]	[2.97]	[1.08]	[−0.29]	[−4.62]	[−5.31]
3	−0.009	−0.121	−0.070	−0.330	−1.074	−1.065
	[−0.11]	[−1.11]	[−0.55]	[−2.13]	[−4.96]	[−4.44]
4	−0.028	−0.051	−0.303	−0.589	−1.204	−1.176
	[−0.30]	[−0.52]	[−2.44]	[−4.41]	[−5.61]	[−5.01]
5 High leverage	−0.101	−0.047	−0.048	−0.948	−1.258	−1.157
	[−0.95]	[−0.36]	[−0.31]	[−4.64]	[−4.22]	[−3.70]
Ranking on (− 1,) controlling for leverage	0.132	0.086	−0.006	−0.455	−1.113	−1.265
	[2.87]	[1.53]	[−0.08]	[−4.53]	[−6.95]	[−7.25]

We compute L-FF alphas of 5 × 5 portfolios first sorted on leverage, defined as the book value of debt divided by the sum of the book value of debt and market value of equity, and then on lagged idiosyncratic volatility, (− 1,). We first sort stocks each month based on leverage and then, within each quintile, we sort stocks on (− 1,). The last row labeled "Ranking on (− 1,) controlling for leverage" reports the L-FF alphas of the five (− 1,)

previous month divided by the total number of shares outstanding at the end of the month. The coefficients are estimated using data only up to time to forecast volatility over to + 1, and we run a new cross-sectional regression at each time period.[6] We focus on cross-sectional regression forecasts because our relation between future returns and lagged idiosyncratic volatility is a cross-sectional effect.

Not surprisingly, the best predictor of future idiosyncratic volatility is lagged idiosyncratic volatility. The cross-sectional correlation of E [(, + 1)] with (− 1,) is 0.95. This high correlation would lead to collinearity problems in placing both these variables in a regression, but we can separate the effect of lagged idiosyncratic volatility and predicted idiosyncratic volatility in a double portfolio sort. Panel A of Table 12 first ranks stocks on E [(, + 1)] and then sorts stocks on (− 1,). Panel B shows that in each E [(, + 1)] quintile, the stocks with high lagged idiosyncratic volatility have low returns. Only in the lowest E [(, + 1)] quintile is the 5–1 difference not statistically significant. In row 5, which contains stocks in the highest quintile of predicted volatility, the 5–1 spread in L-FF alphas is an extremely large −2.18% per month. In the last row, we construct lagged idiosyncratic volatility portfolios that control for E [(, + 1)]. Here, the 5–1 spread is a large −1.07% per month. In summary, lagged idiosyncratic volatility has strong predictive power in addition to the information it contains about future idiosyncratic volatility.

6.4.3. L υ υ

Finally, we examine the relation between lagged idiosyncratic volatility, (− 1,), and realized idiosyncratic volatility, (, + 1). Realized idiosyncratic volatility over the next month is equal to expected idiosyncratic volatility at the beginning of the month plus a rational expectations error, ^{2}(, + 1) = E [((, + 1) − E ((, + 1))^2]+ υ (+ 1). Since any unbiased estimator of true conditional volatility will be equal to realized volatility plus noise, examining how future realized idiosyncratic volatility is related to returns could be a stronger control than using an estimate of conditional volatility.

However, any relation between realized returns and realized volatility is complicated by the fact that estimates of the realized mean and realized variance are correlated because stock return skewness is nonzero.[7] To illustrate this, we compute the sample skewness of firms using daily simple returns over the full sample. The average skewness across firms using simple returns is 1.33. This positive skewness would impart a positive correlation to realized mean returns and realized volatilities. Using log returns can reduce this skewness because log returns do not have the limited liability truncation at −100% of simple returns. If monthly skewness is computed using daily log returns, the average skewness across firms is nearly zero at 0.09.

Of course, the predictive relation between past idiosyncratic volatility and future returns does not change if we measure idiosyncratic volatility using log returns rather than simple returns. For example, if we use log returns to compute idiosyncratic volatility, with all

Table 12
Relation between idiosyncratic volatility and predicted and realized volatility

	Ranking on (− 1,)					
	1 Low	2	3	4	5 High	5–1
Panel A: L-FF alphas of portfolios first sorted on E [(, + 1)], then on (− 1,)						
1 Low E [(, + 1)]	0.069	0.064	0.089	0.079	−0.070	−0.139
	[0.77]	[0.91]	[1.31]	[1.17]	[−0.94]	[−1.14]
2	0.349	0.346	0.161	0.231	−0.089	−0.438
	[3.57]	[3.44]	[1.65]	[2.27]	[−0.92]	[−3.17]
3	0.586	0.520	0.242	−0.007	−0.511	−1.097
	[5.12]	[4.19]	[2.09]	[−0.06]	[−4.03]	[−6.47]
4	0.638	0.183	0.028	−0.442	−0.880	−1.518
	[4.51]	[1.40]	[0.17]	[−2.95]	[−5.19]	[−7.70]
5 High E [(, + 1)]	0.484	−0.617	−1.021	−1.487	−1.691	−2.175
	[2.14]	[−2.91]	[−4.58]	[−6.28]	[−6.45]	[−7.52]
Ranking on (− 1,) controlling for E [(, + 1)]	0.425	0.099	−0.100	−0.325	−0.648	−1.073
	[4.95]	[1.26]	[−1.22]	[−3.90]	[−7.09]	[−9.44]
Panel B: L-FF alphas of portfolios first sorted on L(, + 1), then on L(− 1,)						
1 Low L(, + 1)	−0.081	0.136	0.036	−0.051	−0.490	−0.410
	[−0.91]	[1.92]	[0.50]	[−0.67]	[−5.90]	[−3.43]
2	0.132	0.197	0.105	−0.099	−0.487	−0.619
	[1.57]	[2.54]	[1.38]	[−1.11]	[−3.99]	[−3.93]
3	0.117	0.449	0.451	−0.155	−1.218	−1.335
	[0.96]	[4.83]	[4.74]	[−1.43]	[−8.31]	[−6.36]
4	0.029	0.736	0.137	−0.351	−2.094	−2.122
	[0.13]	[4.56]	[0.94]	[−2.27]	[−11.4]	[−7.58]
5 High L(, + 1)	−0.333	−0.496	0.312	−0.024	−1.870	−1.537
	[−0.74]	[1.68]	[0.94]	[−0.07]	[−5.48]	[−2.95]
Ranking on						

returns in Eq. (1) expressed as continuously compounded returns, then the spread between quintile portfolio L-FF alphas of U.S. stocks ranked on lagged idiosyncratic volatility is −1.27% per month, with a robust -statistic of −6.68, compared to a spread of −1.29% per month with a robust -statistic of −6.71 as reported in the first row of Table 9. It is only the contemporaneous relation between realized returns and realized volatility that is affected by the skewness of stock returns.

Because of the effect of skewness, to investigate how the relation between realized idiosyncratic volatility and realized returns differs from the relation between lagged idiosyncratic volatility and future returns, we consider the idiosyncratic volatility of log returns only, L, which we denote with an *L* to differentiate it from the idiosyncratic volatility of simple returns. Panel B of Table 12 reports L-FF alphas of quintile portfolios of U.S. stocks sorted by realized idiosyncratic volatility, L(, + 1), measured at the end of month + 1, and then sorted on lagged idiosyncratic volatility, L(− 1,). Note that these portfolios are not tradable because the portfolio sorts are done using forward-looking information at the end of the month. These are the returns that would accrue to an investor with perfect knowledge of future idiosyncratic volatility over the next month. We examine these sorts because they help to disentangle the effects of lagged versus contemporaneous idiosyncratic volatility.

Panel B of Table 12 shows that in every L(, + 1) quintile, returns tend to become more negative as lagged idiosyncratic volatility increases. The last column labeled "5–1" is the long-short portfolio that goes long the highest L(− 1,) portfolio and short the lowest L(− 1,) portfolio within each contemporaneous volatility quintile. This column shows that there is a large, statistically significant, negative return spread to lagged idiosyncratic volatility in each of the realized volatility quintiles. This

5–1 spread ranges from −0.41% per month for the first $^{L}(\ ,\ +1)$ quintile portfolio to a very large −2.12% in the fourth $^{L}(\ ,\ +1)$ quintile portfolio.

In the last row of Panel B, we report L-FF alphas of quintile portfolios of $^{L}(\ -1,\ )$ controlling for the effect of contemporaneous volatility. Controlling for contemporaneous idiosyncratic volatility, the 5–1 return spread is a large −1.21% per month, which is highly significant with a -statistic of −6.63. Thus, future exposure to high idiosyncratic volatility does not explain why the rewards to holding stocks with low past idiosyncratic volatility are so low.

7. Conclusion

Around the world, stocks with recent past high idiosyncratic volatility tend to have much lower returns than stocks with recent past low idiosyncratic volatility. We measure idiosyncratic volatility with respect to local, regional, or world versions of the Fama and French (1993, 1998) factor model. After sorting stocks across 23 countries on past idiosyncratic volatility, the difference in alphas adjusting for market, size, and book-to-market factors between stocks in the highest quintile of idiosyncratic volatility and stocks in the lowest quintile of idiosyncratic volatility is a very large −1.31% per month. This effect is also strongly statistically significant. These low returns to high-idiosyncratic-volatility stocks simultaneously appear in different world regions and are robust to controlling for additional factor loadings and firm characteristics. Since these results are out-of-sample relative to the earlier U.S. findings of Ang, Hodrick, Xing, and Zhang (2006), the implication is that the relation between high idiosyncratic volatility and low returns is not just a sample-specific or country-specific effect but is observed worldwide.

We find that the low returns earned by stocks with high idiosyncratic volatility around the world co-move significantly with the idiosyncratic volatility effect in the United States. In particular, after controlling for U.S. portfolios comprising long positions in stocks with high idiosyncratic volatilities and short positions in stocks with low idiosyncratic volatilities, the alphas of portfolio strategies trading the idiosyncratic volatility effect in various international markets are insignificant. Thus, the global idiosyncratic volatility effect is captured by a simple U.S. idiosyncratic volatility factor. In contrast, the low returns of high idiosyncratic stocks in international markets cannot be explained by standard factors or risk loadings.

However, we are hesitant to claim that the low returns to high-idiosyncratic-volatility stocks results from exposure to systematic risk. In further analysis on U.S. data, we rule out complete explanations based on trading or clientele structures, higher moments, and information dissemination. The low returns of stocks with past high idiosyncratic volatility cannot be explained by the leverage interaction story of Johnson (2004) or by future exposure to idiosyncratic volatility. Our strong international results suggest that market-specific stories are also unlikely to hold. We conclude that the puzzle of low returns to high-idiosyncratic-volatility stocks have low returns is a global phenomenon. Further research must investigate if there are true economic sources of risk behind the idiosyncratic volatility phenomenon causing stocks with high volatility to have low expected returns.

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