High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence*

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This Version: 19 January, 2006

JEL Classification: G12, G13
Keywords: cross-section of stock returns, international predictability, factor model

*We thank Kewei Hou and Soeren Hvidjkaer for kindly providing data. Andrew Ang acknowledges support from the NSF.

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Abstract

Stocks with high idiosyncratic volatility have low expected returns around the world. This effect is individually significant in each G7 country. 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. In the U.S., we rule out explanations based on trading frictions, information dissemination, and higher moments. There is strong comovement in the low returns to high idiosyncratic volatility stocks across countries, suggesting that broad, not easily diversifiable factors lie behind this phenomenon.

1 Introduction

If a cross-sectional factor model is correctly specified, then idiosyncratic volatility is diversifiable and there is no relation between idiosyncratic volatility and expected returns. However, in environments with frictions and incomplete information, standard factor models are misspecified and 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 average returns because investors cannot fully diversify away firm-specific risk. Ang, Hodrick, Xing and Zhang (2006) [AHXZ hereafter] recently find the exact opposite relation. They measure idiosyncratic volatility using the Fama and French (1993) model and show that U.S. stocks with high idiosyncratic volatility earn very low average returns. AHXZ's results are surprising for two reasons. First, their findings are inconsistent with existing asset pricing models. Second, the difference in average returns across stocks with low and high idiosyncratic volatility is relatively large. In particular, the spread in average returns between the first and fifth quintile portfolios of stocks sorted by idiosyncratic risk is over 1% per month.

As with any empirical results, there is a danger that AHXZ's finding that high idiosyncratic volatility cross-sectionally predicts low future average returns is spurious (see comments by Lo and MacKinlay, 1990). One way to determine whether an empirical result is important and robust is to examine data from other countries. If a relation between idiosyncratic volatility and expected returns exists in international markets, it is more likely that there is an underlying, perhaps common, economic source behind the idiosyncratic volatility pricing phenomenon. This paper examines if stocks with high idiosyncratic volatility in international markets conform to the same pattern observed in the U.S. cross-section and how the international return patterns are related to the U.S. idiosyncratic volatility effect. We also consider some further possible explanations within the U.S., where more detailed data is available, for the negative idiosyncratic volatility and expected return relation.

The paper contains three main contributions. First, we present evidence that the negative relation between idiosyncratic volatility and expected returns, first found in U.S. data, is observed across a broad sample of international developed markets. In particular, for each of the largest seven equity markets (Canada, France, Germany, Italy, Japan, the U.S., and the U.K.), stocks with high idiosyncratic volatility tend to have low average returns. The negative idiosyncratic volatility–expected return relation is strongly statistically significant in each of these countries and is also observed in the larger sample of 23 developed markets. Second and perhaps most interesting, the negative spread in returns between stocks with high and low idiosyncratic volatility in international markets strongly comoves with the difference in returns between U.S. stocks with high and low idiosyncratic volatilities.

Third, in more detailed analysis in the U.S. market, we also examine other recently proposed explanations of why stocks with high idiosyncratic volatility have low returns, which are not considered by AHXZ. Specifically, stocks with low idiosyncratic volatility may have high trading costs or trade in markets with large frictions, explaining their high returns. We consider the effects of transactions costs by controlling for the incidence of zero returns suggested by Lesmond, Ogden and Trzcinka (1999). To characterize the severity of market frictions, we also 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 (see Chordia, Huh and Subrahmanyam, 2005) and can proxy for the proportion of informed agents (see Brennan and Subrahmanyam, 1995), we investigate if 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 (see Easley, Hvidkjaer and O'Hara, 2002) and to skewness (see Barberis and Huang, 2005). None of these explanations can account for the high idiosyncratic volatility and low average returns relation.

The strong international results and further robustness of the U.S. results to additional controls suggest that it is unlikely that the low returns to high idiosyncratic volatility stocks are a small sample problem. Moreover, explanations based only on trading or clientele structures that are market-specific are also unlikely to hold. The large commonality in comovement 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, but we do not claim that the low average returns to stocks with high idiosyncratic volatility represents a priced risk factor.

In our analysis, we investigate the relation between future returns and past idiosyncratic volatility. Thus, the idiosyncratic volatility effect that we document both in the U.S. and international markets is not a relation that involves expected volatility (see Fu, 2005), which must be proxied. In contrast, past idiosyncratic volatility is observable, easily calculated, and is a measurable stock characteristic that is implementable in a real-time trading strategy. While using lagged idiosyncratic volatility is one estimate of future idiosyncratic volatility, we do not investigate the contemporaneous relation between expected returns and expected idiosyncratic volatility, which is not easily tradeable without a good predictor of future idiosyncratic volatility.

Our results are related to a literature that investigates if idiosyncratic volatility can predict future aggregate market returns (see, for example, Goyal and Santa-Clara, 2003; Guo and Savickas, 2004a; Bali et al., 2005; Wei and Zhang, 2005). In contrast to these papers, our focus is only on the cross-sectional relation between firm-level idiosyncratic volatility and expected returns, but unlike AHXZ, we use a large sample of international markets. Papers building on Miller (1977) have used idiosyncratic volatility as a proxy for differences in opinion (see, for example, Baker, Coval and Stein, 2004) and idiosyncratic volatility is also related to liquidity risk (see, for example, Spiegel and Wang, 2005).[1] Rather than investigating if idiosyncratic volatility is a good proxy for differences in opinion or how idiosyncratic volatility is related to liquidity risk, we focus on how idiosyncratic volatility itself is related to expected returns in the cross-section of international stock returns. Naturally, we control for variables capturing the effects of analyst coverage, liquidity, and other cross-sectional effects, particularly in the U.S. analysis.

The remainder of this paper is organized as follows. Section 2 defines the idiosyncratic volatility of a stock and Section 3 describes the international stock return data set. Section 4 presents a series of Fama-MacBeth (1973) regressions to estimate the relation between expected returns and idiosyncratic volatility in international markets, while Section 5 reports the detailed analysis using U.S. data. In Section 6, we examine how the U.S. discount for stocks with high idiosyncratic volatilities comoves with the low returns for stocks with high idiosyncratic volatilities in international markets. Section 7 concludes.

2 Measuring Idiosyncratic Volatility

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

[1] AHXZ show that differences in opinion measured by analyst dispersion (see Diether, Malloy and Scherbina, 2002) cannot explain the idiosyncratic volatility effect, while Guo and Savickas (2004b) argue that using idiosyncratic volatility to measure differences of opinion is unlikely to cause the low returns of high volatility stocks.

2.1 The Local Fama-French Model

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. For our analysis on only U.S. stocks, our L-FF model is just the 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). Within each country j, we compute the return on zero-cost portfolios SMB^j and HML^j, measuring size and value premiums, respectively. The country-specific factor SMB^j is the return of the smallest 1/3rd of local firms less the return on the firms in the top third ranked by market capitalization. In country j, the value factor HML^j is the return of the portfolio that goes long the top third of local firms with the highest book-to-market ratios and shorts the bottom third of local firms with low book-to-market ratios. The market factor for country j, MKT^j, is computed as the excess return of the local market portfolio over the one-month U.S. T-bill rate.

Similar to AHXZ, we define idiosyncratic volatility with respect to the L-FF model using the following regression on excess stock returns, r_i:

$$r_i = \alpha_i^L + \beta_i^L MKT^L + s_i^L SMB^L + h_i^L HML^L + \varepsilon_i^L, \qquad (1)$$

where r_i is the daily excess U.S. dollar return of stock i and the L-FF factors are also expressed in U.S. dollars. The idiosyncratic volatility for stock i is measured as $\sqrt{\text{var}(\varepsilon_i^L)}$ after estimating equation (1) using daily excess returns over the past month.

2.2 The Regional Fama-French Model

We specify a regional Fama-French model (R-FF hereafter) to be a linear factor model comprising three factors, MKT^R, SMB^R, and HML^R. To compute the regional factors, we group the 23 countries into three regions: North America (the U.S. and Canada), Europe, and the Far East. These regional factors are computed as value-weighted sums of the country factors within each of the three regions. Brooks and Del Negro (2005) show that country-specific factors within regions can be mostly explained by regional factors (see also Bekaert, Hodrick, and Zhang, 2005).

We define idiosyncratic volatility with respect to the R-FF model to be the standard deviation of the residual in the regression:

$$r_i = \alpha_i^R + \beta_i^R MKT^R + s_i^R SMB^R + h_i^R HML^R + \varepsilon_i^R, \qquad (2)$$

using daily U.S. dollar excess returns of stock i over the past month and all of the R-FF factors are expressed in U.S. dollars. We estimate regression (2) using daily observations over the previous month. We compute firm i's idiosyncratic volatility with respect to the R-FF model as $\sqrt{\text{var}(\varepsilon_i^R)}$.

2.3 The World Fama-French Model

The size and value factors in our world version of the Fama-French model (W-FF hereafter), SMB^W and HML^W are computed as the value-weighted sum of the regional Fama-French factors SMB^R and HML^R, respectively, across the North American, European, and the Far Eastern regions. The world market factor, MKT^W, is the excess world market return. To compute idiosyncratic volatility with respect to the W-FF model, we regress daily firm excess returns on the three global factors:

$$r_i = \alpha_i^W + \beta_i^W MKT^W + s_i^W SMB^W + h_i^W HML^W + \varepsilon_i^W, \tag{3}$$

over the previous month. Firm excess returns and the W-FF factors are expressed in U.S. dollars. Idiosyncratic volatility relative to the W-FF model is defined as $\sqrt{\text{var}(\varepsilon_i^W)}$.

3 Data

Our stock return data comprise daily firm returns from 23 developed markets. We study both local and U.S. dollar denominated returns, but compute excess returns using the U.S. one-month T-bill rate. The countries we select are based on the country universe of the MSCI Developed Country Index. Individual stock returns for the U.S. are obtained from COMPUSTAT and CRSP, while stock return data for international countries are obtained from Datastream. For most countries, our sample period spans January 1980 to December 2003, except for Finland, Greece, New Zealand, Portugal, Spain and Sweden, which begin in the mid-1980s. We exclude very small firms by eliminating the bottom 5% of firms with the lowest market capitalization within each country. In addition, for more detailed analysis using U.S. data, we use CRSP returns on all U.S. stocks starting in August 1963.

Panel A of Table 1 presents summary statistics for the firm returns 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 quite wide variation in the firm characteristics across countries, with the average firm size ranging from \$182 million in Greece to \$1,632 million in the Netherlands.

In comparison, the average U.S. firm in our sample has an average market capitalization of $975 million. Japanese firms tend to have the lowest book-to-market ratios (at 0.70), whereas Belgium is the most growth-oriented as measured by the book-to-market ratio variable, with Belgian firms having average book-to-market ratios of 1.40. Note that the average number of firms in the U.S. over our sample, at 5441, dwarfs the number of firms in any other market. The next largest equity market, Japan, contains an average of 1453 firms. Thus, in our empirical work, we are careful to disentangle the effect of the U.S. on any result involving pooled data across international markets.

In Panel A, we report summary statistics for three different volatility measures, which are all reported in annualized terms. The first volatility measure is total volatility, which is computed as the volatility of daily raw returns over the previous month. The second and third measures are idiosyncratic volatility computed with respect to the R-FF model (equation (2)) and the W-FF model (equation (3)). All three volatility measures are highly correlated with each other, with the correlations all above 95% in each country. The U.K. has the lowest idiosyncratic volatility (26% per annum with respect to W-FF), compared to the average W-FF idiosyncratic across countries of 41% per annum.[2] There is also quite wide range in the dispersion of idiosyncratic volatility across markets. For the U.S., the interquartile range (the difference between the 25th and 75th percentiles) of W-FF idiosyncratic volatility is $61.1\% - 25.0\% = 36.1\%$, compared to an interquartile range of $38.4\% - 18.5\% = 19.9\%$ for the other 22 countries.

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 SMB factor for North America is negative, at -0.08% per month because since the size effect was first found by Banz (1981), small firms have not out-performed large firms in the United States. The evidence for the size effect is stronger in the post-1980 sample for Europe and the Far East, where the SMB local factors are positive. Value strategies have also performed better in overseas markets than in the U.S., with high book-to-market stocks significantly underperforming low book-to-market stocks over the late 1990's bull market in the United States. The value premium is particularly strong in the Far East, where the HML factor has a mean of 0.71% per month, causing the world HML factor, HML^W, to have a high mean of 0.42% per month.

[2] While Campbell et al. (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 no evidence for a trend in idiosyncratic volatility in international markets.

4 Idiosyncratic Volatility and Expected Returns

Section 4.1 describes the cross-sectional regression methodology. We report results in Sections 4.2 to 4.4. We begin by looking at U.S. returns in Section 4.2, move to including the G7 developed countries in Sections 4.3, and consider all 23 countries in Section 4.4.

4.1 Methodology

We examine the relation between total volatility and idiosyncratic volatility with respect to the 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 firm excess returns onto idiosyncratic volatility together with factor loadings, firm characteristics and other control variables. In the second stage, we use the time-series of the regression coefficients and test if the coefficient on the previous month's 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:

$$r_{i,t+1} = c + \gamma \sigma_{i,t} + \lambda'_\beta \beta_{i,t+1} + \lambda'_z z_{i,t} + \varepsilon_{i,t+1}, \qquad (4)$$

where $r_{i,t+1}$ is firm i's excess return from t to $t+1$, $\sigma_{i,t}$ is total or idiosyncratic volatility over the previous month from $t-1$ to t, $\beta_{i,t+1}$ is a vector of factor loadings over the month t to $t+1$, and $z_{i,t}$ is a vector of firm characteristics observable at time t. We are especially interested in the coefficient γ on idiosyncratic volatility, which should be zero under the null of a factor model. We run the regression (4) at a monthly frequency in percentage terms using annualized volatility numbers as dependent variables. Note that since our volatility measures are known at the beginning of the month t (with the cross-sectional regression run using data from t to $t+1$), $\sigma_{i,t}$ is a measurable statistic at time t, unlike the factor loadings $\beta_{i,t+1}$ (see comments by Shanken, 1992).

In regression (4), we control for factor exposure by including factor loadings estimated over the current month, but obtain almost identical results if we use past factor loadings, $\beta_{i,t}$, from $t-1$ to t, which 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 the exact form of the Fama-MacBeth regressions run by Black, Jensen and Scholes (1982), Fama and French (1992), and Jagannathan and Wang (1996), among others. We use firm factor loadings from the W-FF model using MKT^W, SMB^W, and HML^W as factors, where the W-FF regression (3) is run using daily returns over the next month, t to $t+1$, to compute the contemporaneous factor loadings. For the U.S., we also consider contemporaneous L-FF factor loadings from equation (1) computed using daily data over the next month.

Given that factor loadings may not account for all variation in expected returns compared to firm-level attributes (see Daniel and Titman, 1997), we also include other firm characteristics in the vector $z_{i,t}$ in the Fama-MacBeth regression. The firm characteristics include size, book-to-market ratios, and lagged returns over the previous six months. We also include country-specific dummies as fixed effects. All of these firm characteristics are observable at the beginning of month t and are measured in U.S. dollars.

We measure the relation between total or idiosyncratic volatility and expected returns by examining the sign and statistical significance of γ, the coefficient on the volatility measure in equation (4). In contrast, AHXZ document a relation between average returns and idiosyncratic volatility by forming portfolios ranked on idiosyncratic volatility and then examining holding-period returns of these portfolios. AHXZ also consider controlling for other effects using a series of double-sorted portfolios, but they do not consider Fama-MacBeth regressions. 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 results in portfolios with few stocks and a lot of noise. This is especially true for countries with only a small number of listed stocks. The disadvantage of Fama-MacBeth regressions is that the γ coefficient on idiosyncratic volatility in equation (4) does not represent an investable return because some of the firm characteristics on the RHS of the regression are not tradeable. We consider forming portfolio returns ranked on idiosyncratic volatility below in Sections 5 and 6.

4.2 U.S. Firms

In Table 2, we report results of the Fama-MacBeth regression (4) for only U.S. firms over 1980-2003. Panel A uses the total volatility of firm excess returns and Panels B and C use idiosyncratic volatility with respect to the L-FF and W-FF models, respectively. Like the other tables in the paper, Table 2 reports the absolute values of robust t-statistics in square brackets to easily facilitate hypothesis tests against the null of zero values of each coefficient. In each panel, Regression I uses a CAPM control with the local market return, MKT^L, while Regression II implements the L-FF model. Regression III also controls for size and book-to-market characteristics and Regression IV adds the Jegadeesh and Titman (1993) momentum control.

Table 2 reports that the factor controls for SMB^L and HMB^L are insignificant and often have the wrong sign predicted by Fama and French (1993). This is partly because the small stock effect and the value premium in the post-1980 sample are weak in U.S. data. In particular, value performed poorly during the late 1990s. In contrast, the size and book-to-market characteristics are strongly significant, but the coefficient on the lagged six-month return is not, indicating the much stronger pricing effects of characteristics as opposed to factor loadings (see Daniel and Titman, 1997). The weak evidence of momentum in stock returns arises because our sample comprises mostly large firms where the momentum effect is weaker than in small firms (see Hong, Lim and Stein, 2000).

Table 2 confirms the findings of AHXZ as the coefficient on total or idiosyncratic volatility is always negative and highly statistically significant. The estimated coefficients on the volatility measures consistently range around -1.8 to -2.1, with absolute values of the robust t-statistics all greater than 4.9. Controlling for factor loadings or characteristics actually tends to increase the magnitude of the coefficient on the volatility measures. That is, stocks with high idiosyncratic volatility that are small or have high book-to-market ratios tend to have much lower returns than typical small or value stocks. In summary, stocks with high total or idiosyncratic volatility have significantly low average returns.

To interpret the magnitude of the coefficient on volatility, we can measure the cross-sectional distribution of volatility over time. For example, the average 25th and 75th percentiles of the cross-sectional distribution of L-FF idiosyncratic volatility are 24.5% and 60.7% in annualized terms, respectively. Hence, a movement in R-FF idiosyncratic volatility from the 25th to the 75th percentile for a typical stock would result in a decrease of $|-2.08| \times (0.607 - 0.245) = 0.75\%$ per month, using the L-FF idiosyncratic volatility coefficient in Regression IV of Panel B. For W-FF idiosyncratic volatility, the 25th to 75th percentiles in annualized terms are very similar, at 25.0% and 61.1%, respectively, so a movement from the 25th to the 75th percentile in terms of W-FF idiosyncratic volatility would result in a decrease of $|-2.02| \times (0.611 - 0.250) = 0.73\%$ per month. These are economically very large differences in average excess returns.

We now consider the relation between idiosyncratic volatility and expected returns in international markets. Like the U.S. results in Table 2, the results are very similar if we use total volatility, or idiosyncratic volatility with respect to either R-FF or W-FF. We report results only for W-FF idiosyncratic volatility, as the W-FF model represents a standard model to control for international systematic exposure. The results for total volatility and R-FF volatility are available upon request.

4.3 Firms in Other Large, Developed Countries

Table 3 reports results of the Fama-MacBeth (1973) regression in equation (4) using stock returns within each of the G7 countries, excluding the United States. The regressions in Panel A of Table 3 use stock excess returns denominated in U.S. dollars. Panel B repeats the cross-sectional regressions using local currency denominated excess returns. In all the regressions, we include controls for contemporaneous factor exposure from the W-FF model in equation (3) and firm characteristics that are observable at the beginning of the month. All regressions are run using monthly excess returns.

Table 3 shows that a strong negative relation between past idiosyncratic volatility and expected excess returns also exists in each of the other non-U.S. G7 countries. The coefficient on W-FF idiosyncratic volatility ranges from -0.87 for the U.K. to less than -2.00 for Germany. In all cases, the coefficients are statistically significant at the 95% level, with the lowest t-statistic occurring for Italy at 2.10. The negative idiosyncratic volatility–expected return relation is statistically strongest for Japan, which has a point estimate of -1.96 with a robust t-statistic of 5.18.

The U.S. coefficient on W-FF idiosyncratic volatility in Panel C of Table 2 is -2.01, which is of comparable magnitude with the other G7 countries. Germany and Japan's coefficients are also right around the -2.00 level at -2.00 and -1.96, respectively. However, the range of idiosyncratic volatility in the U.S. is much larger than in the other large, developed countries. This makes the idiosyncratic volatility effect stronger in the U.S., but it still remains large in economic terms for the other countries. Panel A of Table 3 reports the 25%-tile and the 75%-tile of W-FF idiosyncratic volatility. The interquartile range of W-FF idiosyncratic volatility for the non-U.S. G7 countries is around 0.19, which is around half the average interquartile range in the U.S. at 0.36. Thus, although the W-FF idiosyncratic volatility coefficients are similar, the magnitude of the idiosyncratic volatility effect is approximately half of the U.S. effect because the U.S. tends to have stocks with a much wider dispersion of idiosyncratic volatility.

This is seen directly in the last row of Panel A, which reports the economic effect, expressed in monthly percentage expected excess returns, of moving from the 25th to the 75th percentile of W-FF idiosyncratic volatility. For example, for Canada, a move from the 25th to the 75th percentile of W-FF idiosyncratic volatility would result in a decrease in a stock's expected return of $|-1.224| \times (0.460 - 0.208) = 0.31\%$ per month. These numbers average around 0.20-0.30% per month, which is less than half of the expected 0.73% per month decrease using only U.S. firms. Nevertheless, these decreasing expected returns for higher idiosyncratic volatility are still large for the G7 countries other than the United States.

Panel B of Table 3 repeats the cross-sectional regressions using firm excess returns that are translated to local currency terms. We also use W-FF factors denominated in local currency returns to compute contemporaneous factor loadings in equation (3). These results are similar to using USD denominated returns in Panel A; all the coefficients on idiosyncratic volatility are negative and highly statistically significant. The biggest change occurs for Japan and the U.K., where the idiosyncratic volatility coefficient increases (decreases) from -1.96 (-0.88) in USD returns to -0.87 (-2.07) in local returns. Nevertheless, in all cases, the negative coefficients are still significant to at least the 95% level, with the average magnitudes being almost identical using either USD or local denominated returns.

In summary, a strong negative relation between expected returns and past idiosyncratic volatility also exists in the other large, developed markets. The economic effect is stronger in the U.S., not because the coefficient on idiosyncratic volatility is much more negative in the U.S., but because the range of idiosyncratic volatility is more dispersed in U.S. markets than in other countries. Nevertheless, the strong relation between idiosyncratic volatility and average returns sets a high bar for any potential explanation. For example, Jiang, Xu and Yao (2005) recently argue that firms with past high idiosyncratic volatility tend to have more negative future unexpected earnings surprises, leading to their low future returns. Given the higher reporting and accounting standards in the U.S., the scope for greater dispersion in future unexpected earnings is larger, particularly for more negative unexpected earnings surprises, in international markets with lower reporting and disclosure requirements. This might imply a more negative relation between idiosyncratic volatility and expected returns in other countries, but our international results show that this is not the case.

4.4 Pooling Across Developed Countries

Table 4 extends our analysis to incorporate all 23 developed countries. We report Fama-MacBeth coefficients for Europe and the Far East, the G7 (with and without the U.S.) and all countries (with and without the U.S.). 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 U.K.), and the last dummy corresponds to all other developed countries. Thus, this approach implicitly treats the U.S. 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.

Table 4 shows that high idiosyncratic volatility stocks in Europe and the Far East also have low expected returns. The coefficients on idiosyncratic volatility are -0.67 and -1.18 for Europe and the Far East, respectively, and are somewhat smaller in magnitude than the U.S. coefficient of -2.01, the idiosyncratic volatility effect is highly statistically significant. Like the G7 individual country regressions in Tables 2 and 3, it is important to control for firm size and book-to-market characteristics, whereas the factor loadings on the W-FF model have little explanatory power with the exception of MKT^W.

The third and fourth columns of Table 4 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 large robust absolute t-statistic of 6.40. Not surprisingly, this coefficient is an average of the individual G7 country coefficients in Table 3. Clearly, the effect of low expected returns to stocks with high idiosyncratic volatility is very strong across the largest developed markets. However, Table 4 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 an absolute t-statistic of 4.14.

The final two columns of Table 4 pool across all 23 developed countries. Across all countries, the coefficient on idiosyncratic volatility is -1.54 and is highly significant. This translates into a large economic decrease of $|-1.54| \times (0.505 - 0.203) = 0.47\%$ per month when we move from the 25th to the 75th percentile of W-FF idiosyncratic volatility across all countries, where the interquartile range of W-FF idiosyncratic volatility is $50.5\% - 20.3\% = 30.2\%$ per annum over all countries. When the U.S. is excluded, the coefficient on idiosyncratic volatility falls in magnitude to -0.60 from -1.54, but this is still significant with a robust t-statistic that has an absolute value of 2.32. The economic effect weakens when the U.S. is excluded for two reasons. First, the coefficient on idiosyncratic volatility decreases in absolute value and second, the U.S. market lists stocks that have the largest range of idiosyncratic volatility. Excluding the U.S., the interquartile range of W-FF idiosyncratic volatility is $38.4\% - 18.5\% = 19.9\%$, so increasing a typical non-U.S. stock's idiosyncratic volatility from the 25th to the 75th percentile results in a decrease in expected returns of $|-0.60| \times (0.384 - 0.185) = 0.12\%$ per month.

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 a small firm. Placing greater weight on small firms may generate noise, and although it measures the effect of a typical firm, it may not reflect the effect of an average dollar. To allay these concerns, we report weighted Fama-MacBeth regressions in Table 5, where each firm 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 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 regression is analogous to creating equal-weighted portfolios.

Table 5 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 the value-weighted coefficient is -2.24 in Table 5 compared to the equal-weighted coefficient of -2.01 from Table 2. This result is also documented by Bali and Cakici (2005) for the U.S. only, but Table 5 shows that the same effect holds true for all international markets. Similarly, the coefficient on idiosyncratic volatility for the Far East (the G7 countries) is -1.27 (-1.97) when using market capitalization weights in Table 5, which are higher in magnitude than the equal-weighted idiosyncratic volatility coefficient -1.18 (-1.75) in Table 3. For all countries, the value-weighted coefficient is -1.54 with an absolute robust t-statistic of 5.82. This implies that the volatility effect is stronger among larger companies, rather than very small firms. This is unusual for a CAPM anomaly because most mispricing effects are less pronounced in the universe of larger firms with smaller trading frictions.

In summary, across all 23 developed markets, stocks with high idiosyncratic volatility tend to have low expected returns. This 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.

5 A More Detailed Look at the U.S.

This section focuses on the United States to examine some potential explanations for the low returns earned by high idiosyncratic volatility stocks. We do this for three reasons. First, the effect is strongest in the U.S., which allows greater power to investigate its cross-sectional determinants. Second, the U.S. market has more detailed data on trading costs and other market frictions than other countries. Third, understanding the effect in the world's largest and most liquid market is a first step before examining how the effect in other countries is related to the U.S. idiosyncratic volatility effect, which we investigate in Section 6. Section 5.1 lists six potential explanations behind the intriguingly low returns to high idiosyncratic volatility stocks.[3] Section 5.2 reports results in a Fama-MacBeth framework and Section 5.3 reports the results of investable portfolios.

5.1 Potential Explanations

Private Information

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 "PIN" measure of private information. They show that stocks with high PIN have significantly higher expected returns than stocks with low PIN. It is possible that stocks with low idiosyncratic volatility are stocks whose trades contain very high amounts of private information. This would cause stocks with low volatility to command high average returns.

[3] AHXZ consider additional controls for size and value effects; liquidity and coskewness risk; exposure to aggregate market volatility risk measured by VIX; and volume, turnover, bid-ask spread, and dispersion in analysts' forecasts characteristics. None of these can account for the low returns earned by stocks with high idiosyncratic volatility. AHXZ also report detailed controls for momentum strategies using one-, six-, and 12-month past returns and show that the idiosyncratic volatility effect persists for holding periods up to at least one year.

One drawback of the PIN measure is that it is constructed using intra-day trades, restricting the sample to post-1984.

Transaction Costs

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 transactions costs, but their measure requires only the time series of daily security returns. We examine if the volatility effect is concentrated in stocks with the highest transactions costs where arbitrage is difficult, with transactions costs measured by the Lesmond, Ogden and Trzcinka statistic.

Analyst Coverage

Controlling for the amount of analyst coverage skews our sample to large firms, which tend to be covered more by analysts than small firms. Hou and Moskowitz (2005) show that with fewer analysts, prices incorporate new information more slowly. This slow dissemination of news leads to high expected returns for stocks that are covered by few analysts. If stocks with low volatility have low amounts of analyst coverage, these stocks would require higher returns to compensate for the slower dissemination of news. Following Diether, Malloy, and Scherbina (2002), we define analyst coverage as the number of analysts providing current fiscal year annual earnings estimates each month as in the I/B/E/S database, available from July 1976 onwards.

Institutional Ownership

Stocks with lower amounts of institutional ownership tend to be stocks with more uninformed traders (see, for example, Kumar, 2005). Naturally, stocks with low amounts of institutional ownership tend to be stocks, in general, followed less by analysts. These stocks also tend to be smaller and more illiquid stocks, and their prices tend to respond more slowly to news announcements. Stocks with low idiosyncratic volatility could be stocks with low amounts of institutional ownership, leading to these stocks having low average returns. Institutional ownership comes from Standard & Poors and starts from July 1981.

Delay

Hou and Moskowitz (2005) develop a new measure which captures how fast a stock's price responds to information. To construct this measure, they regress each stock's weekly returns on contemporaneous and lagged market returns. If a stock responds immediately to market news, coefficients on the lagged market returns will be equal to zero. Their delay measure takes the ratio of the R^2 from a regression with only a contemporaneous market return to the R^2 from a regression with both contemporaneous and lagged market returns. They find that the most severely delayed firms command large return premiums. These stocks could be low idiosyncratic volatility stocks, leading to low idiosyncratic volatility stocks having high returns because their prices respond with long delay to new information. We use the Hou and Moskowitz delay measure starting from 1965.

Skewness

While a premium for coskewness has been shown to exist in the cross-section (see Harvey and Siddique, 2000), Barberis and Huang (2005) detail a behavioral setting where the individual skewness itself of stock returns may be priced. Under Tversky and Kahneman (1992) cumulative prospect theory preferences, investors transform objective probabilities using a weighting function that overweights the tails of the probability distribution. This causes positively skewed securities to become overpriced and to earn negative average excess returns. If high idiosyncratic volatility stocks are stocks with positive skewness, then the Barberis and Huang argument would explain why stocks with high idiosyncratic volatility have low returns.

5.2 Controls for Various Explanations

To control for these potential risk explanations, we augment the Fama-MacBeth regressions for the U.S. with the additional control variables. Table 6 reports seven cross-sectional regressions on U.S. firms, all of which control for contemporaneous L-FF factor loadings, and size, book-to-market, and momentum characteristics at the beginning of the month, similar to the regressions in Tables 2 to 5. In addition, we include the Easley, Hvidkjaer and O'Hara's (2002) PIN measure, the percentage of zero returns, number of analysts, proportion of institutional ownership, the Moskowitz and Hou (2005) delay measure, and individual stock skewness, separately in Regressions I-VI. In Regression VII, we include all of the various control variables, except PIN because of its shorter sample. All the cross-sectional regressions are run at a monthly frequency.

Panel A of Table 6 shows that in all of the regression specifications, the coefficient on L-FF idiosyncratic volatility is negative and significant. In contrast, in regressions I-V, the coefficients on the control variables are actually insignificant and some carry the wrong sign. For example, for the Lesmond, Ogden and Trzcinka (1999) measure of the proportion of zero returns, the negative coefficient of -0.51 indicates that average firm excess returns decrease, rather than increase as transactions costs increase. Similarly, as firms experience more delay in news dissemination, their expected returns fall, rather than increase as predicted.

Looking individually at each Regression I to VI, we observe that in each case where just one additional control variable is added, the coefficients on L-FF idiosyncratic volatility are reduced by about half, in absolute value, from the value of -2.08 in Table 2. This is caused partly by the regressions in Table 6 necessarily having many fewer stocks than the Fama-MacBeth regressions for the U.S. in Table 2, with the exception of the regressions using the percentage of zero returns and skewness. This reduces power and also skews the data towards the largest firms. The coefficient on L-FF idiosyncratic volatility is smallest in magnitude in Regression IV, which controls for institutional ownership, where the L-FF idiosyncratic volatility coefficient is -0.76. However, this regression uses very few firms, on average only 384, and these firms tend to be relatively very large. But, even for these firms, the -0.76 volatility coefficient is significant with a p-value less than 5%. In Regression IV, the coefficient on the institutional ownership variable is close to zero and statistically insignificant.

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 sign compared to the theoretical predictions. The institutional ownership, delay measures, and past skewness have insignificant explanatory power. The coefficient on L-FF idiosyncratic volatility is -1.81, with a large robust absolute t-statistic of 4.27. This is close to the -2.08 coefficient without these controls reported in Table 2 over the January 1980 to December 2003 sample. Thus, it is very unlikely that any of these variables can explain the idiosyncratic volatility effect.

Panels B and C of Table 6 report coefficients on total volatility and W-FF idiosyncratic volatility. For each regression specification, we use the same variables as Panel A, except that 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 -1.74 and -1.84, respectively, compared to -1.82 in Panel A for L-FF idiosyncratic volatility. In summary, none of these explanations resolves the puzzle of the low expected returns to stocks with high idiosyncratic volatility.

5.3 U.S. Portfolio Returns

While the Fama-MacBeth regressions capture a statistical relation between expected returns and idiosyncratic volatility, while controlling for potentially many risk factors or characteristics, the coefficients on idiosyncratic volatility do not represent realizable returns. 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 using daily returns in equation (2) over the previous month, and 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 equation (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 7, under "No Controls," reports the results of this procedure after sorting firms into L-FF idiosyncratic quintile portfolios with no other controls over the whole U.S. sample, from 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 goes short stocks in the lowest idiosyncratic volatility quintile. The no control row reports the result found by AHXZ, where the 5–1 difference in alphas is -1.29% per month, which is highly statistically significant with the t-statistic having an absolute value of 6.71. The difference in raw average returns between the first and the fifth volatility quintile portfolios is a very large -0.97% per month, which is slightly smaller than the difference in the L-FF alphas.

In the remaining rows of Table 7, we form portfolios that control for the various variables (PIN, the proportion of zero returns, analyst coverage, institutional ownership, delay, and skewness). We first sort stocks on the control variable into quintiles 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 thus represent idiosyncratic volatility quintile portfolios that control for the characteristic. Note that this procedure only controls for a single characteristic, but the computation of the ex-post L-FF alpha also controls for market, size, and value 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. 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 and are all below -1.00% per month. In particular, controlling for skewness has almost no difference from the no control strategy. 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 (2003) delay measure. Controlling for analyst coverage and delay shrink the L-FF alpha of the 5–1 trading strategy to -0.69% and -0.67% per month. Both effects are still significant above the 95% confidence level and both are also 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, tradeable portfolios in the U.S. formed on idiosyncratic volatility exhibit large differences in returns between stocks with high and low idiosyncratic volatilities. These differences are robust after creating portfolios that control for the degree of informed trading, transactions costs, analyst coverage, institutional ownership, price responsiveness to information, and skewness. Creating tradeable portfolios in the U.S. is comparatively easy because of the relatively large number of stocks traded on U.S. markets. We now discuss how we create tradeable international portfolios that contain stocks with different levels of idiosyncratic volatility.

6 International Portfolio Returns

Section 6.1 discusses how we create idiosyncratic volatility portfolios across regions and across all 23 countries. We examine the comovement between these portfolios in Section 6.2.

6.1 Regional and World Idiosyncratic Volatility Portfolios

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 equation (3). For small countries, each quintile portfolio may 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 USD market capitalizations of the corresponding quintile portfolio of each country. The quintile portfolios are rebalanced every month and all portfolio returns are expressed in U.S. dollars.

Table 8 lists the returns of the international quintile W-FF idiosyncratic volatility portfolios. Panel A reports W-FF alphas using the full sample of monthly returns for each regional quintile portfolio. These alphas are the estimates of the α_i^W coefficient in equation (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 an absolute robust t-statistic of 3.01. In the Far East, the trading strategy is less profitable, but it still has a large W-FF alpha of -0.53% per month, with a t-statistic with a lower magnitude of 1.84.

For the Far East, the difference between the modestly strong results for the tradeable portfolios in Table 8 and the large, significantly negative Fama-MacBeth coefficient on the previous month's W-FF idiosyncratic volatility in Tables 4 and 5 arises because the significant Fama-MacBeth coefficient does not take into account the smaller range of idiosyncratic volatility in the Far East. We could obtain a higher dispersion of idiosyncratic volatility across portfolios by creating more extreme portfolios, for example, by forming decile portfolios. The average W-FF idiosyncratic volatility for the Far East first and fifth quintile portfolios are 17.1% and 62.1% in annualized terms, respectively, compared to 16.7% and 92.0% per annum for forming portfolios over the same sample period using only U.S. stocks. Despite the smaller range of idiosyncratic volatility in Far Eastern stocks, the 5–1 W-FF alpha for the Far East is still economically large, at -0.53% per month.

Panel A of Table 8 also reports W-FF alphas for idiosyncratic volatility portfolios formed across the G7 countries and across all 23 countries, in both cases with and without U.S. stocks. The returns to the 5–1 strategy are considerably more negative when the U.S. is included. This is consistent with the slightly stronger Fama-MacBeth coefficient on idiosyncratic volatility in the U.S. than in other countries (see Tables 2 and 3), but it is mainly caused by the wider range of idiosyncratic volatility across stocks in U.S. stocks. Without the U.S., 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 p-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 8. 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 U.S. dominates. For example, the average raw 5–1 return difference is -0.89% per month across all 23 countries, but shrinks in magnitude to -0.40% when U.S. stocks are removed. Even without the U.S., this difference in raw returns is still economically large, but only when the U.S. is included are the differences statistically significant.

We illustrate the cumulative raw returns to the world idiosyncratic volatility portfolios in Figure 1, which plots the value of a portfolio beginning with one USD at the beginning of January 1980. We either invest in the quintile portfolio 1, which contains the lowest idiosyncratic volatility stocks, or portfolio 5, which contains the highest volatility stocks. In all the panels of Figure 1, there is a noticeable gap between the returns of low and high idiosyncratic volatility portfolios. Figure 1 also clearly shows the larger difference between high and low idiosyncratic volatility portfolio returns for the U.S. than in other geographic regions. Most interestingly, Figure 1 also suggests that the returns to a 5–1 strategy are correlated across regions. For example, after 2000, the U.S. returns on portfolio 5 decline significantly. The European and the Far Eastern regional quintile 5 portfolios also simultaneously decline, together with stocks across all countries. We now further examine this international comovement in the idiosyncratic volatility effect.

6.2 International Comovement

We construct 5–1 strategies that go long the quintile portfolio containing firms with the highest idiosyncratic volatility and go short the lowest idiosyncratic volatility quintile portfolio in each of the various regions. 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 U.S. as VOL^{US} to signify that it represents the payoffs to trading stocks with high or low idiosyncratic volatility.

Panel A of Table 9 reports the results of time-series regressions using the W-FF model where the W-FF alpha in equation (3) represents a tradeable return not explained by existing risk factors. The alphas reported in Panel A correspond to the 5–1 alphas reported in Table 8. 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 U.S., VOL^{US}, in Panels B and C. In our discussion, we focus on the geographic areas excluding the U.S., since, by construction, we can always partly explain regional returns that include the U.S. with U.S. returns. Nevertheless, we include all the regions in Table 9 for completeness.

Panel B shows that there are large and significant comovements between the idiosyncratic volatility portfolio returns in international markets and in the United States. If the 5–1 idiosyncratic volatility returns are regressed only on a constant and VOL^{US}, the alphas are all statistically insignificant. The VOL^{US} loadings range from 0.27 for the Far East to 0.36 for the G7 countries excluding the U.S. market. All these VOL^{US} loadings are highly statistically significant, with the lowest robust t-statistic occurring for the Far East at 7.29. Moreover, if we just add VOL^{US} as an explanatory variable, the alphas for all the international 5–1 returns become insignificantly different from zero.

Controlling for the W-FF factors in Panel C generally also does not remove the explanatory power of the VOL^{US} returns for the international idiosyncratic volatility trading strategies. For Europe, the loading on VOL^{US} of 0.32 is similar to the 0.37 loading without W-FF factors and is still significant at the 99% level. The coefficient on VOL^{US} for the G7 excluding the U.S. falls slightly from 0.72 to 0.63, while the corresponding loading for all countries excluding the U.S. decreases from 0.67 to 0.58, when the W-FF factors are added. These coefficients are still significant with p-values above 5.4. Only in the case of the Far East is the loading on VOL^{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 which go long stocks with high idiosyncratic volatility stocks 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 U.S., there are no excess returns. But, without controlling for U.S. exposure, the low returns to high idiosyncratic volatility stocks cannot be explained by standard risk factors. This high degree of comovement 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.

7 Conclusion

Around the world, stocks with high idiosyncratic volatility tend to have much lower returns than stocks with low idiosyncratic volatility. We measure idiosyncratic volatility with respect to local, regional, or local 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 the highest quintile of idiosyncratic volatility stocks and the lowest quintile of idiosyncratic volatility stocks 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 (2005), they suggest that the high idiosyncratic volatility and low return relation is not just a sample-specific or country-specific effect, but it is a global phenomenon.

We find that the low returns earned by stocks with high idiosyncratic volatility around the world comove 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. In contrast, the low returns of high idiosyncratic stocks in international markets cannot be explained by standard factors or risk loadings. Thus, the global idiosyncratic volatility effect is captured by a simple U.S. idiosyncratic volatility factor.

However, we do not intend to push the story 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. Our strong international results suggest that market-specific stories are also unlikely to hold. We conclude that the puzzle of why high idiosyncratic volatility stocks have low returns is a global phenomenon. The low returns of high idiosyncratic volatility stocks are also highly correlated across international markets and this effect is largely captured simply by trading just U.S. stocks with high idiosyncratic volatility.

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Table 1: Summary statistics

Panel A: Individual Country Returns

	Starting Year	Book-to-Market	Size	Number of Firms	Number of Months	Total Volatility	Idiosyncratic Volatility W-FF	Idiosyncratic Volatility R-FF
G7 Countries								
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%
Other Developed Markets								
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		Far East	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
MKT	0.54%	0.25%	0.65%	0.27%	0.62%	0.29%	0.45%	0.38%
SMB	0.16%	0.20%	-0.08%	0.27%	0.22%	0.17%	0.53%	0.27%
HML	0.42%	0.13%	0.14%	0.17%	0.57%	0.12%	0.71%	0.23%

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 "Number of Months" reports the number of monthly observations for each country. The last three columns report total volatility, idiosyncratic volatility with respect to the R-FF (see equation (2)) and W-FF models (see equation (3)) using daily data over the previous month in both regressions, with the exception of the U.S., which is marked with a †, where we report L-FF idiosyncratic volatility (see equation (1)) in place of R-FF idiosyncratic volatility. We report the average time-series of volatilities across each firm in each country in annualized terms. In Panel B, we report monthly means and standard deviations for W-FF and L-FF factors with the sample period January 1980 to December 2003.

Table 2: Volatility and Expected Returns for U.S. Firms

	I	II	III	IV
Panel A: Using Total Volatility				
Constant	1.282	1.270	1.816	1.777
	[4.72]	[4.82]	[3.95]	[3.88]
Total Volatility	-1.835	-1.835	-1.805	-1.900
	[4.94]	[5.18]	[5.79]	[6.53]
$\beta(MKT^L)$	0.274	0.303	0.400	0.391
	[5.19]	[4.21]	[4.78]	[4.76]
$\beta(SMB^L)$		-0.017	-0.054	-0.048
		[0.43]	[1.29]	[1.19]
$\beta(HML^L)$		-0.023	-0.057	-0.058
		[0.91]	[1.89]	[1.91]
Size			-0.156	-0.151
			[3.04]	[2.98]
Book-to-Market			0.266	0.276
			[3.58]	[3.82]
Lagged Return				-0.001
				[0.28]
Adjusted R^2	0.025	0.033	0.042	0.047
Panel B: Using L-FF Idiosyncratic Volatility				
Constant	1.193	1.173	1.788	1.751
	[4.49]	[4.54]	[3.94]	[3.86]
L-FF Idiosyncratic Volatility	-1.926	-1.949	-1.984	-2.080
	[4.91]	[5.19]	[6.18]	[6.98]
$\beta(MKT^L)$	0.296	0.324	0.435	0.425
	[4.44]	[3.43]	[4.06]	[4.02]
$\beta(SMB^L)$		0.022	-0.010	-0.005
		[0.36]	[0.16]	[0.08]
$\beta(HML^L)$		-0.046	-0.088	-0.089
		[1.27]	[2.03]	[2.04]
Size			-0.171	-0.167
			[3.38]	[3.34]
Book-to-Market			0.276	0.285
			[3.70]	[3.94]
Lagged Return				-0.001
				[0.27]
Adjusted R^2	0.024	0.032	0.042	0.047

Table 2 Continued

	I	II	III	IV
Panel C: Using W-FF Idiosyncratic Volatility				
Constant	1.224	1.214	1.784	1.746
	[4.50]	[4.62]	[3.90]	[3.83]
W-FF Idiosyncratic Volatility	-1.921	-1.909	-1.913	-2.014
	[4.87]	[5.06]	[5.89]	[6.67]
$\beta(MKT^L)$	0.267	0.287	0.385	0.376
	[5.02]	[3.91]	[4.53]	[4.52]
$\beta(SMB^L)$		-0.018	-0.056	-0.049
		[0.44]	[1.28]	[1.19]
$\beta(HML^L)$		-0.016	-0.051	-0.051
		[0.64]	[1.67]	[1.69]
Size			-0.160	-0.157
			[3.18]	[3.14]
Book-to-Market			0.273	0.282
			[3.63]	[3.87]
Lagged Return				-0.001
				[0.28]
Adjusted R^2	0.023	0.032	0.041	0.046

The table reports Fama-MacBeth (1973) regressions from equation (4) for only U.S. stock returns. We regress monthly excess stock returns onto a constant; total or idiosyncratic volatility over the past month with respect to the L-FF or W-FF models in equations (1) and (3), respectively; contemporaneous factor loadings, $\beta(MKT^L)$, $\beta(SMB^L)$ and $\beta(HML^L)$ with respect to the L-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. We report absolute values of robust t-statistics in square brackets below each coefficient. The row "Adjusted R^2" reports the average of the cross-sectional adjusted R^2s. The sample period is from January 1980 to December 2003.

Table 3: Idiosyncratic Volatility and Expected Returns in non-U.S., Large, Developed Markets

	Canada	France	Germany	Italy	Japan	U.K.
Panel A: USD Denominated Returns						
Constant	1.723	0.602	0.753	0.425	0.948	0.480
	[3.68]	[1.13]	[1.87]	[0.76]	[1.25]	[1.03]
W-FF Idiosyncratic Volatility	-1.224	-1.439	-2.003	-1.572	-1.955	-0.871
	[2.46]	[2.14]	[3.85]	[2.10]	[5.18]	[2.54]
$\beta(MKT^W)$	0.344	0.059	0.277	-0.083	0.323	0.178
	[2.20]	[0.44]	[1.93]	[0.32]	[3.12]	[1.46]
$\beta(SMB^W)$	0.009	0.015	-0.083	0.116	0.050	0.032
	[0.12]	[0.17]	[0.82]	[0.56]	[0.76]	[0.42]
$\beta(HML^W)$	-0.070	-0.069	0.076	-0.221	-0.025	-0.077
	[0.95]	[0.94]	[1.00]	[1.98]	[0.35]	[1.30]
Size	-0.253	-0.067	-0.044	-0.031	-0.132	-0.058
	[4.81]	[1.08]	[1.09]	[0.47]	[1.72]	[1.16]
Book-to-Market	0.369	0.569	0.176	0.239	0.550	0.365
	[3.68]	[4.59]	[1.35]	[1.48]	[3.84]	[4.46]
Lagged Return	0.014	0.001	0.003	0.001	-0.011	0.012
	[3.57]	[0.10]	[1.01]	[0.15]	[2.85]	[4.07]
Adjusted R^2	0.118	0.108	0.114	0.147	0.124	0.078
Percentiles of W-FF Idiosyncratic Volatility						
25th Percentile	20.8	21.4	16.3	21.5	23.1	13.9
75th Percentile	46.0	39.2	34.8	38.4	39.6	31.3
Economic Effect Moving from the 25th to the 75th W-FF Idiosyncratic Volatility Percentiles						
25% → 75%	-0.31%	-0.26%	-0.37%	-0.27%	-0.32%	-0.15%
Panel B: Local Currency Denominated Returns						
Constant	0.633	0.786	0.519	0.982	0.551	1.485
	[1.20]	[1.96]	[0.92]	[1.31]	[1.18]	[2.85]
W-FF Idiosyncratic Volatility	-1.358	-2.014	-1.810	-1.941	-0.867	-2.068
	[2.06]	[3.90]	[2.56]	[5.16]	[2.57]	[3.79]
$\beta(MKT^W)$	0.059	0.239	-0.098	0.297	0.140	0.014
	[0.47]	[1.69]	[0.39]	[2.82]	[1.19]	[0.10]
$\beta(SMB^W)$	-0.029	-0.083	0.140	0.034	0.001	0.039
	[0.33]	[0.83]	[0.63]	[0.53]	[0.01]	[0.38]
$\beta(HML^W)$	-0.097	0.075	-0.233	-0.022	-0.089	-0.096
	[1.35]	[0.96]	[2.11]	[0.32]	[1.68]	[1.11]
Size	-0.070	-0.041	-0.033	-0.132	-0.059	-0.150
	[1.14]	[1.04]	[0.49]	[1.73]	[1.15]	[2.29]
Book-to-Market	0.554	0.158	0.239	0.556	0.339	0.518
	[4.51]	[1.20]	[1.50]	[3.84]	[4.13]	[4.26]
Lagged Return	0.001	0.004	0.001	-0.011	0.012	0.007
	[0.12]	[1.03]	[0.15]	[2.84]	[4.07]	[1.84]
Adjusted R^2	0.115	0.108	0.113	0.146	0.123	0.076

Note to Table 3

The table reports Fama-MacBeth (1973) regressions (equation (4)) for the individual G7 countries, excluding the United States. We regress monthly excess firm returns onto a constant; idiosyncratic volatility over the past month with respect to the W-FF model in equation (3); contemporaneous factor loadings, $\beta(MKT^W)$, $\beta(SMB^W)$ 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. We report absolute values of robust t-statistics in square brackets below each coefficient. The row "Adjusted R^2" reports the average of the cross-sectional adjusted R^2s. Each cross-sectional regression is run separately for each country using USD denominated firm excess returns in Panel A and local currency denominated firm excess returns in Panel B. In Panel A, we also report the 25th and 75th percentiles of each country's W-FF idiosyncratic volatility and compute the economic effect of moving from the 25th to the 75th percentile. For example, for Canada, a move from the 25th to the 75th percentile of W-FF idiosyncratic volatility would result in a decrease in a stock's expected return of $|-1.224| \times (0.460 - 0.208) = 0.31\%$ per month. The sample period is from January 1980 to December 2003 for all countries.

Table 4: Idiosyncratic Volatility and Expected Returns Across All Countries

	Geographic Areas		G7 Countries		All Countries	
	Europe	Far East	G7	G7 Ex U.S.	All	All Ex U.S.
Constant	0.823	1.402	1.382	0.871	1.320	0.861
	[2.11]	[2.27]	[3.64]	[2.11]	[3.58]	[2.15]
W-FF Idiosyncratic Volatility	-0.668	-1.177	-1.747	-1.069	-1.536	-0.604
	[2.33]	[3.17]	[6.40]	[4.14]	[5.82]	[2.32]
$\beta(MKT^W)$	0.145	0.209	0.367	0.331	0.314	0.238
	[1.31]	[2.18]	[4.52]	[3.73]	[3.94]	[2.78]
$\beta(SMB^W)$	0.026	-0.020	-0.055	-0.031	-0.048	-0.039
	[0.39]	[0.26]	[1.38]	[0.59]	[1.15]	[0.71]
$\beta(HML^W)$	-0.071	-0.039	-0.057	-0.067	-0.048	-0.051
	[1.48]	[0.59]	[1.77]	[1.22]	[1.57]	[1.02]
Size	-0.087	-0.190	-0.111	-0.099	-0.107	-0.107
	[2.45]	[3.19]	[2.89]	[2.73]	[2.95]	[3.16]
Book-to-Market	0.189	0.517	0.293	0.275	0.268	0.241
	[5.51]	[3.52]	[6.01]	[5.15]	[6.79]	[5.85]
Lagged Return	0.010	-0.006	0.000	0.003	0.001	0.004
	[3.57]	[1.45]	[0.12]	[1.31]	[0.58]	[1.78]
Dummy Canada			-0.054	0.240	-0.055	0.190
			[0.26]	[0.81]	[0.26]	[0.64]
Dummy France	0.254		-0.060	0.275	-0.024	0.278
	[0.79]		[0.15]	[0.84]	[0.06]	[0.84]
Dummy Germany	-0.190		-0.552	-0.195	-0.527	-0.190
	[0.59]		[1.49]	[0.58]	[1.41]	[0.58]
Dummy Italy	0.517		0.291	0.636	0.324	0.630
	[1.01]		[0.52]	[1.22]	[0.58]	[1.22]
Dummy Japan			-0.128	-0.043	-0.133	-0.040
			[0.25]	[0.10]	[0.26]	[0.08]
Dummy U.K.			-0.311		-0.280	
			[0.94]		[0.84]	
Dummy Other Country	0.081				-0.104	0.176
	[0.34]				[0.33]	[0.79]
Adjusted R^2	0.114	0.115	0.105	0.168	0.099	0.144

The table reports Fama-MacBeth (1973) regressions (equation (4)) for all 23 countries. The regressions are split into geographic areas (Europe and the Far East), the G7 (with and without the U.S.) and all countries (with and without the U.S.). We regress next month excess firm returns onto a constant; idiosyncratic volatility over the past month with respect to the W-FF model in equation (3); contemporaneous factor loadings, $\beta(MKT^W)$, $\beta(SMB^W)$ 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 belongs to one of Canada, France, Germany, Italy, Japan, U.K., or another non-U.S. country, and zero otherwise. We report absolute values of robust t-statistics in square brackets below each coefficient. The row "Adjusted R^2" reports the average of the cross-sectional adjusted R^2s. Each cross-sectional regression is run separately for each geographic area or group of countries using USD 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).

Table 5: Weighted Fama-MacBeth (1973) Regressions

	Geographic Areas			G7 Countries		All Countries	
	U.S.	Europe	Far East	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]
$\beta(MKT^W)$	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]
$\beta(SMB^W)$	-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 R^2	0.053	0.123	0.120	0.126	0.181	0.120	0.158

The table reports Fama-MacBeth (1973) regressions (equation (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 the Far East), the G7 (with and without the U.S.) and all countries (with and without the U.S.). We regress next month excess firm returns onto a constant; idiosyncratic volatility over the past month with respect to the W-FF model in equation (3); contemporaneous factor loadings, $\beta(MKT^W)$, $\beta(SMB^W)$ 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 belongs to one of Canada, France, Germany, Italy, Japan, U.K., or another non-U.S. country, and zero otherwise. We report absolute values of robust t-statistics in square brackets below each coefficient. The row "Adjusted R^2" reports the average of the cross-sectional adjusted R^2s. Each cross-sectional regression is run separately for each geographic area or group of countries using USD 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).

Table 6: Further 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]
$\beta(MKT^L)$	0.012	-0.002	0.148	-0.001	-0.019	0.023	0.101
	[0.15]	[0.04]	[1.82]	[0.01]	[0.33]	[0.42]	[1.19]
$\beta(HML^L)$	-0.011	0.017	-0.067	-0.013	0.018	0.007	-0.075
	[0.24]	[0.64]	[1.53]	[0.28]	[0.60]	[0.24]	[1.51]
$\beta(SMB^L)$	-0.151	-0.060	-0.114	-0.087	-0.032	-0.057	-0.117
	[3.58]	[2.67]	[2.61]	[1.64]	[0.98]	[2.38]	[2.15]
Size	0.007	-0.222	-0.217	-0.068	-0.085	-0.179	-0.278
	[0.13]	[5.72]	[3.83]	[1.47]	[2.12]	[4.61]	[3.29]
Book-to-Market	0.217	0.404	0.448	0.452	0.549	0.422	0.431
	[2.82]	[7.35]	[4.04]	[4.11]	[7.80]	[7.39]	[3.37]
Lagged Return	0.686	0.606	1.280	0.894	0.808	0.616	0.966
	[3.17]	[3.74]	[6.42]	[4.82]	[4.17]	[3.74]	[4.08]
PIN	0.351						
	[0.62]						
Percentage of Zero Returns		-0.459					-1.654
		[1.65]					[3.80]
Analyst Coverage			0.012				0.026
			[1.32]				[2.49]
Institutional Ownership				0.004			0.001
				[1.47]			[0.49]
Delay					-0.099		0.723
					[0.10]		[0.34]
Skewness						-0.148	0.048
						[6.76]	[1.12]
Adjusted R^2	0.052	0.051	0.075	0.059	0.067	0.049	0.088
Average Number of Stocks	744	3447	444	384	934	3447	526
Sample Period	Jan 84– Dec 01	Aug 63– Dec 03	Jul 76– Jun 01	Jul 81– Jun 00	Jul 65– Dec 01	Aug 63– Dec 03	Jul 81– Jun 00
Panel B: Coefficients Using Total Volatility							
Total Volatility	-1.043	-0.968	-1.673	-0.723	-0.717	-0.884	-1.730
	[3.18]	[4.67]	[4.80]	[2.21]	[2.88]	[4.09]	[4.10]
Panel C: Coefficients Using W-FF Idiosyncratic Volatility							
W-FF Idiosyncratic Volatility	-1.084	-0.778	-1.642	-0.797	-0.693	-0.636	-1.873
	[3.17]	[3.10]	[4.23]	[2.31]	[2.37]	[2.43]	[4.25]

Note to Table 6

In Panel A reports Fama-MacBeth (1973) regressions from equation (4) for all the U.S. using L-FF idiosyncratic volatility in equation (1). We regress next month excess firm returns onto a constant; idiosyncratic volatility over the past month with respect to the L-FF model; contemporaneous factor loadings, $\beta(MKT^L)$, $\beta(SMB^L)$ and $\beta(HML^L)$ with respect to the L-FF model; firm characteristics at the beginning of the month, and various control variables. "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. "PIN" is the Easley, Hvidkajer and O'Hara (2002) measure of private information; "Percentage of Zero Returns" is the proportion of daily returns equal to zero constructed by Lesmond, Ogden and Trzcinka (1999); The "Analyst Coverage," "Institutional Ownership," and "Delay" measures are from Hou and Moskowitz (2003). In Panels B and C, we report only the Fama-MacBeth coefficients on total volatility and W-FF idiosyncratic volatility using equation (3), but the regressions use the same variables as Panel A, except these are not reported to save space. We report absolute values of robust t-statistics in square brackets below each coefficient. The row "Adjusted R^2" reports the average of the cross-sectional adjusted R^2s. The sample periods in Panel B are exactly the same as Panel A. In Panel C, the end of the sample periods are exactly the same as Panel A, but regressions II, III, V, and VI, start in August 1980, whereas the sample periods for regressions I, IV and VII are identical to Panel A.

Table 7: L-FF Alphas of U.S. Portfolios Sorted on Idiosyncratic Volatility

	Ranking on Idiosyncratic Volatility							
	1 Low	2	3	4	5 High	5-1	Ave No of Stocks	Sample
No Controls	0.103	0.027	0.067	-0.398	-1.186	-1.290	1104	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	1089	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	1089	Aug 63 – Dec 03
	[1.02]	[0.84]	[0.31]	[3.35]	[6.94]	[6.23]		

The table reports L-FF alphas (see equation (1)) for the U.S. only for forming portfolios ranked on L-FF idiosyncratic volatility each month (quintile portfolios 1–5 from “1 Low” to “5 High”) and for a strategy that goes long the highest volatility quintile and short the lowest volatility quintile (“5-1”). In controlling for PIN, the proportion of zero returns, analyst coverage, institutional ownership, and skewness, we first sort stocks each month based on the first 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 thus represent idiosyncratic volatility quintile portfolios that control for the characteristic. The PIN variable is computed by Easley, Hvidkajer and O’Hara (2002). The analyst coverage, institutional ownership, and delay measures are provided by Hou and Moskowitz (2003). The column “Ave No of Stocks” reports the average number of stocks in each idiosyncratic volatility quintile portfolio. We report absolute values of robust t-statistics in square brackets below each L-FF alpha.

Table 8: International Idiosyncratic Volatility Portfolios

	Geographic Areas		G7 Countries		All Countries	
	Europe	Far East	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 equation (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 the Far East), 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 country quintile portfolios. Portfolio 1 contains firms with the lowest volatilities and portfolio 5 contains firms with the highest volatilities, while "5-1" represents a strategy that goes long the highest volatility quintile and goes short the lowest volatility quintile. In Panel A, we report the time-series alpha with respect to the W-FF model for different regions and in Panel B, we report the raw return differences between the fifth and first quintile portfolios. We report absolute values of robust t-statistics in square brackets below each W-FF alpha (Panel A) and below the differences in raw returns (Panel B). The sample period is January 1980 to December 2003.

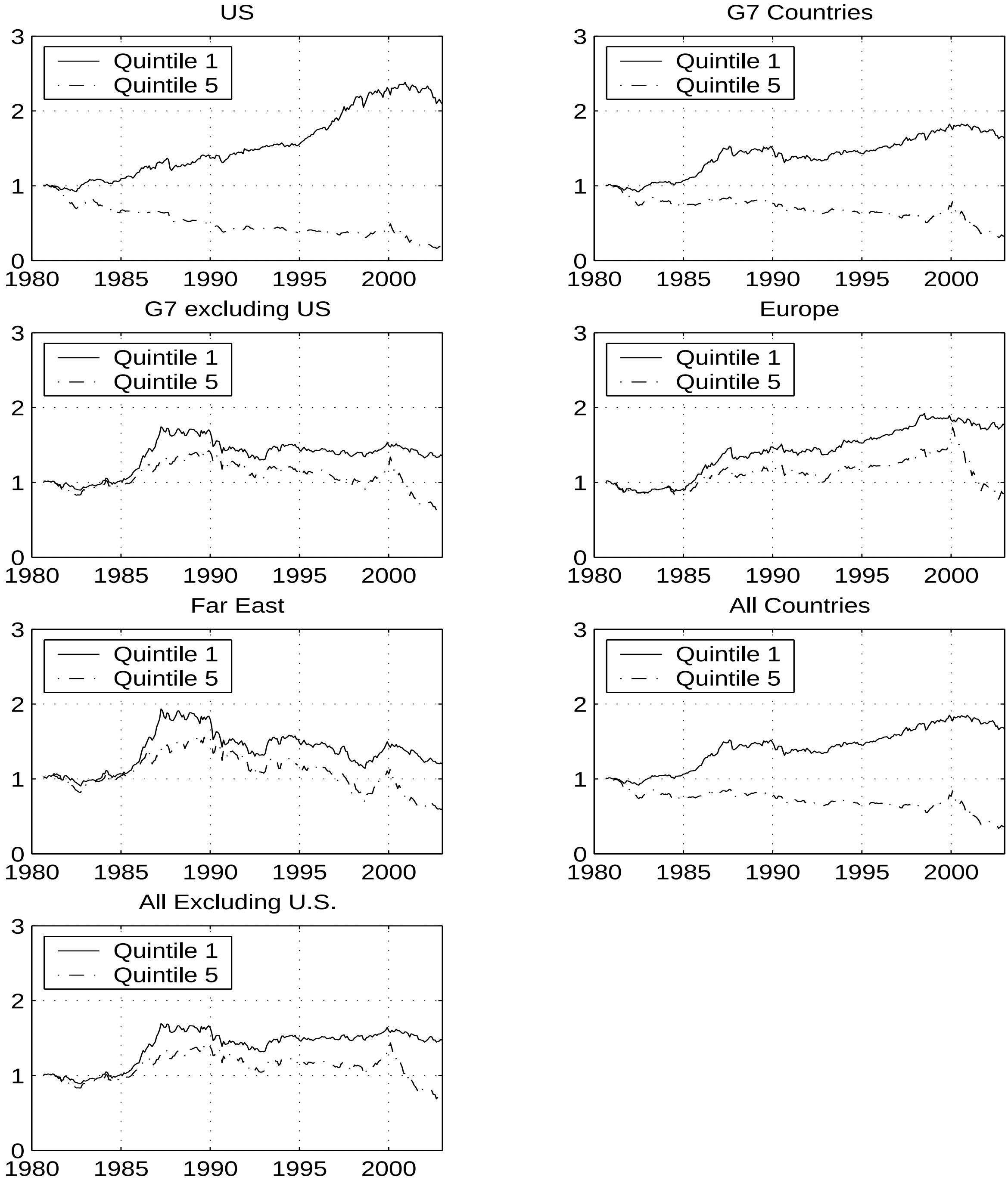
Table 9: International Comovement in Idiosyncratic Volatility Portfolios

	Alpha	$\beta(MKT^W)$	$\beta(SMB^W)$	$\beta(HML^W)$	VOL^{US}	Adjusted R^2
Panel A: Using the W-FF Model						
U.S. (VOL^{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]		
Far East	-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]	[10.57]	[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 VOL^{US}						
Europe	0.134				0.370	0.42
	[0.63]				[14.1]	
Far East	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 VOL^{US}						
Europe	-0.104	0.223	0.018	0.103	0.317	0.44
	[0.46]	[3.78]	[0.23]	[1.01]	[8.61]	
Far East	-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]	

Note to Table 9

For every month, within each country, we sort firms into quintile portfolios according to the W-FF idiosyncratic volatility measure (see equation (3)) using daily firm returns over the previous month. We aggregate the country quintile portfolios into regional quintile portfolios, for geographic areas (Europe and the Far East), 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 goes short the quintile portfolio with the highest idiosyncratic volatility stocks. For the U.S., we denote this 5–1 strategy as VOL^{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 VOL^{US} returns. We report absolute values of robust t-statistics in square brackets below each coefficient. The sample period is January 1980 to December 2003.

Figure 1: Cumulative Returns on International Idiosyncratic Volatility Portfolios



For every month, within each country, we sort firms into quintile portfolios according to W-FF volatility over the previous month (see equation (3)). We aggregate the country quintile portfolios into regional portfolios, where each regional W-FF idiosyncratic volatility quintile portfolio is a value-weighted sum of country quintile portfolios, with the weights being the market capitalization of the corresponding country quintile portfolios. Portfolio 1 contains firms with the lowest volatilities, and portfolio 5 contains firms with the highest volatilities, In each panel, we graph the cumulative value of a portfolio that starts with \$1 invested in each of portfolio 1 and 5 at the beginning of January 1980 and ends in December 2003. All returns are expressed in U.S. dollars.