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

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This Version: 9 September 2007

*We thank Tobias Adrian, Kewei Hou, Soeren Hvidjkaer, and Joshua Rosenberg for kindly providing data. We thank Tim Johnson and seminar participants at the CRSP Forum at the University of Chicago, the American Finance Association, Columbia University, NYU, SAC Capital, and the University of Toronto for helpful comments. The paper has benefited from the excellent comments of an anonymous referee. Andrew Ang acknowledges support from the NSF.

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

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 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 may lie behind this phenomenon.

1 Introduction

In a recent paper, Ang, Hodrick, Xing and Zhang (2006) (hereafter AHXZ) show that volatility of the market return is a priced cross-sectional risk factor. After demonstrating this fact, AHXZ sorted firms on the basis of their idiosyncratic stock return volatility, measured relative to the Fama and French (1993) model. They reasoned that the idiosyncratic errors of a misspecified factor model would 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 found that U.S. stocks with high lagged idiosyncratic volatility earn very low future average returns, and these assets were 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 highest idiosyncratic volatility by over 1% per month. Second, AHXZ demonstrate that their findings could not 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.

The 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 may be dependent only on a particular small sample. AHXZ's results could be data-snooping, 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 if stock returns in international markets

[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), Bali and Cakici (2005), Jiang, Tao and Yao (2005), Huang et al. (2006), and Zhang (2006).

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 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–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 comoves with the difference in returns between U.S. stocks with high and low idiosyncratic volatilities. 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 may lie behind this effect. However, we do not claim that the low average returns to stocks with high idiosyncratic volatility represents 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 an option pricing explanation. 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 (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). 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 both in the U.S. and international markets is not necessarily a relation that involves expected volatility (see 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 if idiosyncratic volatility can predict future aggregate market returns (see, for example, 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, unlike these papers, our focus is on the cross-sectional, as opposed to the aggregate time-series, relation between firm-level idiosyncratic volatility and expected returns. Other authors, like Campbell et al. (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, for example, Baker, Coval and Stein, 2004). We do not investigate the success of idiosyncratic volatility to proxy for different economic effects.[3] Our focus is on how idiosyncratic volatility itself is related to expected returns in the cross-section of international stock returns. Similarly, idiosyncratic volatility may be related to other economic factors, like liquidity risk (see, for example, Spiegel and Wang, 2005). Hence, we specifically

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[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 relationship between average idiosyncratic volatility and market returns at the aggregate level.

[3] AHXZ show that differences in opinion measured by analyst dispersion (see Diether, Malloy and Scherbina, 2002) cannot account for the idiosyncratic volatility effect.

control for the effect of other risk loadings or risk characteristics in our analysis of idiosyncratic volatility.

The remainder of this 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. We also report the relation between idiosyncratic volatility measured in local currency and excess returns expressed in local currency terms for robustness.

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. When we analyze 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). The market factor for country j, MKT^j, 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 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.

Similar to AHXZ, we define idiosyncratic volatility with respect to the L-FF model using the following regression:

$$r_i = \alpha_i^L + \beta_i^L MKT^L + s_i^L SMB^L + h_i^L HML^L + \varepsilon_i^L, \tag{1}$$

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 the standard deviation of the residuals ε_i^L after estimating equation (1) using daily excess returns over the past month.

2.2 The Regional Fama-French Model

Brooks and Del Negro (2005) show that country-specific factors within regions can be mostly explained by regional factors. We specify a regional Fama-French model (R-FF hereafter) as 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.

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

$$r_i = \alpha_i^R + \beta_i^R MKT^R + s_i^R SMB^R + h_i^R HML^R + \varepsilon_i^R, \tag{2}$$

using daily U.S. dollar excess returns of stock i over the past month and expressing all of the R-FF factors in U.S. dollars.

2.3 The World Fama-French Model

Our world version of the Fama-French model (W-FF hereafter) uses the value-weighted world market excess return, MKT^W, and the world size and value factors, SMB^W and HML^W, computed as the value-weighted sums of the three regional Fama-French factors. We define idiosyncratic volatility with respect to the W-FF model to be the standard deviation of the residual ε_i^W in the regression:

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

using daily U.S. dollar excess returns of stock i over the past month and expressing all of the W-FF factors in U.S. dollars.

2.4 Data

Our stock return data comprise daily returns on firms from 23 developed markets. We select these countries as they comprise 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 U.S. 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 the 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 Belgium firms have the largest (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. 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 volatility across countries of 41% per annum.[4] There is also quite a wide range in the dispersion of idiosyncratic volatility across markets. For the U.S., the interquartile

[4] 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 similar results in international markets.

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 U.S., 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%.

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 SMB factor for North America is slightly negative, at -0.08% per month, indicating that small firms have not out-performed 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 the Far East, where the regional SMB factors have positive means. 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 during the late 1990s bull market in the United States. The value premium is particularly strong in the Far East, 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 Methodolgy

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 if 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:

$$r_i(t, t+1) = c + \gamma\, \sigma_i(t-1, t) + \lambda_\beta' \beta_i(t, t+1) + \lambda_z' z_i(t) + \varepsilon_i(t+1), \tag{4}$$

where $r_i(t, t+1)$ is stock i's excess return from month t to $t+1$, $\sigma_i(t-1, t)$ is stock i's idiosyncratic volatility computed using daily data over the previous month from $t-1$ to t,

$\beta_i(t, t+1)$ is a vector of risk factor loadings over the month t to $t+1$, and $z_i(t)$ is a vector of firm characteristics observable at time t. We use the notation $(t-1, t)$ and $(t, t+1)$ to emphasize the timing of the statistics that are computed using data from month $t-1$ to t and over month t to $t+1$, 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 regression (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, $\sigma_i(t-1, t)$ is a measurable statistic at time t. Regression (4) controls for exposures to risk factors by including contemporaneous factor loadings estimated over the current month, $\beta_i(t, t+1)$ (see Shanken, 1992), but we obtain almost identical results if we use past factor loadings, $\beta_i(t-1, t)$. 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 MKT^W, SMB^W, and HML^W as factors, where the W-FF regression (3) is run using daily returns over the month from t to $t+1$. For the U.S., we also consider contemporaneous L-FF factor loadings from equation (1) computed using daily data over the month from t to $t+1$.

Daniel and Titman (1997) report that factor loadings may not account for all variation in expected returns compared to firm-level characteristics. Hence, we also include other firm characteristics in the vector $z_i(t)$ in the Fama-MacBeth regression. All of these characteristics are known at time t. 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 equation (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 Firms in Large, Developed Countries

Table 2 reports results of the Fama-MacBeth (1973) regressions in equation (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 U.S., the estimated coefficient on W-FF idiosyncratic volatility is -2.01, with a robust t-statistic of -6.67. After the U.S., the negative lagged 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 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 smallest magnitude of the t-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 SMB^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, there is a statistically significant size effect in Canada and the U.S., 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 where 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 25th percentile of W-FF idiosyncratic volatility in each country. Using these percentiles, we can translate the coefficients on L-FF idiosyncratic volatility to an economic effect by asking the 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 U.S., 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. 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. 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 U.S. 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 25th 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. Nevertheless, these decreasing expected returns for higher idiosyncratic volatility are still economically large for the non-U.S. G7 countries.

Panel B of Table 2 repeats the cross-sectional regressions using firm excess returns that are expressed in local currency terms. Panel B measures idiosyncratic volatility using the L-FF model. We also use W-FF factors denominated in local currency to compute contemporaneous factor loadings in equation (3).[5] 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 U.K., the volatility coefficients increase in magnitude using L-FF idiosyncratic volatility.

In summary, similar to the finding in AHXZ for the U.S., we find 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 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 the U.S. 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 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.

[5] The results are almost unchanged if R-FF or L-FF factors denominated in local currency are used. These results are available upon request.

Another potential explanation is that the negative relation between idiosyncratic volatility and returns persists due to lack of overall liquidity. Yet, the U.S. 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 Results From Pooling Across Developed Countries

Standard Fama-MacBeth (1973) Regressions

Table 3 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.[6]

The first two columns of Table 3 show 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. 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 t-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 t-statistic of -4.14.

[6] We have also included a dummy to represent technology, media, and telecommunications sectors following Brooks and Del Negro (2004). Including this dummy variable has very little change on our results. We have also excluded the late 1990s by ending the sample in 1997, and this 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.

The final two columns of Table 3 pool the data across all 23 developed countries. Pooling across all countries, the coefficient on idiosyncratic volatility is -1.54 and is 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 U.S. 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 t-statistic of -2.32. Thus, while the idiosyncratic volatility effect is concentrated in the U.S., it is still strongly observed across the world.

Robustness to Value Weighting

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 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 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 t-statistic goes from -6.67 to -7.00. This result is also documented by Bali and Cakici (2005) for the U.S. only, but Table 4 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 4, which are higher in magnitude than the equal-weighted idiosyncratic volatility coefficient -1.18 (-1.75) in Table 2. 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.

Robustness to Different Formation Periods

In the analysis done so far, idiosyncratic volatility is computed using daily returns over the past calendar month, controlling for market, size, and value factors. Since volatility is well well known to be persistent, 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 ($\sigma_i(t-1,t)$), we compute idiosyncratic volatility using daily returns over the past 3, 6, or 12 months, denoted by $(t-3,t)$, $(t-6,t)$, and $(t-12,t)$, respectively. This is done relative to the W-FF model of equation (3) with all volatilities expressed in annualized terms. We report the results of the U.S., all countries, and all countries excluding the U.S.

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 U.S., 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 $\sigma_i(t-1,t)$, so using the past three months of daily returns actually makes the idiosyncratic volatility effect stronger. These patterns are also repeated for all countries and for all countries excluding the U.S. Like the results in previous tables, the magnitude of the coefficients decrease 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 volatility remain roughly the same because of the strong cross-sectional persistence of idiosyncratic volatility. The results are slightly stronger using three-month formation periods, rather than one-month, for all cases in Table 5 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.

Summary

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 comovement. To investigate this we create idiosyncratic volatility portfolios across regions and across all 23 countries.

5.1 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, are 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 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 a 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 of -1.84.

For the Far East, the difference between the modestly strong results for the tradeable 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 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 annualized W-FF idiosyncratic volatilities for the Far East first and fifth quintile portfolios are 17.1% and 62.1%, 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. When decile portfolios ranked on idiosyncratic volatility are formed in the Far East, the 10-1 difference in the extreme decile portfolio W-FF alphas is 0.79%, with a t-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 U.S. is included. 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 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 U.S. 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 U.S., this difference in raw returns is still economically large, but only when the U.S. is included are the differences in raw returns statistically significant.

5.2 International Comovement

This section investigates the degree of international comovement in returns of stocks with high idiosyncratic volatilities. 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 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 U.S. as VOL^{US}.

Panel A of Table 7 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 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 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 which include the U.S. with U.S. returns. Nevertheless, we include all the regions in Table 7 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 portfolio 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 absolute t-statistic value occurring for the Far East at 7.29.

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 of 0.32 on VOL^{US} is similar to the 0.37 loading without W-FF factors. 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 highly significant with t-statistics 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.

6 A More Detailed Look at the U.S.

Sections 4 and 5 show that around the world, stocks with high idiosyncratic volatility have low returns. The effect is strongest in the U.S., and we observe significant comovement between the returns of high idiosyncratic volatility stocks in non-U.S. countries with the returns of high idiosyncratic volatility stocks in the U.S. 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 already find that the U.S. idiosyncratic volatility effect is robust to controlling for standard risk and firm characteristics such as size, value, liquidity, and coskewness. They find that exposure to aggregate market volatility risk measured by VIX cannot explain the effect.[7] Simple micro-structure 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 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 transactions costs; in particular, we use a recently developed measure for assessing the amount of

[7] 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 (2006) 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.

private information in trades. We also examine economic stories which involve how different types of investor clienteles may analyze and process information. Stocks with different idiosyncratic volatility may 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 Potential Economic 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 measure of private information, denoted PIN. They show that stocks with high PINs have significantly higher expected returns than stocks with low PINs. It is possible that stocks with low idiosyncratic volatility are stocks whose trades contain very high amounts of private information, and conversely, high idiosyncratic volatility could be stocks whose trades contain very 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 intra-day trades, which restricts the sample to post-1984.

Transactions 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. 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 transactions costs where arbitrage is difficult.

Analyst Coverage

Stocks with few analysts may incorporate new information into prices more slowly. Hou and Moskowitz (2005) hypothesize that if investors value fast information dissemination, stocks covered by fewer analysts will have higher returns than stocks tracked by many 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, which is available from July 1976 onwards. Controlling for the amount of analyst coverage skews our sample toward larger firms, which tend to be covered more by analysts than small firms.

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 institutional holdings tend to be stocks that are followed less closely by analysts. These stocks also tend to be smaller and more illiquid, and their prices could respond more slowly to news announcements. Stocks with low idiosyncratic volatility could be stocks with low amounts of institutional ownership causing these stocks to have high average returns. Institutional ownership comes from Standard & Poors and starts in 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 and there would be no improvement in the R^2 in adding the lagged market return to the regression. The Hou-Moskowitz (2005) delay measure uses 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

Barberis and Huang (2005) develop a behavioral setting in which the individual skewness of stock returns may be priced.[8] Under the cumulative prospect theory preferences of Tversky and Kahneman (1992), 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, the Barberis and Huang (2005) argument would explain why stocks with high idiosyncratic volatility have low returns.

6.2 Cross-Sectional Regression Results

In order to control for these potential economic explanations of the idiosyncratic volatility phenomenon, we include the characteristic controls described above with other risk controls in Fama-MacBeth (1973) regressions along with the L-FF idiosyncratic volatility measured over the past month. Table 8 reports time series average coefficients from seven cross-sectional regression specifications for U.S. data. All of the specifications control for contemporaneous L-FF factor loadings, and for past size, book-to-market, and momentum characteristics. The specifications use different numbers of stocks because of data availability issues. In regressions I-VI, we separately include the Easley, Hvidkjaer and O'Hara's (2002) PIN measure, the percentage of zero returns, the number of analysts, the proportion of institutional ownership, the Moskowitz and Hou (2005) delay measure, and the individual skewness of the return. Regressions I, III, and IV control for these variables constructed by other authors, which approximately halves our full sample period and takes many fewer stocks. In Regression VII, we include all of the various control variables, except PIN because of its shorter sample. All the cross-sectional regressions are rerun every month. Because of the data requirements of book values and past six-month returns, the dependent variable returns of these regressions begin seven months after the beginning of the sample period listed in Table 8.

Panel A shows that in all of the regression specifications, the Fama-MacBeth coefficient on L-FF idiosyncratic volatility is negative and strongly significant. In contrast, in regressions

[8] AHXZ rule out that exposure to coskewness (see Harvey and Siddique, 2000) can explain the low returns of stocks with high idiosyncratic volatility.

I-V, the coefficients on the control variables are actually insignificantly different from zero, and some carry the wrong sign. For example, if expected returns increase with transactions 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 transactions costs increase.[9]

Looking individually at each regression I to VI, we observe that the coefficient on L-FF idiosyncratic volatility is smallest in magnitude in regression IV, which controls for institutional ownership, with a 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 very large. But, even for these firms, the -0.79 volatility coefficient is significant with a robust t-statistic of -2.31. In regression IV, the coefficient on the institutional ownership variable is close to zero and is 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 t-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 measure, and past skewness have insignificant explanatory power. The coefficient on L-FF idiosyncratic volatility is -1.81, with a robust t-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 inference 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

[9] To take account of potential non-linearities in transactions 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.

idiosyncratic volatility are -1.73 and -1.87, respectively, compared to -1.81 in Panel A for L-FF idiosyncratic volatility.

6.3 Idiosyncratic Volatility Portfolios

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 equation (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 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 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 goes 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 t-statistic of -6.71. For comparison, the difference in raw average returns between the first and the fifth volatility quintile portfolios is a large -0.97% per month and is highly statistically significant.

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 ex-post L-FF alpha also controls for the MKT, SMB, 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 (2003) 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 t-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 U.S. 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, transactions costs, analyst coverage, institutional ownership, price responsiveness to information, and skewness.

6.4 An Options Story

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 may 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 may be related negatively 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) first interpret equity as a call option on the firm's underlying assets. Johnson (2004) takes this framework and, following Merton (1974), derives that the return of a stock, dP_t/P_t in excess of a constant risk free rate, r_f, is given by:

$$dP_t/P_t - r_f dt = (\pi \Delta S_t/P_t)dt + (\sigma_a \Delta S_t/P_t)dW_t, \tag{5}$$

where π is the risk premium on the unlevered stock, S_t is the price of an unlevered claim on the firm's assets, σ_a is the firm's underlying asset volatility, Δ is a standard option delta, $\Delta = \partial P/\partial S$, and dW_t is a Brownian motion term. The total stock volatility, σ, comprises both underlying asset volatility, σ_a, as well as the variance of uncertainty of the current value of the firm's assets, ω. 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, just as $\partial\Delta/\partial\sigma < 0$ 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 $\partial\Delta/\partial\omega$ 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 that the dispersion of beliefs is positively correlated with idiosyncratic volatility and this is true in the data; the dispersion of analysts' forecasts as constructed by Diether, Malloy and Scherbina (2002) has a cross-sectional correlation of 0.201 with lagged idiosyncratic volatility. Thus, Johnson's interpretation for 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 may 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 σ 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 negative relation between Δ and volatility may change sign as the default boundary approaches. 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 expectations 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.

Idiosyncratic Volatility and Leverage

To first the leverage interaction effect, we first examine the coefficient on lagged volatility in equation (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 book value of debt and 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 MKT, SMB, and HML contemporaneous factor loadings and size, book-to-market, and past return characteristics. Idiosyncratic volatility has a coefficient of -1.14 with a t-statistic of -4.45. Regression I reports that the coefficient on idiosyncratic volatility without the leverage and interaction controls (but retaining the MKT, SMB, and HML factor loadings and size, book-to-market, and past return characteristics) is -0.94, with a t-statistic of -2.24. Thus, controlling for leverage does not decrease the idiosyncratic volatility effect, but 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 this 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 $\sigma_i(t-1,t)$ in columns. Panel A reports the results listing L-FF alphas of each of these 25 portfolios. The last column labelled "5–1" is the long-short portfolio which goes long the highest $\sigma_i(t-1,t)$ portfolio and goes short the lowest $\sigma_i(t-1,t)$ 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.[10] 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.

Idiosyncratic Volatility and Conditional Volatility

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, $\mathrm{E}_t[\sigma_i(t, t+1)]$, by running a cross-sectional regression of $\sigma_i(t, t+1)$ on firm characteristics at time t. We use lagged idiosyncratic volatility, size, the book-to-market ratio, past six-month return, 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 previous month divided by total number of shares outstanding at the end of the month. The coefficients are estimated using data only up to time t to forecast volatility over t to $t+1$, and we run a new cross-sectional regression at each time period.[11] We focus on cross-sectional regression forecasts as 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 $\mathrm{E}_t[\sigma_i(t, t+1)]$ with $\sigma_i(t-1, t)$ is 0.95. This high correlation would lead to colinearity 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 $\mathrm{E}_t[\sigma_i(t, t+1)]$ and then sorts stocks on $\sigma_i(t-1, t)$. Panel B shows that in each $\mathrm{E}_t[\sigma_i(t, t+1)]$ quintile, the stocks with

[10] If we use predicted idiosyncratic volatility instead of lagged idiosyncratic volatility, we also do not find the 5–1 spread to be most pronounced for stocks with the highest volatility.

[11] We also construct a time-series estimate of conditional idiosyncratic volatility at the firm level using a time-series regression of $\sigma_i(t, t+1)$ on lagged idiosyncratic volatility, firm size, firm book-to-market ratio, past six-month return, stock return skewness, and turnover over the previous month. All the RHS variables are measured at time t. We obtain similar results using these time-series forecasts as the cross-sectional forecasts reported here. These results are available upon request. Spiegel and Wang (2005) report a positive relation between conditional volatility and returns using estimates of conditional volatility computed from past monthly frequency returns. In unreported results, we obtain a negative relation between returns and an estimate of conditional volatility over the next day from an EGARCH(1,1) model estimated on the previous month of daily data.

high lagged idiosyncratic volatility have low returns. Only in the lowest $\mathrm{E}_t[\sigma_i(t, t+1)]$ 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 $\mathrm{E}_t[\sigma_i(t, t+1)]$. 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.

Lagged and Future Idiosyncratic Volatility

Finally, we examine the relation between lagged idiosyncratic volatility, $\sigma_i(t-1, t)$, and realized idiosyncratic volatility, $\sigma_i(t, t+1)$. Realized idiosyncratic volatility over the next month is equal to expected idiosyncratic volatility at the beginning of the month plus a rational expectations error, $\sigma_i^2(t, t+1) = \mathrm{E}_t[(r_i(t, t+1) - \mathrm{E}_t(r_i(t, t+1))^2] + u_i(t+1)$. 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 may 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 non-zero.[12] 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 returns in equation (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 t-statistic of -6.68, compared to a spread of -1.29% per month, with a robust t-statistic of -6.71 reported in the first row of Table 9. It is only the contemporaneous relation between realized returns and realized volatility which is affected by the skewness of

[12] We thank a referee for raising this point.

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, σ_i^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, $\sigma_i^L(t, t+1)$, measured at the end of month $t+1$, and then sorted on lagged idiosyncratic volatility, $\sigma_i^L(t-1, t)$. Note that these portfolios are not tradeable 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 foresight 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 $\sigma_i^L(t, t+1)$ quintile, returns tend to become more negative as lagged idiosyncratic volatility increases. The last column labelled "5–1" is the long-short portfolio which goes long the highest $\sigma_i^L(t-1, t)$ portfolio and short the lowest $\sigma_i^L(t-1, t)$ 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 $\sigma_i^L(t, t+1)$ quintile portfolio to a very large -2.12% in the fourth $\sigma_i^L(t, t+1)$ quintile portfolio.

In the last row of Panel B, we report L-FF alphas of quintile portfolios of $\sigma_i^L(t-1, t)$ 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 t-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 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 (2006), they suggest that the high idiosyncratic volatility and low return relation is not just a sample-specific or country-specific effect, but it is observed world-wide.

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. 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 why 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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Table 1: Summary Statistics of International Data

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	0.55%	4.37%	0.66%	4.61%	0.63%	4.94%	0.45%	6.54%
SMB	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 "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 firms in each country and express the units in annualized terms by multiplying by $\sqrt{250}$. In Panel B, we report means and standard deviations of monthly W-FF and R-FF factors over the sample period January 1980 to December 2003.

Table 2: Idiosyncratic Volatility and Expected Returns in G7 Countries

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A: USD Denominated Returns							
Constant	1.723	0.602	0.753	0.425	0.948	0.480	1.746
	[3.68]	[1.13]	[1.87]	[0.76]	[1.25]	[1.03]	[3.83]
W-FF Idiosyncratic Volatility	-1.224	-1.439	-2.003	-1.572	-1.955	-0.871	-2.014
	[-2.46]	[-2.14]	[-3.85]	[-2.10]	[-5.18]	[-2.54]	[-6.67]
$\beta(MKT^W)$	0.344	0.059	0.277	-0.083	0.323	0.178	0.376
	[2.20]	[0.44]	[1.93]	[-0.32]	[3.12]	[1.46]	[4.52]
$\beta(SMB^W)$	0.009	0.015	-0.083	0.116	0.050	0.032	-0.049
	[0.12]	[0.17]	[-0.82]	[0.56]	[0.76]	[0.42]	[-1.19]
$\beta(HML^W)$	-0.070	-0.069	0.076	-0.221	-0.025	-0.077	-0.051
	[-0.95]	[-0.94]	[1.00]	[-1.98]	[-0.35]	[-1.30]	[-1.69]
Size	-0.253	-0.067	-0.044	-0.031	-0.132	-0.058	-0.157
	[-4.81]	[-1.08]	[-1.09]	[-0.47]	[-1.72]	[-1.16]	[-3.14]
Book-to-Market	0.369	0.569	0.176	0.239	0.550	0.365	0.282
	[3.68]	[4.59]	[1.35]	[1.48]	[3.84]	[4.46]	[3.87]
Lagged Return	0.014	0.001	0.003	0.001	-0.011	0.012	-0.001
	[3.57]	[0.10]	[1.01]	[0.15]	[-2.85]	[4.07]	[0.28]
Adjusted R^2	0.118	0.108	0.114	0.147	0.124	0.078	0.046
Percentiles of W-FF Idiosyncratic Volatility							
25th Percentile	20.8	21.4	16.3	21.5	23.1	13.9	25.0
75th Percentile	46.0	39.2	34.8	38.4	39.6	31.3	61.1
Economic Effect of 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%	-0.73%
Panel B: Local Currency Denominated Returns							
Constant	1.730	0.319	0.554	0.653	0.657	0.513	
	[3.70]	[0.56]	[1.34]	[1.10]	[0.94]	[1.11]	
L-FF Idiosyncratic Volatility	-1.332	-1.057	-1.769	-1.865	-2.035	-0.934	
	[-2.59]	[-1.64]	[-3.38]	[-2.76]	[-5.89]	[-2.63]	
$\beta(MKT^W)$	0.422	0.133	0.413	0.014	0.999	0.525	
	[2.64]	[0.71]	[2.13]	[0.05]	[5.76]	[3.59]	
$\beta(SMB^W)$	0.123	-0.044	0.037	-0.011	-0.016	-0.048	
	[1.30]	[-0.45]	[0.37]	[-0.07]	[-0.15]	[-0.54]	
$\beta(HML^W)$	-0.077	0.114	0.178	-0.126	0.012	-0.022	
	[-0.82]	[1.31]	[2.10]	[-1.11]	[0.10]	[-0.38]	
Size	-0.254	-0.041	-0.039	-0.080	-0.143	-0.090	
	[-4.84]	[-0.65]	[-0.95]	[-1.19]	[-2.01]	[-1.72]	
Book-to-Market	0.406	0.571	0.147	0.253	0.552	0.321	
	[3.68]	[4.74]	[1.03]	[1.77]	[3.94]	[4.04]	
Lagged Return	0.015	0.001	0.001	0.001	-0.011	0.012	
	[3.69]	[0.29]	[0.42]	[0.16]	[-2.90]	[4.09]	
Adjusted R^2	0.110	0.107	0.115	0.144	0.131	0.073	

Note to Table 2

The table reports Fama-MacBeth (1973) regressions (equation (4)) for the individual G7 countries. 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 the 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 3: 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 the 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 4: 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 the 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: Effect of Different Formation Periods to Compute Idiosyncratic Volatility

	U.S.			All Countries			All Excluding U.S.		
Formation Period	$(t-3,t)$	$(t-6,t)$	$(t-12,t)$	$(t-3,t)$	$(t-6,t)$	$(t-12,t)$	$(t-3,t)$	$(t-6,t)$	$(t-12,t)$
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]
$\beta(MKT^W)$	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]
$\beta(SMB^W)$	-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 R^2	0.048	0.048	0.050	0.101	0.101	0.105	0.145	0.143	0.149

Note to Table 5

The table reports Fama-MacBeth (1973) regressions (equation (4)) for all 23 countries. The regressions are split into three groups U.S., all countries, and all countries excluding the U.S. We regress next month excess firm returns onto a constant; idiosyncratic volatility computed using daily returns over the past 3, 6, or 12 months with respect to the W-FF model in equation (3) all expressed in annualized terms, which are denoted as denoted by $(t-3,t)$, $(t-6,t)$, and $(t-12,t)$, respectively; 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 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: 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 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 from September 1980 to December 2003.

Table 7: International Comovement in Idiosyncratic Volatility Portfolios

	Alpha	MKT^W	SMB^W	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]	[10.6]	[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 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 7

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 the robust t-statistics in square brackets below each coefficient. The sample period is from September 1980 to December 2003.

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]
$\beta(MKT^L)$	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	1675	3447	697	776	994	3447	556
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 8

Panel A reports Fama-MacBeth (1973) regressions in equation (4) for U.S. stocks using L-FF idiosyncratic volatility (see 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 U.S. L-FF model; firm characteristics at the beginning of the period, 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); "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 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 9: 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	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 equation (1)) for only U.S. stocks for forming portfolios ranked on L-FF idiosyncratic volatility at the beginning of 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. All portfolios are value weighted. 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 robust t-statistics in square brackets below each L-FF alpha.

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
	[-2.24]	[-4.45]
$\beta(MKT^L)$	-0.038	-0.016
	[-0.77]	[-0.36]
$\beta(HML^L)$	0.034	0.026
	[1.32]	[0.99]
$\beta(SML^L)$	-0.056	-0.057
	[2.50]	[-2.45]
Size	-0.217	-0.228
	[-6.04]	[-6.05]
Book-to-Market	0.056	0.085
	[3.35]	[3.00]
Lagged Return	0.151	0.165
	[0.89]	[0.97]
Leverage		-0.921
		[-3.66]
Leverage $\times$ L-FF Idiosyncratic Volatility		1.585
		[2.48]
Adjusted R^2	0.051	0.061

We report Fama-MacBeth (1973) regressions (see equation (4)) for U.S. stocks using L-FF idiosyncratic volatility (see 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 U.S. L-FF model; and firm characteristics at the beginning of the period. "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. Leverage is defined as the book value of debt over the sum of the book value of debt and the market value of equity. We report 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 August 1963 to December 2003.

Table 11: Relation Between Idiosyncratic Volatility and Leverage

	Ranking on $\sigma_i(t-1,t)$					
	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 $\sigma_i(t-1,t)$	0.132	0.086	-0.006	-0.455	-1.113	-1.265
Controlling for Leverage	[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, $\sigma_i(t-1,t)$. We first sort stocks each month based on leverage and then, within each quintile, we sort stocks on $\sigma_i(t-1,t)$. The last row labelled "Ranking on $\sigma_i(t-1,t)$ Controlling for Leverage" reports the L-FF alphas of the five $\sigma_i(t-1,t)$ portfolios averaged over each of the five leverage portfolios and thus represent lagged idiosyncratic volatility quintile portfolios which control for leverage. All portfolios are value weighted. All computations are done using only U.S. stocks over the sample period August 1963 to December 2003.

Table 12: Relation Between Idiosyncratic Volatility and Predicted and Realized Volatility

Panel A: L-FF Alphas of Portfolios First Sorted on $\mathrm{E}_t[\sigma_i(t,t+1)]$, Then on $\sigma_i(t-1,t)$

	Ranking on $\sigma_i(t-1,t)$					
	1 Low	2	3	4	5 High	5–1
1 Low $\mathrm{E}_t[\sigma_i(t,t+1)]$	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 $\mathrm{E}_t[\sigma_i(t,t+1)]$	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 $\sigma_i(t-1,t)$	0.425	0.099	-0.100	-0.325	-0.648	-1.073
Controlling for $\mathrm{E}_t[\sigma_i(t,t+1)]$	[4.95]	[1.26]	[-1.22]	[-3.90]	[-7.09]	[-9.44]

Panel B: L-FF Alphas of Portfolios First Sorted on $\sigma_i^L(t,t+1)$, Then on $\sigma_i^L(t-1,t)$

	Ranking on $\sigma_i^L(t-1,t)$					
	1 Low	2	3	4	5 High	5–1
1 Low $\sigma_i^L(t,t+1)$	-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 $\sigma_i^L(t,t+1)$	-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 $\sigma_i^L(t-1,t)$	-0.027	0.403	0.208	-0.136	-1.232	-1.205
Controlling for $\sigma_i^L(t,t+1)$	[-0.21]	[5.06]	[2.53]	[-1.54]	[-11.48]	[-6.63]

Note to Table 12

In Panel A, we compute L-FF alphas of 5×5 portfolios first sorted on predicted idiosyncratic volatility, $\mathrm{E}_t[\sigma_i(t, t+1)]$, and then on lagged idiosyncratic volatility, $\sigma_i(t-1, t)$. We first sort stocks each month based on $\mathrm{E}_t[\sigma_i(t, t+1)]$, and then, within each quintile, we sort stocks on $\sigma_i(t-1, t)$. The last row labelled "Ranking on $\sigma_i(t-1, t)$ Controlling for $\mathrm{E}_t[\sigma_i(t, t+1)]$" reports the L-FF alphas of the five $\sigma_i(t-1, t)$ portfolios averaged over each of the five $\mathrm{E}_t[\sigma_i(t, t+1)]$ portfolios and thus represent lagged idiosyncratic volatility quintile portfolios which control for predicted volatility. All portfolios are value weighted. Predicted volatility is computed using a cross-sectional regression using lagged idiosyncratic volatility, firm size, firm book-to-market ratio, past 6-month return, stock return skewness, and turnover over the previous month. Different cross-sectional regressions are run each month. Panel B contains a 5×5 portfolio sort similar to Panel A. In Panel B, we report L-FF alphas for 5×5 portfolios constructed first sorting on realized idiosyncratic volatility using log returns, $\sigma_i^L(t, t+1)$, and then on lagged idiosyncratic volatility using log returns, $\sigma_i^L(t-1, t)$. The idiosyncratic volatilities are computed using log returns in equation (1). All computations are done using only U.S. stocks over the sample period August 1963 to December 2003.