Average Idiosyncratic Volatility in G7 Countries

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Abstract

We argue that changes in average idiosyncratic volatility provide a proxy for changes in the investment opportunity set and that this proxy is closely related to the book-to-market factor. We test this idea in two ways using G7 countries' data. First, we show that idiosyncratic volatility has statistically significant predictive power for aggregate stock market returns over time. Second, we show that idiosyncratic volatility performs just as well as the book-to-market factor in explaining the cross section of stock returns. Our results suggest that the hedge against changes in investment opportunities is an important determinant of asset prices.

Keywords: Idiosyncratic Volatility, Stock Market Volatility, Value Premium, Stock Return Predictability, ICAPM, Unit Root, Deterministic Trend, and Granger Causality.

JEL number: G1.

There is an ongoing debate about whether average firm-level idiosyncratic stock return volatility forecasts stock market returns. Using monthly U.S. data over the period July 1962 to December 1999, Goyal and Santa-Clara (2003) report that the *equal-weighted* total volatility is positively and significantly related to future stock market returns, although stock market volatility has negligible predictive power.[1] However, subsequent studies, e.g., Bali, Cakici, Yan, and Zhang (2005) and Wei and Zhang (2005), show that neither idiosyncratic volatility nor stock market volatility forecasts stock market returns in an extended sample ending in 2001. In contrast, using quarterly data over the period 1963 to 2002, Guo and Savickas (2006) find that, when combined with stock market volatility, the *value-weighted* idiosyncratic volatility is negatively and significantly related to stock market returns.[2] Consistent with the CAPM, Guo and Savickas also document a positive relation between stock market volatility and returns.

In this paper, we try to shed light on this controversy by arguing that changes in idiosyncratic volatility provide a proxy for changes in investment opportunities. Specifically, we argue that this proxy is closely related to the book-to-market factor advocated by Fama and French (1996). The main idea is as follows. Technological innovations—which are an important component of a firm's investment opportunities—have two major effects on the firm's stock price. First, they tend to increase the level of the firm's stock price because of growth options. Second, they also tend to increase the volatility of the firm's stock price because of the uncertainty about which firms will benefit from the new opportunities. That is, as confirmed by recent empirical studies, e.g., Duffee (1995), Mazzucato (2002), Pastor and Veronesi (2003, 2005), and Agarwal, Bharath, and Viswanathan (2004), firms that adopt new technologies tend to have higher stock market valuations and higher stock price volatility than firms that do not adopt new technologies. Moreover, Berk, Green, and Naik (1999) show that the valuation of a firm’s investment opportunities depends crucially on the time-varying cost of capital. And their model implies that the aggregate book-to-market ratio forecasts stock market returns because of its comovements with the conditional equity premium. Therefore, because a firm’s volatility is closely related to its investment opportunities and thus its book-to-market ratio, the average idiosyncratic volatility is negatively related to future stock market returns possibly because of its negative correlation with the aggregate book-to-market ratio.

We test this idea in two ways. First, we show that idiosyncratic volatility has predictive power for aggregate stock market returns across time. For robustness, we use both U.S. data obtained from CRSP (the Center for Research in Security Prices) and the other G7 countries’ data obtained from Datastream. We find that, for most G7 countries, idiosyncratic volatility and stock market volatility jointly forecast stock market returns, although neither variable has significant predictive power individually. Moreover, U.S. idiosyncratic volatility has significant predictive power for international stock market returns, even after we control for the local counterparts. Similarly, because of their strong comovements with U.S. data, idiosyncratic volatility of the other G7 countries also forecasts U.S. stock market returns.

Second, we show that idiosyncratic volatility is closely related to the book-to-market factor. As hypothesized, in U.S. data, the relation between idiosyncratic volatility and the aggregate book-to-market ratio is significantly negative. More importantly, we find that idiosyncratic volatility performs just as well as the book-to-market factor in explaining the cross section of stock returns on the 25 Fama and French (1993) portfolios sorted on size and book-to-market ratio. We also find a very similar result using the Fama and French (1998) international value and growth portfolios.

Hamao, Mei, and Xu (2003) and Frazzini and Marsh (2003) have investigated idiosyncratic volatility for Japan and the U.K., respectively. However, unlike this paper, those studies focus on idiosyncratic volatility of a particular country and do not address its commonality across countries. Moreover, some of our results are different from theirs. For example, Hamao, Mei, and Xu fail to reject a unit root in Japanese value-weighted idiosyncratic volatility but it is found to be stationary here. Also, we find a significantly negative relation between the value-weighted idiosyncratic volatility and future stock market returns for the U.K., in contrast with the positive relation reported by Frazzini and Marsh (2003).

The remainder of the paper is organized as follows. Because we use idiosyncratic volatility as a new risk factor, it is important to understand its statistical properties. This issue is addressed in Section 1. We investigate predictive abilities of average idiosyncratic volatility for stock market returns and the value premium in Section 2, and provide some discussion, as well as additional evidence in Section 3. Concluding remarks are offered in Section 4.

1. Data

We obtain from the CRSP database daily value-weighted stock market return and daily individual stock return data for the U.S. over the period July 1962 to December 2003. We obtain from Datastream the same variables denominated in local currencies over the period January 1965 to December 2003 for the U.K. and over the period January 1973 to December 2003 for Canada, France, Germany, Italy, and Japan. As in Campbell, Lettau, Malkiel, and Xu (2001), we assume that the daily risk-free rate is the rate which, over the number of calendar days, compounds to the monthly T-bill rate. The monthly T-bill rate is obtained from International Financial Statistics (IFS) for all countries.

We construct the realized average idiosyncratic volatility and stock market volatility similarly to Campbell, Lettau, Malkiel, and Xu (2001) and Goyal and Santa-Clara (2003), and define quarterly equal-weighted idiosyncratic volatility as:

$$EWIV_t = \sum_{i=1}^{N_t} \omega_{it} [\sum_{d=1}^{D_{it}} \eta_{id}^2 + 2\sum_{d=2}^{D_{it}} \eta_{id}\eta_{id-1}] \quad and\ \omega_{it} = \frac{1}{N_t}, \tag{1}$$

where N_t is the number of stocks in quarter *t*, D_{it} is the number of trading days for stock *i* in quarter *t*, and η_{id} is the idiosyncratic shock to the excess return on stock *i* in day *d* of quarter *t*.

Similarly, quarterly value-weighted idiosyncratic volatility is defined as:

$$VWIV_t = \sum_{i=1}^{N_t} \omega_{it} \left[\sum_{d=1}^{D_{it}} \eta_{id}^2 + 2\sum_{d=2}^{D_{it}} \eta_{id}\eta_{id-1} \right] \quad and\ \omega_{it} = \frac{v_{it-1}}{\sum_{j=1}^{N_t} v_{jt-1}}, \tag{2}$$

where v_{it-1} is the market capitalization of stock *i* at the end of quarter *t*–1. Following Merton (1980) and Andersen, Bollerslev, Diebold, and Labys (2003), we define realized stock market volatility as:

$$MV_t = \sum_{d=1}^{D_t} (e_{md})^2, \tag{3}$$

where e_{md} is the excess stock market return in day *d* of quarter *t*. The volatility measure in Equation (3) is potentially biased if there is serial correlation in daily stock market returns. However, we find essentially the same results by adjusting for the serial correlation, as in French, Stambaugh, and Schwert (1987). To conserve space, these results are not reported here but are available on request.

In this paper, we use the CAPM to control for systematic risk.[3] The idiosyncratic shock, η_{id}, is thus the residual from the regression of the excess return, er_{id}—the difference between the return on stock *i* and the risk free rate—on the excess stock market return, e_{md}:

$$er_{id} = \alpha + \beta \cdot e_{md} + \eta_{id} . \qquad (4)$$

Factor loadings, β, might change over time; therefore, we estimate Equation (4) using a rolling sample. For example, the idiosyncratic shock at time *d* is equal to $er_{id} - \hat{\alpha} - \hat{\beta} \cdot e_{md}$, where we obtain the coefficient estimates $\hat{\alpha}$ and $\hat{\beta}$ using the daily data from *d*–130 to *d*–1. We require a minimum of 45 daily observations in order to obtain less-noisy parameter estimates. Similar to Goyal and Santa-Clara (2003), we exclude stocks that have fewer than eight return observations in a quarter and drop the term $2\sum_{d=2}^{D_{it}} \eta_{id}\eta_{id-1}$ from Equations (1) and (2) if $\sum_{d=1}^{D_{it}} \eta_{id}^2 + 2\sum_{d=2}^{D_{it}} \eta_{id}\eta_{id-1}$ is less than zero. We also drop stocks if their market capitalization data at the end of the previous quarter are missing. Some additional filters are also imposed on the Datastream data to remove potential coding errors. For the U.S., data are available from both Datastream and CRSP; and we obtain essentially the same results using the data from the two sources. See Appendix A for a detailed discussion on the Datastream data.

1.1 Stock market volatility

Figure 1 plots quarterly stock market volatility of the G7 countries. We observe a big spike in stock market volatility during the 1987 stock market crash in all countries, although it appears to be especially pronounced for the U.S. and Canada. To minimize the outlier effect of the 1987 crash, in our empirical analysis, we follow Campbell, Lettau, Malkiel, and Xu (2001) and many others by replacing realized volatility of 1987:Q4 with the second-largest observation in the sample for the U.S. and Canada.[4] We also observe strong comovements of stock market volatility during other periods; for example, in all countries, it rose in the past few years and then fell at the end of the sample. Consistent with the visual inspection, Table 1 shows that stock market volatility in the other G7 countries is closely correlated with its U.S. counterpart.

Figure 1 shows that stock market volatility is serially correlated in the G7 countries (see also Table 1). In Table 2, we investigate whether it has a stochastic trend using the augmented Dick-Fuller (DF) unit root test. We consider two specifications: one with a constant and the other with a linear time trend. For both specifications, we choose the number of lags (reported in parentheses) using the general-to-specific method recommended by Campbell and Perron (1991) and Ng and Perron (1995).[5] We reject the null hypothesis of a stochastic trend for all countries except Japan in the constant specification. We also reject a Japanese unit root after we take into account its upward trend, which, as we will discuss next, is statistically significant. To summarize, our results suggest that stock market volatility appears to be stationary.

Lastly, consistent with the early studies, e.g., Schwert (1989), Figure 1 shows that there is no trend in U.S. stock market volatility over the post-World War II sample. Similarly, we find no obvious trend for Canada, France, Italy, or the U.K. However, stock market volatility appears to have increased substantially for Germany and Japan over the period 1973 to 2003. In Table 3, we formally investigate this issue using Vogelsang's (1998) PS^1 test.[6] Consistent with Figure 1, we find a significant upward trend in stock market volatility for Germany and Japan but not the other countries. Our results are not specific to the Datastream data because we obtain the same conclusion using the MSCI (Morgan Stanley Capital International) daily market return data.[7] The existing literature provides no explanation for the puzzling upward trend; however, a formal investigation is beyond the scope of this paper and we leave it for future research.

1.2 Idiosyncratic volatility

Figure 2 plots the equal-weighted idiosyncratic volatility (thin line) along with the value-weighted idiosyncratic volatility (thick line).[8] We observe strong comovements in both measures of idiosyncratic volatility across countries. For example, it rose sharply around the late 1990s and then fell steeply afterward. It is also interesting to note that, in contrast with stock market volatility, the 1987 stock market crash has a relatively small effect on idiosyncratic volatility. Consistent with the visual inspection, Table 1 shows that idiosyncratic volatility in the other G7 countries, both value- (Panel A) and equal-weighted (Panel B), is highly correlated with its U.S. counterpart. To our best knowledge, this result has not been reported elsewhere.

We also investigate in Table 2 whether idiosyncratic volatility has a stochastic trend. Consistent with the early authors, e.g., Campbell, Lettau, Malkiel, and Xu (2001), we reject the null hypothesis of a unit root in U.S. value-weighted idiosyncratic volatility at the 5% significance level in the constant specification. We also reject the unit root in the value-weighted idiosyncratic volatility at the 1% significance level for Japan, the 5% level for the U.K., and the 10% level for Germany and Italy.[9] We find similar results in the trend specification, although the evidence against the unit root is somewhat weaker than in the constant specification. The latter result reflects the fact that the trend specification has less power because, as we will show below, we find no deterministic trend in the value-weighted idiosyncratic volatility of all G7 countries. In contrast, the evidence against the unit root is much weaker for the equal-weighted idiosyncratic volatility. It is rejected only for Italy in the constant specification and is also rejected for the U.S. and Japan after we take into account their positive trends, which, as we will show below, are statistically significant.

For robustness, we also conduct Elliott, Rothenberg, and Stock's (1996) DF-GLS test, which has better power than the augmented DF test. To conserve space, we only briefly summarize the main results. (Details are available on request.) For the value-weighted idiosyncratic volatility, we find two more rejections of the unit root—Canada and France—at the 10% significance level in the constant specification. However, we fail to reject the unit root for Germany, which is found to be stationary in the augmented DF test. The results of the other countries are qualitatively the same as those reported in Table 2. Also, the evidence is again noticeably weaker for the trend specification because of the lack of power. The results for the equal-weighted idiosyncratic volatility, however, are similar to those reported in Table 2. To summarize, the value-weighted idiosyncratic volatility appears to contain no unit root in G7 countries; however, the results are much less conclusive for the equal-weighted measure.

Lastly, consistent with Campbell, Lettau, Malkiel, and Xu (2001) and Comin and Mulani (2006), among others, Figure 2 shows that there appears to be an upward trend in U.S. idiosyncratic volatility, especially for the equal-weighted measure. The equal-weighted idiosyncratic volatility is substantially higher than its value-weighted counterpart as well. Figure 2 reveals a very similar pattern in the other G7 countries. The equal-weighted idiosyncratic volatility has risen quite substantially in all countries except Italy; however, the increase is much less pronounced for the value-weighted measure. Again, the equal-weighted idiosyncratic volatility is substantially higher than its value-weighted counterpart in all the other G7 countries.

Table 3 shows that the PS^1-statistic is always positive for both equal- (Panel A) and value-weighted (Panel B) measures of idiosyncratic volatility, indicating that idiosyncratic volatility has increased in the past three decades. However, for all G7 countries, the positive trend in the value-weighted idiosyncratic volatility is statistically insignificant at the 10% level.

In contrast, consistent with Campbell, Lettau, Malkiel, and Xu (2001), there is a significant positive deterministic trend in U.S. equal-weighted idiosyncratic volatility. We also document a significant upward trend in Japanese equal-weighted idiosyncratic volatility. The upward trends in the equal-weighted idiosyncratic volatility, however, are statistically insignificant for the other countries. The latter result is somewhat puzzling because Figure 2 shows a substantial increase in the level of the equal-weighted idiosyncratic volatility in all these countries except Italy. One possible explanation is that the equal-weighted idiosyncratic volatility is found to be nonstationary for all these countries except Italy (Table 2) and the PS^1 test has poor power properties for nonstationary variables.

To summarize, we find that, consistent with U.S. data, the equal-weighted idiosyncratic volatility appears to have increased in the past three decades in the other G7 countries. Comin and Philippon (2005) have proposed several explanations for the upward trend in idiosyncratic volatility. In particular, they argue that it might be related to increased competition; for example, the turnover of industry leaders has trended upward in the U.S. over the past 50 years. This interpretation appears to be consistent with our empirical finding that the upward trend is more pronounced for the equal-weighted idiosyncratic volatility than the value-weighted idiosyncratic volatility. This is because, although small firms may not matter much when they enter, they may be very important in forcing the large firms to innovate and compete. A formal investigation of these issues (e.g., the turnover of industry leaders) using international data will shed light on the theoretical explanations proposed by Comin and Philippon. However, we leave this important question for future research because the main focus of this paper is the relation between average idiosyncratic volatility and stock returns.

1.3 Lead-lag relationships of volatility

Campbell, Lettau, Malkiel, and Xu (2001) find that stock market volatility is a strong predictor of idiosyncratic volatility and vice versa. Similarly, Stivers (2003) reports that the cross-sectional return dispersion, which is closely related to idiosyncratic volatility, also forecasts stock market volatility for the U.S., the U.K., and Japan. Moreover, Table 2 shows that stock market volatility and idiosyncratic volatility of the other G7 countries are highly correlated with their U.S. counterparts. In this subsection, we briefly discuss the lead-lag relationships of various volatility measures. We obtain very similar results using both equal- and value-weighted idiosyncratic volatility and, for brevity, focus only on the latter.

We first conduct the Granger causality test between stock market volatility and the value-weighted idiosyncratic volatility using a bivariate vector autoregression (VAR). We choose the number of lags by the Akaike information criterion. Consistent with Campbell, Lettau, Malkiel, and Xu (2001) and Stivers (2003), in the U.S., there is a significant Granger causality from average idiosyncratic volatility to stock market volatility. It is also significant in France, Germany, and Italy and is marginally significant in Japan but insignificant in the U.K. and Canada. The latter result contrasts with Stivers (2003), who finds that for the U.K. the cross-sectional return dispersion is a strong predictor of future stock market volatility. The difference reflects the fact that Stivers uses lower-frequency data (monthly) over a much shorter period (1980 to 1999), as opposed to our study. We also confirm that in the extended U.S. sample there is a strong Granger causality from stock market volatility to idiosyncratic volatility. The Granger causality is also significant for the U.K. and Germany and is marginally significant for France; however, it is insignificant for Canada, Italy, and Japan.

We then investigate the lead-lag relationships of volatility between the U.S. and the other G7 countries. For the value-weighted idiosyncratic volatility, the U.S. has significant influence on all the other countries; similarly, France, Germany, and Japan have a significant effect, and the U.K. and Italy have a marginally significant effect, on the U.S. In contrast, we do not observe any significant Granger causality of stock market volatility between the U.S. and the other countries, possibly because the transmission of stock market volatility across countries is quick.

2. Forecasting Stock Returns

In this section, we investigate whether average idiosyncratic volatility forecasts stock market returns and the value premium in major international stock markets. We provide theoretical explanations for our results in the next section.

2.1 Forecasting one-quarter-ahead stock market returns

This subsection investigates whether average idiosyncratic volatility and stock market volatility jointly forecast stock market returns in G7 countries. We use the gross return indices constructed by Datastream as proxies for stock market returns for Canada, Germany, France, Italy, Japan, and the U.K. and the CRSP value-weighted stock market return for the U.S. The excess stock market return is the difference between the stock market return and the T-bill rate obtained from the IFS.

We first investigate whether, as in Goyal and Santa-Clara (2003), the equal-weighted idiosyncratic volatility (*EWIV*) is positively related to stock market returns and report the results in Panel A of Table 4. Because the equal-weighted idiosyncratic volatility exhibits an upward deterministic trend in some countries (Table 3), we also include a linear time trend in the forecasting regression but, to conserve space, do not report it here. The Newey-West (1987) t-statistics with 4 lags are in parentheses; and we find essentially the same results using the White (1980)-consistent t-statistics.

Consistent with Bali, Cakici, Yan, and Zhang (2005) and Wei and Zhang (2005), Table 4 shows that, in U.S. data, the effect of the equal-weighted idiosyncratic volatility by itself is positive but statistically insignificant. It is statistically insignificant in the other G7 countries as well. Moreover, in contrast with U.S. data, its coefficient is actually negative for France, Germany, and the U.K.

For comparison, in Panel B of Table 4, we show that stock market volatility (*MV*) does not forecast stock market returns either. In contrast with the CAPM, its coefficient is actually negative for France, Germany, and the U.K., although statistically insignificant. However, if we include both stock market volatility and the equal-weighted idiosyncratic volatility in the forecasting equation, the effect of the equal-weighted idiosyncratic volatility becomes significantly negative for the U.K. and Germany at the 5% and 10% levels, respectively (Panel C). Idiosyncratic volatility has an (insignificantly) positive effect on stock market returns in only two countries; therefore, the international evidence provides little support for the nondiversification hypothesis advanced by Levy (1978) and Malkiel and Xu (2002), for example.

Interestingly, Table 4 also shows that controlling for the equal-weighted idiosyncratic volatility helps uncover a positive risk-return tradeoff: Stock market volatility is always positive, and it is significant or marginally significant for five countries, including the U.S.[10] Our findings that idiosyncratic volatility and stock market volatility forecast stock returns only jointly but not individually might reflect a classic omitted variable problem.[11] To illustrate this point, we adopt a textbook example of the omitted variable problem from Greene (1997, p. 402). Suppose *ER* is the dependent variable, *IV* is the omitted variable with the true parameter *B1*, and *MV* is the included variable with the true parameter *B2*. Then the point estimate of the coefficient of *MV* is $\hat{B}2 = B2 + \frac{Cov(MV, IV)}{Var(IV)} B1$. Because *B1* is negative and $Cov(MV, IV)$ is positive, the point estimate $\hat{B}2$ is biased downward towards zero. As we will explain in the next section, our results reflect the fact that the component of aggregate risk, which is not correlated with micro risk, has a positive impact on returns. In other words, macro risk without micro risk is bad news.

We then investigate the forecasting power of the value-weighted idiosyncratic volatility (*VWIV*) and report the results in Table 5. We do not include a linear time trend in the forecasting regression because we fail to detect it in the value-weighted idiosyncratic volatility (see Table 3), although doing so does not change our results in any qualitative manner. Again, the value-weighted idiosyncratic volatility itself does not forecast stock market returns in any country (Panel A). However, Panel B shows that, consistent with Guo and Savickas (2006), when combined with stock market volatility, both variables are strong predictors of stock market returns in U.S. data, with an adjusted R-squared of 8%. Also, while idiosyncratic volatility has a negative sign, stock market volatility is positively related to stock market returns, as stipulated by the CAPM. Interestingly, we find very similar results in U.K. data: Stock market volatility is significantly positive, and the value-weighted idiosyncratic volatility is significantly negative.[12] Moreover, in sharp contrast with the univariate regression results reported in Panel B of Table 4, stock market volatility is positive for all G7 countries and is statistically significant for four countries. Similarly, idiosyncratic volatility is also negative for Germany, Italy, and Japan, although statistically insignificant. These results are also qualitatively similar to those reported in Table 4 for the equal-weighted idiosyncratic volatility. For brevity, in the remainder of the paper, we discuss only the results for the value-weighted idiosyncratic volatility because it appears to have better-behaved statistical properties, e.g., stationarity, than its equal-weighted counterpart.

Panel B of Table 5 shows that, although qualitatively similar, the forecasting power of idiosyncratic volatility and stock market volatility is noticeably weaker in the other G7 countries than in the U.S. One possible explanation is that, if capital markets are integrated, international stock market returns are more influenced by the U.S. variables than their local counterparts [see, e.g., Harvey (1991)]. We investigate this issue in Panel C of Table 5. Consistent with Guo and Savickas (2006), we find that U.S. idiosyncratic volatility is always negative and U.S. stock market volatility is always positive in the forecasting regression of international stock market returns. Also, both variables are significant or marginally significant in most cases.[13] Moreover, if we use both the country-specific and U.S. predictive variables, as shown in Panel D of Table 5, the coefficient of U.S. idiosyncratic volatility is negative and statistically significant or marginally significant in all countries except Japan. Our results are thus consistent with the conjecture that U.S. idiosyncratic volatility is a proxy for systematic risk in international stock markets, although the country-specific variables also matter for some countries.

Lastly, if it is a proxy for systematic risk, we expect that average idiosyncratic volatility of the other countries should forecast U.S. stock market returns as well because of its strong comovements with U.S. variables (Table 1). Consistent with this hypothesis, Table 6 shows that the two-quarter-lagged value-weighted idiosyncratic volatility of the other G7 countries is negatively related to U.S. excess stock market returns and the relation is significant or marginally significant for all countries except Canada (Panel A).[14] However, with only one exception—the German idiosyncratic volatility—the international variables lose their forecasting power after we control for U.S. stock market volatility and idiosyncratic volatility in the forecasting equation

(Panel B). These results suggest that the commonality in idiosyncratic volatility might reflect systematic risk.

2.2 Forecasting the one-quarter-ahead value premium

As we will explain in the next section, idiosyncratic volatility might be a proxy for volatility of the value premium, which is a risk factor in the Fama and French (1993) three-factor model. In particular, we expect that stock market volatility and idiosyncratic volatility jointly forecast the value premium. We investigate this issue in Table 7 using the value premium data obtained from Kenneth French at Dartmouth College.

Table 7 shows that, consistent with Guo and Savickas (2006), while stock market volatility is negatively related to the one-quarter-ahead value premium, the effect of the value-weighted idiosyncratic volatility is significantly positive in U.S. data. Interestingly, we find very similar results for Germany, Japan, and the U.K., in which the value-weighted idiosyncratic volatility is positively and significantly correlated with the value premium. Similarly, realized stock market volatility is negative except for Canada and France; and it is statistically significant for Germany and marginally significant for Italy.

It is interesting to note that stock market volatility is statistically significant in more cases than the value-weighted idiosyncratic volatility in the forecast of stock market returns (Panel B of Table 5). However, the converse is true in the forecast of the value premium (Table 7). This pattern appears to be consistent with the hypothesis that, as we will elaborate in the next section, average idiosyncratic volatility is a proxy for volatility of a risk-factor omitted from the CAPM, i.e., the value premium. In particular, if stock returns are generated by a two-factor model, the expected stock market return is a linear function of conditional stock market variance and its covariance with the other risk factor. Therefore, idiosyncratic volatility forecasts stock market returns because of its correlation with the covariance term, which is likely to be imperfect. This helps explain why stock market volatility is statistically significant in more cases than the value-weighted idiosyncratic volatility in the forecast of stock market returns. Similarly, if the value premium is a priced risk factor, the expected value premium is a linear function of its conditional variance and its conditional covariance with stock market returns. In this case, idiosyncratic volatility forecasts the value premium because it is a proxy for volatility of the value premium. In contrast, stock market volatility forecasts the value premium because of its correlation with the covariance term, which, again, is likely to be imperfect. This helps explain why the value-weighted idiosyncratic volatility is statistically significant in more cases than stock market volatility in the forecast of the value premium.

2.3 Bootstrapping standard errors

Table 1 shows that both stock market volatility and idiosyncratic volatility are serially correlated; therefore, the ordinary least squares (OLS) estimates are potentially biased in small samples [see, e.g., Stambaugh (1999)]. To address this issue, we use the bootstrapping approach to obtain the empirical distribution of the t-statistics, as in Goyal and Santa-Clara (2003). In particular, we assume that stock market returns, stock market volatility, and the value-weighted idiosyncratic volatility follow a VAR(1) process with the restrictions under the null hypothesis that the expected excess stock market return is constant. We estimate the VAR system using the actual data and then generate the simulated data 10,000 times by drawing error terms with replacement. Table 8 reports the p-value of the t-statistic obtained from the bootstrapping. To conserve space, we report only the forecasting regressions of the stock market return (Panel A) and the value premium (Panel B) on realized stock market volatility and the value-weighted idiosyncratic volatility; we find very similar results for the other regressions, which are available on request. Consistent with Goyal and Santa-Clara, the bootstrapping p-values (in angle brackets) are consistent with those obtained from the asymptotic t-statistic (in parentheses). Our results indicate that the small sample bias is small possibly because, as shown in Table 1, our forecasting variables are not as persistent as those cautioned by Stambaugh (1999), for example, the dividend yield.

3. Discussion

Levy (1978) and Malkiel and Xu (2002), among others, argue that idiosyncratic volatility is positively related to expected stock returns because many investors hold poorly diversified portfolios. The nondiversification hypothesis, however, cannot explain our results because we find that average idiosyncratic volatility is actually negatively related to future stock market returns in most G7 countries.

Alternatively, we suggest that, by construction, average idiosyncratic volatility is a proxy for volatility of a risk factor omitted from the CAPM, as suggested by Lehmann (1990), among others. In particular, if the data-generating process is a two-factor model, Appendix B shows that, under some moderate conditions, the expected stock return is a linear function of stock market volatility and average idiosyncratic volatility.[15] Below, we explain that this simple two-factor model is consistent with existing economic theory and empirical evidence. In doing so, we also provide additional empirical results using both U.S. and international data.

3.1 Refutable propositions

In particular, we argue that a firm's stock price volatility moves closely with its investment opportunities, the valuation of which depends crucially on the time-varying cost of capital. For example, when a new technology is discovered, it creates opportunities for some firms, but not for others. The new technology has two effects on the firms that are capable of adopting it. First, Pastor and Veronesi (2003), for example, argue that the new technology is likely to increase the firms' stock price volatility because of the uncertainty about its effects on future cash flows. That is, with everything else equal, firms that adopt new technologies tend to have higher stock price volatility than firms that do not adopt new technologies. Second, the new technology increases the firms' stock prices because it improves the firms' investment opportunities. For example, in Berk, Green, and Naik's (1999) model, firms have assets in place, as well as real growth options. They show that acquiring an asset with low systematic risk leads to a decrease in the book-to-market ratio and thus lower future returns. That is, with everything else equal, firms that adopt new technologies tend to have a lower book-to-market ratio than firms that do not adopt new technologies.

These two conjectures are consistent with existing empirical evidence. In particular, Duffee (1995) documents a positive contemporaneous relation between stock returns and volatility at the firm level. Similarly, Pastor and Veronesi (2003) find that firms with higher stock price volatility tend to have a lower book-to-market ratio, even after they control for various firm-specific characteristics. These results suggest that a positive piece of news about future prospects could lead to an increase in firm stock price volatility. More specifically, recent authors have identified technological innovations as one of the driving forces for the positive comovements between a firm's stock prices and volatility. For example, Agarwal, Bharath, and

Viswanathan (2004) conduct an event study using a sample of “brick and mortar” firms that announced their initiation of e-commerce in the late 1990s. They find that these firms experienced significant increases in both stock prices and volatility after the announcements. Similarly, Mazzucato (2002) studies the U.S. auto industry from 1899 to 1929 and the U.S. PC industry from 1974 to 2000, and Pastor and Veronesi (2005) examine American railroads from 1830 to 1861. These authors find that, in these industries, firm volatility—as measured with both real variables and stock prices—increases sharply when there are radical technological changes that also initially drove up the stock prices of the firms in these industries.

Based on these empirical observations, we argue that technological innovations might be important for understanding the predictive power of idiosyncratic volatility for stock market returns and the value premium. The argument closely follows the partial equilibrium model developed by Berk, Green, and Naik (1999). These authors show that the time-varying cost of capital influences the valuation of a firm’s investment opportunities; as a result, the aggregate book-to-market ratio is positively related to future stock market returns because of its comovements with the conditional equity premium. Therefore, because a firm’s volatility is closely related to its investment opportunities and thus its book-to-market ratio, the average firm volatility is negatively related to future stock market returns, possibly because of its negative correlation with the aggregate book-to-market ratio.

More specifically, Appendix B shows that the conditional equity premium is a linear function of conditional variances of the priced risk factors. In Berk, Green, and Naik’s (1999) model, the aggregate book-to-market ratio is a proxy for the conditional equity premium; therefore, it should comove with these conditional variances. In particular, if average idiosyncratic volatility is a measure of realized variance of the risk factor omitted from the

CAPM, we expect that the aggregate book-to-market ratio should be correlated with idiosyncratic volatility and stock market volatility. This is our first refutable proposition.

While Berk, Green, and Naik (1999) establish a theoretical link between the aggregate book-to-market ratio and the conditional equity premium, they do not explain why the cost of capital changes over time because they assume an exogenous process for the pricing kernel. One possibility is that, as argued by Campbell and Vuolteenaho (2004), there are two types of risk: the discount-rate shock and the cash-flow shock. These authors find that growth stocks are more sensitive to the discount-rate shock than value stocks, possibly because growth stocks have a longer duration than value stocks.[16] Recall that growth stocks also tend to have higher firm-level volatility than value stocks. Therefore, average idiosyncratic volatility is likely to be closely correlated with volatility of the discount-rate shock across time. Moreover, because the value premium is closely correlated with the discount-rate shock [Campbell and Vuolteenaho (2004)], we expect that average idiosyncratic volatility should move closely with the volatility of the value premium. This is our second refutable proposition.

Equation (B5) implies that the expected return on any asset is a function of conditional variances of stock market returns, $r_{M,t+1}$, and the risk factor, $r_{H,t+1}$, omitted from the CAPM:

$$\begin{aligned} E_t r_{i,t+1} &= \gamma_M Cov_t(r_{i,t+1}, r_{M,t+1}) + \gamma_H Cov_t(r_{i,t+1}, r_{H,t+1}) \\ &= \gamma_M \frac{Cov_t(r_{i,t+1}, r_{M,t+1})}{Var_t(r_{M,t+1})} Var_t(r_{M,t+1}) + \gamma_H \frac{Cov_t(r_{i,t+1}, r_{H,t+1})}{Var_t(r_{H,t+1})} Var_t(r_{H,t+1}) \\ &= \gamma_M \beta_{i,M,t} Var_t(r_{M,t+1}) + \gamma_H \beta_{i,H,t} Var_t(r_{H,t+1}). \end{aligned} \tag{5}$$

Equation (B15) shows that, under some moderate conditions, average idiosyncratic volatility proxies for volatility of $r_{H,t+1}$. Therefore, we can rewrite Equation (5) as:

$$r_{i,t+1} = \alpha_{i,t} + \gamma_M \beta_{i,M} MV_t + \gamma_H \beta_{i,H} IV_t + \zeta_{i,t+1}, \tag{6}$$

where *MV* is stock market volatility and *IV* is average idiosyncratic volatility. For simplicity, we assume that betas are constant in Equation (6), as in Lettau and Ludvigson (2001), for example. In Equation (6), the loading on stock market volatility is equal to the market beta scaled by the price of market risk, γ_M. Similarly, the loading on idiosyncratic volatility is equal to the beta on the omitted risk factor scaled by its risk price, γ_H. Therefore, we can use Equation (6) to explain the cross section of stock returns, even though we do not observe the risk factor $r_{H,t+1}$. This approach provides a direct link between time-series and cross-sectional stock return predictability; to our best knowledge, it is novel. If the value premium is an omitted risk factor, as argued by Fama and French (1996), we expect that its volatility should have predictive power for stock returns similar to that of average idiosyncratic volatility in both the time-series and cross-sectional regressions. This is our third refutable proposition.

Before turning to the empirical investigation of the refutable propositions, we briefly explain the signs of stock market volatility, *MV*, and average idiosyncratic volatility, *IV*, in the forecast regression of stock market returns:

$$r_{M,t+1} = \alpha_{M,t} + \gamma_M MV_t + \gamma_H \beta_{M,H} IV_t + \zeta_{M,t+1}. \tag{7}$$

Note that we have used the relation $\beta_{M,M} = 1$ to derive Equation (7) from Equation (6). Campbell and Vuolteenaho (2004) show that investors require positive risk prices for both the discount-rate shock and the cash-flow shock or that γ_M and γ_H are both positive. Consistent with Campbell and Vuolteenaho's results, we find that stock market volatility has a positive coefficient in the forecasting regression for stock market returns.

We find that the coefficient for average idiosyncratic volatility is negative in Equation (7). This result reflects the fact that investors require a lower risk price for the discount-rate shock than the cash-flow shock: γ_H is smaller than γ_M [Campbell and Vuolteenaho (2004)]. In particular, because stock market volatility includes volatilities of both the discount-rate shock and the cash-flow shock, the discount-rate shock is over-priced in the first right-hand-side term of Equation (7). Therefore, the second right-hand-side term serves as a correction for the mispricing because average idiosyncratic volatility is closely related to the volatility of the discount-rate shock. This result is also consistent with the interpretation that average idiosyncratic volatility is a measure of volatility of the value premium: $\beta_{M,H}$ is negative because stock market returns and the value premium are negatively correlated in the data or stock market returns serve as a hedge for changes in investment opportunities. For the value premium, stock market volatility has a negative coefficient while average idiosyncratic volatility has a positive coefficient because the value premium is negatively correlated with stock market returns.

3.2 U.S. evidence

To investigate the first refutable proposition, in Panel A of Table 9, we present the OLS regression results of the aggregate book-to-market ratio (*BM*) on contemporaneous stock market volatility (*MV*) and average idiosyncratic volatility (*IV*) over the period 1963:Q4 to 2004:Q4. We also include two lags of the dependent variable because *BM* is serially correlated; for brevity, we do not report the estimation results for these additional variables. As expected, *BM* is negatively related to *IV*, indicating that a high level of average firm volatility is usually associated with a high level of stock market prices. This is because an increase in *IV* indicates a decrease in expected future returns and thus stock prices must rise immediately. Similarly, *BM* is positively correlated with *MV* because an increase in *MV* indicates an increase in expected future returns and thus stock prices must fall immediately. For robustness, we also consider two other commonly used measures of the relative stock market value: the price-earnings ratio (*PE*) and the dividend yield (*DY*). Again, we find that *IV* has a positive correlation and *MV* has a negative correlation with stock market prices. Panels B and C show that these relations are also stable in subsamples.

We also find strong support for the second refutable implication. The value-weighted idiosyncratic volatility is highly correlated with volatility of the value premium, with a correlation coefficient of 88% over the period 1963:Q4 to 2004:Q4.[17]

To address the third refutable proposition, we first compare the forecast power of idiosyncratic volatility with that of value premium volatility (*V_HML*) in time-series regressions. In Panel A of Table 10, we show that *V_HML* by itself has a negative but insignificant effect on future stock market returns. However, when in conjunction with *MV*, the negative effect of *V_HML* becomes highly significant; *MV* is also positively and significantly related to future stock market returns. Interestingly, *V_HML* loses its forecasting power after we include *IV* as an additional predictive variable. These results are consistent with those reported in Guo, Savickas, Wang, and Yang (2007) and indicate that *IV* and *V_HML* have similar forecasting power for stock market returns.

Early authors [e.g., Fama and French (1989), Kothari and Shanken (1997), and Pontiff and Schall (1998)] find that the scaled stock prices, for example, the aggregate book-to-market ratio (*BM*), the price-earning ratio (*PE*), and the dividend yield (*DY*), forecast stock market returns. One possible explanation is that, as argued by Berk, Green, and Naik (1999), these variables co-move with conditional stock market returns. Therefore, their forecasting power should be closely related to that of average idiosyncratic volatility and stock market volatility. Consistent with this conjecture, Panels B to D of Table 10 show that controlling for both *MV* and

IV in the forecasting equations substantially reduces the t-statistics of *BM*, *PE*, and *DY*. It is also interesting to note that *PE* becomes marginally significant when combined with *MV*, although it is insignificant by itself. Similarly, the t-statistic for *DY* increases substantially when combined with *MV*. The latter results help explain why the scaled stock prices lose the predictive power in the recent data, as emphasized by Goyal and Welch (2006). That is, *IV* has a much stronger influence on these variables than *MV* during the dramatic stock price run-up in the late 1990s; however, *IV* forecasts stock returns only when combined with *MV*.

Table 11 compares the cross-sectional predictive power of average idiosyncratic volatility with that of value premium volatility using 25 Fama and French (1993) portfolios sorted on size and book-to-market ratio.[18] Panel A replicates the well-documented result that average excess portfolio returns are positively related to the book-to-market ratio.

We also run the OLS regression of excess portfolio returns on a constant, stock market volatility, and idiosyncratic volatility for each of the 25 Fama and French (1993) portfolios. Panel B of Table 11 reports the point estimates of the coefficient on stock market volatility, which is equal to the loading on the market return, $\beta_{i,M}$, scaled by γ_M [see Equation (6)]. The point estimates are positive for all the portfolios. This result should not be too surprising because all the portfolios have positive loadings on the market risk and the price of stock market risk, γ_M, is positive as well. Consistent with Fama and French (1993) and many others, the coefficient on *MV* tends to correlate negatively with the book-to-market ratio. This result confirms that the CAPM cannot explain the value premium. Panel D shows that the coefficient is statistically significant at the 5% level for all 25 portfolios.

Panel C of Table 11 shows that the coefficient on idiosyncratic volatility is negative for all the 25 Fama and French (1993) portfolios. As mentioned above, if idiosyncratic volatility is a proxy for volatility of the discount-rate shock, its negative coefficient reflects the correction for the CAPM because investors require a lower risk price for the discount-rate shock than the cash-flow shock. Interestingly, the coefficient relates positively to the book-to-market ratio. This result is consistent with the finding by Campbell and Vuolteenaho (2004) that growth stocks tend to have higher loadings on the discount-rate shock and thus need larger (negative) corrections than value stocks. Idiosyncratic volatility is statistically significant at the 10% level for most portfolios (Panel E). Panel F shows that R-squared values tend to be higher for growth stocks than value stocks. This result is consistent with the empirical finding that the discount-rate shock, which affects stock prices only temporarily, has larger effects on growth stocks than value stocks.

In Panel H of Table 11, we present the cross-sectional regression results using the Fama and MacBeth (1973) method. In particular, for each quarter, we run a regression of the excess portfolio returns on their loadings on *MV* and *IV*, as reported in Panel B and Panel C, respectively. We also include a constant term in the cross-sectional regression. The Fama and MacBeth t-statistics are reported in parentheses and the Shanken (1992) corrected t-statistics are in brackets. The coefficient of *IV* is significantly positive. The coefficient of *MV* is also positive; however, it is statistically insignificant. Overall, our simple two-factor model accounts for about 60% of cross-sectional variations in average excess portfolio returns. Panel G presents fitted excess portfolio returns from the estimation. Consistent with the sample average returns reported in Panel A, the expected returns tend to increase with the book-to-market ratio. Figure 3 shows that the fitted returns from the model and the average realized returns tend to move closely with each other, although there are still noticeable pricing errors for some portfolios.

We repeat the above analysis by using value premium volatility instead of average idiosyncratic volatility and find very similar results. For brevity, we focus only on the cross-sectional regression. (The other results are available on request.) Panel H of Table 11 shows that the coefficient of value premium volatility is significantly positive. Again, the coefficient of stock market volatility is positive but statistically insignificant. Overall, the R-squared is about 45%.[19] To further investigate whether the cross-sectional explanatory powers of average idiosyncratic volatility and value premium volatility are related, we include both variables in the cross-sectional regression. Consistent with the time-series results (Table 10), average idiosyncratic volatility drives out value premium volatility from the cross-sectional regression, indicating that the two variables have very similar forecasting powers for stock returns.

To summarize, our results suggest that average idiosyncratic volatility might be a proxy for volatility of a risk factor omitted from the CAPM. In particular, we find that average idiosyncratic volatility is closely related to the volatility of the value premium.

3.3 International evidence

As a robustness check, we also run cross-sectional regressions using the updated Fama and French (1998) international data obtained from Ken French at Dartmouth College. The dataset includes 13 countries—U.S., Japan, U.K., France, Germany, Italy, the Netherlands, Belgium, Switzerland, Sweden, Australia, Hong Kong, and Singapore—as well as the world market for the period 1975 to 2004. As in Fama and French (1998), we do not include Canada in our analysis because Canadian data are unavailable until 1977; however, including Canada does not change our results in any qualitative manner.

Fama and French (1998) construct a value portfolio and a growth portfolio for each country, as well as the world market using four different criteria: the book-to-market ratio, the cash flows-to-prices ratio, the earnings-to-prices ratio, and the dividends-to-prices ratio. The value portfolio includes stocks with the ratio in the top 30% and the growth portfolio includes stocks with the ratio in the bottom 30%. All the portfolio returns are denominated in U.S. dollars. We find similar results using all four criteria; for brevity, we discuss only the portfolios sorted on the cash flow-to-price ratio.

Table 12 shows that, consistent with Fama and French (1998), value stocks have substantially higher expected returns than do growth stocks for all countries except the Netherlands. Also, the quarterly average return on the world value portfolio is 2.9%, compared with only 1.1% for the world growth portfolio. Because they subsume the information content of their local counterparts, we use U.S. *MV* and *IV* to forecast international portfolio returns. The international evidence is very similar to that obtained from U.S. data, as reported in Table 11. First, the forecasting power of *MV* and *IV* is usually statistically significant. Second, the R-squared is higher for growth stocks than value stocks for all countries except Switzerland, Hong Kong, and Singapore. Third, while growth stocks tend to have higher loadings on *MV* than value stocks, their loadings on *IV* are usually smaller than those of value stocks. Fourth, both *MV* and *IV* are positively priced in the cross-sectional regression, and the price of risk for *IV* is also statistically significant at the 5% level. Lastly, realized variance of the U.S. value premium is also positively and significantly priced in the cross-sectional regression.

For comparison, we also run the cross-sectional regression using the world market return (*MKT*) and the world value premium (*HML*) as explanatory variables. Panel B of Table 12 shows that, consistent with Fama and French (1998), *HML* is positively and significantly priced.

However, the cross-sectional R-squared is only 24%. Therefore, the explanatory power of *MV* and *IV* is similar to that of the international ICAPM proposed by Fama and French (1998).

4. Conclusion

In this paper, we find that average idiosyncratic volatility is highly correlated across G7 countries. Also, there is a significant Granger causality of idiosyncratic volatility from the U.S. to the other countries and vice versa. These results suggest that idiosyncratic volatility might be a pervasive financial variable.

Consistent with U.S. data, we find that, when in conjunction with stock market volatility, average idiosyncratic volatility is a significant predictor of stock market returns in many other G7 counties. Moreover, while U.S. average idiosyncratic volatility is a strong predictor of international stock returns, the other countries' average idiosyncratic volatility helps forecast U.S. stock returns, as well because of its strong comovements with the U.S. counterpart. Our results suggest that average idiosyncratic volatility might be a proxy for systematic risk.

In particular, we document a strong link between average idiosyncratic volatility and the value premium. First, average idiosyncratic volatility has significant forecasting power for the value premium. Second, average idiosyncratic volatility helps explain the cross section of stock returns on portfolios sorted by size and book-to-market ratio. Third, the explanatory power of average idiosyncratic volatility for stock returns is very similar to that of value premium volatility in both the time-series and cross-sectional regressions. These results suggest that average idiosyncratic volatility is a proxy for risk factors omitted from the CAPM.

Our analysis can be extended along two dimensions. First, while we argue that our results are consistent with the theoretical model by Berk, Green, and Naik (1999), a formal theoretical investigation should help us better understand the relation between idiosyncratic volatility and stock returns at both the firm and aggregate levels. Second, consistent with U.S. evidence documented by Campbell, Lettau, Malkiel, and Xu (2001) and Comin and Mulani (2006), we find that average idiosyncratic volatility, especially the equal-weighted measure, has increased substantially in most of the other G7 countries. A formal investigation similar to Comin and Philippon (2005) using international data should help us better understand its economic implications.

Figure Legends

Figure 1. Stock Market Volatility.

Figure 2. Value- (Thick Line) and Equal-Weighted Idiosyncratic Volatility (Thin Line) of All Stocks.

Figure 3. Fitted versus Realized Excess Portfolio Returns.

Figure A1. U.S. Value-Weighted Idiosyncratic Volatility of 500 Largest Stocks from Datastream (Solid Line) and CRSP (Dotted Line).

Appendix A. Filters in the Datastream Data

We impose some additional filters on the Datastream data for potential errors. (1) The return index (Datastream variable RI) is rounded off by Datastream to the nearest tenth and this rounding introduces substantial errors in returns of low RI stocks. Therefore, if the return index of a stock is below three in a day, we set the corresponding return to a missing value for that day. Note that the beginning RI for each stock is set at 100 by Datastream. Thus, an RI of three or below indicates that the firm has lost 97% or more of its value over its life. (2) If the return on a stock is greater than 300% in a day, we set that return to a missing value. (3) If the absolute value of changes in capitalization is more than 50% in one day, the return for this stock is set to a missing value on that day. (4) If the price of a stock falls by more than 90% in a day and it has increased by more than 200% within the previous 20 days (approximately a trading month), we set the returns between the two dates to missing values. (5) If the price of a stock increases by more than 100% in a day and has decreased by more than 200% within the previous 20 days, we set the returns between the two dates to missing values. Figure A1 shows that the value-weighted idiosyncratic volatility of the largest 500 stocks constructed from the filtered Datastream return data is very similar to that from the CRSP data, with a correlation coefficient of over 0.98. Moreover, our main results for the U.S. using CRSP are essentially the same as those using the Datastream data, which are available on request.

Appendix B. Realized Volatility of an Omitted Risk Factor

This appendix investigates the conditions under which our measures of average idiosyncratic volatility provide a proxy for realized volatility of a risk factor omitted from the CAPM. Suppose that the data-generating process is a two-factor model:

$$r_{i,t+1} = E_t(r_{i,t+1}) + b_{i1,t}(f_{1,t+1} - E_t f_{1,t+1}) + b_{i2,t}(f_{2,t+1} - E_t f_{2,t+1}) + \varepsilon_{i,t+1}, \qquad \text{(B1)}$$

where $r_{i,t+1}$ is the return on asset *i* in excess of a risk-free rate; $f_{1,t+1}$ and $f_{2,t+1}$ are two orthogonal risk factors; $\varepsilon_{i,t+1}$ is the idiosyncratic shock orthogonal to the risk factors; $b_{i1,t}$ and $b_{i2,t}$ are factor loadings; and E_t is the expectation operator conditional on information available at time *t*. We can motivate Equation (B1) from Campbell and Vuolteenaho's (2004) ICAPM, for example, in which there are two risk factors: a stock market return and a shock to expected future stock market returns. That is, we can think of $f_{1,t+1}$ and $f_{2,t+1}$ as Cholesky transformations of the original factors. Moreover, Bai and Ng (2002) also argue for a two-factor structure in the U.S. stock market using principal component analysis.

The value-weighted excess stock market return is:

$$r_{M,t+1} = \sum_{i}^{N_t} \omega_{i,t+1}[E_t(r_{i,t+1}) + b_{i1,t}(f_{1,t+1} - E_t f_{1,t+1}) + b_{i2,t}(f_{2,t+1} - E_t f_{2,t+1}) + \varepsilon_{i,t+1}], \qquad \text{(B2)}$$

where N_t is the number of stocks at the time from *t* to *t*+1, and $\omega_{i,t+1} = \frac{v_{it}}{\sum_{j=1}^{N_t} v_{jt}}$ is the weight by stock market capitalization at the end of time *t*: $v_{i,t}$. If N_t is large, the value-weighted idiosyncratic shock, $\sum_{i}^{N_t} \omega_{i,t+1}\varepsilon_{i,t+1}$, is equal to zero and the stock market return is a linear function of the two risk factors:

$$r_{M,t+1} = E_t r_{M,t+1} + b_{M1,t}(f_{1,t+1} - E_t f_{1,t+1}) + b_{M2,t}(f_{2,t+1} - E_t f_{2,t+1})$$
$$E_t r_{M,t+1} = \sum_i^{N_t} \omega_{i,t+1} E_t(r_{i,t+1}), \quad b_{M1,t} = \sum_i^{N_t} \omega_{i,t+1} b_{i1,t}, \quad b_{M2,t} = \sum_i^{N_t} \omega_{i,t+1} b_{i2,t} . \qquad \text{(B3)}$$

There is another linear combination of the risk factors, which are not perfectly correlated with the stock market return:

$$r_{H,t+1} = E_t(r_{H,t+1}) + b_{H1,t}(f_{1,t+1} - E_t f_{1,t+1}) + b_{H2,t}(f_{2,t+1} - E_t f_{2,t+1}) . \qquad \text{(B4)}$$

While $r_{H,t+1}$ could be one of many possible linear combinations of the orthogonal factors, $f_{1,t+1}$, and $f_{2,t+1}$, we interpret it as the excess return on a hedge portfolio that has the maximum correlation with changes in investment opportunities, as in Campbell and Vuolteenaho (2004) and others.

Merton's (1973) and Campbell's (1993) ICAPM stipulates that the expected excess return on asset *i* is:

$$E_t r_{i,t+1} = \gamma_M Cov_t(r_{i,t+1}, r_{M,t+1}) + \gamma_H Cov_t(r_{i,t+1}, r_{H,t+1}) , \qquad \text{(B5)}$$

where γ_M and γ_H are risk prices and Cov_t is the conditional covariance, e.g., $Cov_t(r_{i,t+1}, r_{M,t+1}) = E_t[(r_{M,t+1} - E_t(r_{M,t+1}))(r_{i,t+1} - E_t(r_{i,t+1}))]$.

We can project $(r_{i,t+1} - E_t r_{i,t+1})$ on a constant and the stock market return, $(r_{M,t+1} - E_t r_{M,t+1})$, and obtain the following decomposition:

$$r_{i,t+1} - E_t r_{i,t+1} = \beta_{i,t}(r_{M,t+1} - E_t r_{M,t+1}) + \eta_{i,t+1}$$
$$\beta_{i,t} = \frac{Cov_t(r_{i,t+1}, r_{M,t+1})}{Var_t(r_{M,t+1})} , \qquad \text{(B6)}$$
$$\eta_{i,t+1} = (b_{i1,t} - \beta_{i,t} b_{M1,t})(f_{1,t+1} - Ef_{1,t+1}) + (b_{i2,t} - \beta_{i,t} b_{M2,t})(f_{2,t+1} - Ef_{2,t+1}) + \varepsilon_{i,t+1}$$

where $Var_t(r_{M,t+1})$ is the conditional stock market variance. Equation (B6) highlights the fact that if the true data-generating process is a two-factor model, the CAPM is not adequate to capture all the systematic risk.

Given that the idiosyncratic shock, $\varepsilon_{i,t+1}$, is uncorrelated with the risk factors, the conditional variance of the CAPM-based idiosyncratic shock is:

$$Var_t(\eta_{i,t+1}) = (b_{i1,t} - \beta_{i,t} b_{M1,t})^2 Var_t(f_{1,t+1}) + (b_{i2,t} - \beta_{i,t} b_{M2,t})^2 Var_t(f_{2,t+1}) + Var_t(\varepsilon_{i,t+1}) . \quad \text{(B7)}$$

We define the conditional equal-weighted average idiosyncratic volatility (EWIV) as:

$$\begin{aligned} EWIV_t &= \sum_{i=1}^{N_t} \frac{1}{N_t} Var_t(\eta_{i,t+1}) \\ &= (\sum_{i=1}^{N_t} \frac{1}{N_t} (b_{i1,t} - \beta_{i,t} b_{M1,t})^2) \sigma_{f1,t}^2 + (\sum_{i=1}^{N_t} \frac{1}{N_t} (b_{i2,t} - \beta_{i,t} b_{M2,t})^2) \sigma_{f2,t}^2 + \sum_{i=1}^{N_t} \frac{1}{N_t} Var_t(\varepsilon_{i,t+1}) \end{aligned} , \quad \text{(B8)}$$

where $\sigma_{1,t}^2$ and $\sigma_{2,t}^2$ are the conditional variances of factors $f_{1,t+1}$ and $f_{2,t+1}$, respectively. If the cross-sectional distribution of factor loadings is constant over time, i.e., $\sum_{i=1}^{N_t} \frac{1}{N_t} (b_{i1,t} - \beta_{i,t} b_{M1,t})^2$ and $\sum_{i=1}^{N_t} \frac{1}{N_t} (b_{i2,t} - \beta_{i,t} b_{M2,t})^2$ are constant, we can rewrite Equation (B8) as:

$$\begin{aligned} EWIV_t &= b_1 \sigma_{f1,t}^2 + b_2 \sigma_{f2,t}^2 + \sigma_{IV,t}^2 \\ b_1 &= \sum_{i=1}^{N_t} \frac{1}{N_t} (b_{i1,t} - \beta_{i,t} b_{M1,t})^2 \\ b_2 &= \sum_{i=1}^{N_t} \frac{1}{N_t} (b_{i2,t} - \beta_{i,t} b_{M2,t})^2 \\ \sigma_{IV,t}^2 &= \sum_{i=1}^{N_t} \frac{1}{N_t} Var_t(\varepsilon_{i,t+1}) \end{aligned} . \quad \text{(B9)}$$

The conditional value-weighted average idiosyncratic volatility (*VWIV*) is:

$$VWIV_t = \sum_{i=1}^{N_t} \omega_{i,t+1} Var_t(\eta_{i,t+1})$$
$$= (\sum_{i=1}^{N_t} \omega_{i,t+1}(b_{i1,t} - \beta_{i,t} b_{M1,t})^2)\sigma^2_{f1,t} + (\sum_{i=1}^{N_t} \omega_{i,t+1}(b_{i2,t} - \beta_{i,t} b_{M2,t})^2)\sigma^2_{f2,t} \quad (B10)$$
$$+(\sum_{i=1}^{N_t} \omega_{i,t+1} Var_t(\varepsilon_{i,t+1}))$$

Similarly, if value-weighted factor loadings have a stable cross-sectional distribution over time, *VWIV* can also be rewritten as a linear function of factor volatilities:

$$\begin{aligned} VWIV_t &= b_1\sigma^2_{f1,t} + b_2\sigma^2_{f2,t} + \sigma^2_{IV,t} \\ b_1 &= (\sum_{i=1}^{N_t} \omega_{i,t+1}(b_{i1,t} - \beta_{i,t} b_{M1,t})^2) \\ b_2 &= (\sum_{i=1}^{N_t} \omega_{i,t+1}(b_{i2,t} - \beta_{i,t} b_{M2,t})^2) \\ \sigma^2_{IV,t} &= (\sum_{i=1}^{N_t} \omega_{i,t+1} Var_t(\varepsilon_{i,t+1})) \end{aligned} \quad (B11)$$

If the cross-sectional distribution of factor loadings is constant, Equation (B3) implies:

$$\sigma^2_{M,t} = b^2_{M1}\sigma^2_{f1,t} + b^2_{M2}\sigma^2_{f2,t}. \quad (B12)$$

Equations (B11) and (B12) imply that average idiosyncratic volatility and stock market volatility are a linear function of factor volatilities and vice versa:

$$\begin{bmatrix} \sigma^2_{f1,t} \\ \sigma^2_{f2,t} \end{bmatrix} = \begin{bmatrix} b_1 & b_2 \\ b_{M1} & b_{M2} \end{bmatrix}^{-1} \begin{bmatrix} IV_t - \sigma^2_{IV,t} \\ \sigma^2_{M,t} \end{bmatrix}, \quad IV_t = EWIV_t, VWIV_t. \quad (B13)$$

From Equations (B1), (B3), (B4), and (B5), we obtain:

$$\begin{aligned} E_t r_{i,t+1} &= \gamma_M Cov_t(r_{i,t+1}, r_{M,t+1}) + \gamma_H Cov_t(r_{i,t+1}, r_{H,t+1}) \\ &= [\gamma_M b_{i1,t} b_{M1,t} + \gamma_H b_{i1,t} b_{H1,t} \quad \gamma_M b_{i2,t} b_{M2,t} + \gamma_H b_{i2,t} b_{H2,t}] \begin{bmatrix} \sigma^2_{f1,t} \\ \sigma^2_{f2,t} \end{bmatrix}. \end{aligned} \quad (B14)$$

Substituting Equation (B13) into Equation (B14), we obtain:

$$E_t r_{i,t+1} =$$

$$[\gamma_M b_{i1,t} b_{M1,t} + \gamma_H b_{i1,t} b_{H1,t} \quad \gamma_M b_{i2,t} b_{M2,t} + \gamma_H b_{i2,t} b_{H2,t}]\begin{bmatrix} b_1 & b_2 \\ b_{M1} & b_{M2} \end{bmatrix}^{-1}\begin{bmatrix} IV_t - \sigma^2_{IV,t} \\ \sigma^2_{M,t} \end{bmatrix}. \qquad \text{(B15)}$$

$$IV_t = EWIV_t, VWIV_t$$

By definition, $\sigma^2_{IV,t}$ is not correlated with stock returns; therefore, Equation (B15) indicates that the conditional stock return is a linear function of conditional average idiosyncratic volatility (IV_t) and conditional stock market volatility ($\sigma^2_{M,t}$). Moreover, if average idiosyncratic volatility and stock market volatility follow an AR(1) process, the stock return is then a linear function of realized average idiosyncratic volatility and stock market volatility.

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[1] Campbell, Lettau, Malkiel, and Xu (2001) adopt a nonparametric approach to decompose an individual stock return into three components: a market-wide return, an industry-specific residual, and a firm-specific residual. Other authors, e.g., Bali, Cakici, Yan, and Zhang (2005), Wei and Zhang (2005), and Guo and Savickas (2006), use the CAPM or the Fama and French (1993) three-factor model to adjust for systematic risk. In general, the results are not sensitive to any particular measure of idiosyncratic volatility because Goyal and Santa-Clara (2003) show that total stock price volatility is predominantly composed of idiosyncratic volatility.

[2] Idiosyncratic volatility and stock market volatility have stronger forecasting power for stock returns in quarterly data than monthly data possibly because, as pointed out by Ghysels, Santa-Clara, and Valkanov (2005), realized volatility is a function of long distributed lags of daily returns. We also use quarterly data in this paper.

[3] We do not use the more elaborate Fama and French (1993) three-factor model because the daily factor data are directly available only for the U.S. However, the additional factors are unlikely to affect our results in any qualitative manner because we find essentially the same results for the U.S. by controlling for systematic risk using the daily Fama and French three-factor model data obtained from Kenneth French at Dartmouth College. To converse space, these results are not reported here but are available on request.

[4] Schwert (1990) finds that the behavior of realized volatility around the crash is unusual in many ways. Seyhun (1990) argues that the crash is not explained by the fundamentals. Hong and Stein (2003) suggest that the large fluctuations in stock prices immediately after the crash represented a working-out of microstructural distortions created on that chaotic day (e.g., jammed phone lines, overwhelmed market makers, and unexecuted orders).

[5] In particular, we assume that the maximum number of lags is 12 and first test whether the 12th lag is statistically significant. If it is, we set the optimal number of lags to be 12; otherwise, we test whether the 11th lag is significant using exactly the same sample and so on. Table 2 reports the augmented DF test based on the optimal lags and all available observations.

[6] Vogelsang (1998) shows that the PS^1 test has good size properties and is valid even in the presence of nonstationarity. Moreover, it also has good power properties for stationary variables. Nevertheless, our main results are qualitatively unchanged in various tests discussed in Vogelsang (1998).

[7] Hamao, Mei, and Xu (2003) also document an upward trend in Japanese stock market volatility.

[8] Before 1989, Datastream includes only Toronto Stock Exchange issues for Canada; however, it also includes firms listed on the Vancouver Stock Exchange afterward. As a result, the number of stocks used in our calculation increases sharply from 345 in the last quarter of the year 1988 to 743 in the first quarter of the year 1989. Because the Vancouver Stock Exchange had many small and highly risky natural resource exploration stocks (see, for example, "Scam capital of the world," *Forbes*, May 29, 1989), the inclusion of Vancouver stocks dramatically raises the equal-weighted idiosyncratic volatility for Canada but has small effects on the value-weighted measure.

[9] Our results contrast those of Hamao, Mei, and Xu (2003), who find that the value-weighted Japanese idiosyncratic volatility is nonstationary over a similar period. The difference possibly reflects the fact that these authors use low-frequency (monthly) return data to construct idiosyncratic volatility.

[10] We find similar results using the first difference of the equal-weighted idiosyncratic volatility if it is found to be nonstationary in Table 2.

[11] Note that because of the correlation between market volatility and idiosyncratic volatility, there is a potential concern over multicollinearity. However, multicollinearity cannot explain our results because it usually leads to low t-statistics, in contrast with the increase of t-statistics when both variables are included. Moreover, the characteristic-root-ratio test proposed by Belsley, Kuh, and Welsch (1980) confirms that multicollinearity is unlikely to plague our results.

[12] Our results contrast with those reported by Frazzini and Marsh (2003), who find a positive relation between idiosyncratic volatility and future stock returns. The difference reflects the fact that Frazzini and Marsh use monthly data, as opposed to the quarterly data in this paper.

[13] The forecasting abilities reported in Panel C of Table 5 are somewhat weaker than those in Guo and Savickas (2006) because they instead use stock return indices dominated in U.S. dollars.

[14] We find similar but somewhat weaker results using the one-period-lagged idiosyncratic volatility, possibly because of the strong lead-lag relationship, as reported in subsection 1.3.

[15] Fama and French (1993) and many others have shown that the CAPM does not explain the cross section of stock returns and advocated for multifactor models. Recent authors, e.g., Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), and Petkova (2006), argue that the shock to investment opportunities is also an important risk factor, in addition to stock market returns. Interestingly, Bai and Ng (2002) find the evidence of a two-factor structure in the U.S. stock market using the principal component analysis.

[16] Berk, Green, and Naik (2004) endogenously generate a long duration for growth stocks in a partial equilibrium model. Lettau and Wachter (2007) develop a partial equilibrium model to illustrate that a distinction between the discount-rate shock and the cash-flow shock can explain the value premium.

[17] Quarterly realized variance of the value premium is the sum of the squared daily value premium in a quarter. We obtain daily value premium data from Ken French at Dartmouth College.

[18] Ang, Hodrick, Xing, and Zhang (2006a, 2006b) find that stocks with high idiosyncratic volatility tend to have lower expected returns than stocks with low idiosyncratic volatility. To address this issue, we construct 25 portfolios sorted on size and past idiosyncratic volatility, and find that average idiosyncratic volatility also helps explain the cross-section of these portfolio returns. For brevity, these results are not reported here but are available on request.

[19] We obtain a substantially higher R-squared (about 80%) if we use the Fama and French (1993) three-factor model in the cross-sectional regression. The difference reflects the fact that loadings are much less precisely estimated in the first-pass regression for our forecasting model than the Fama and French three-factor model. To improve efficiency, we can impose the restriction that the constant term is equal to zero in the first-pass regression; and we find that the coefficient of value premium volatility is statistically significant at the 5% level and the R-squared is about 80%. We find very similar results for average idiosyncratic volatility.

Table 1 Univariate Statistics

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A. Value-Weighted Idiosyncratic Volatility							
Mean	0.021	0.019	0.013	0.016	0.024	0.016	0.023
Standard Deviation	0.012	0.010	0.011	0.010	0.013	0.010	0.014
Autocorrelation	0.751	0.660	0.813	0.585	0.768	0.738	0.829
Correlation with U.S.	0.875	0.776	0.843	0.527	0.689	0.873	1.000
Panel B. Equal-Weighted Idiosyncratic Volatility							
Mean	0.139	0.037	0.031	0.028	0.039	0.036	0.084
Standard Deviation	0.105	0.025	0.030	0.016	0.018	0.021	0.046
Autocorrelation	0.955	0.851	0.920	0.506	0.788	0.795	0.826
Correlation with U.S.	0.785	0.696	0.669	0.259	0.678	0.705	1.000
Panel C. Stock Market Volatility							
Mean	0.004	0.009	0.007	0.012	0.007	0.007	0.005
Standard Deviation	0.004	0.008	0.007	0.010	0.007	0.008	0.005
Autocorrelation	0.446	0.318	0.504	0.461	0.467	0.364	0.529
Correlation with U.S.	0.802	0.760	0.745	0.292	0.511	0.576	1.000
Panel D. Excess Stock Market Return							
Mean	0.006	0.018	-0.001	0.002	0.001	0.012	0.012
Standard Deviation	0.085	0.123	0.107	0.140	0.107	0.103	0.087
Autocorrelation	0.117	0.070	0.001	0.050	-0.019	0.094	0.028
Correlation with U.S.	0.829	0.668	0.662	0.493	0.555	0.705	1.000

Note: The table reports summary statistics of average idiosyncratic volatility, stock market volatility, and excess stock market returns. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 2 Augmented Dick-Fuller Tests

	VWIV		*EWIV*		*MV*	
	Constant	Trend	Constant	Trend	Constant	Trend
Canada	-2.23	-2.71	-1.64	-2.48	-3.67***	-6.80***
	(2)	(2)	(5)	(5)	(2)	(0)
France	-1.80	-2.26	-0.05	-1.72	-7.87***	-7.96***
	(5)	(5)	(7)	(7)	(0)	(0)
Germany	-2.76*	-3.42**	-0.27	-1.74	-3.57***	-7.41***
	(12)	(12)	(2)	(2)	(2)	(0)
Italy	-2.69*	-2.78	-3.45***	-3.54**	-6.61***	-6.59***
	(5)	(5)	(8)	(8)	(0)	(0)
Japan	-3.96***	-3.33*	-1.85	-3.58**	-1.88	-7.92***
	(0)	(12)	(9)	(12)	(8)	(0)
U.K.	-2.89**	-3.15*	-1.64	-2.27	-8.43***	-8.40***
	(6)	(6)	(9)	(9)	(0)	(0)
U.S.	-3.00**	-3.39*	-1.87	-3.13*	-7.06***	-7.83***
	(3)	(3)	(3)	(4)	(0)	(0)

Note: The table reports the results of augmented Dick-Fuller unit root tests. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. The critical values corresponding to these significance levels are (-2.57, -2.86, -3.43) for the test with a constant and (-3.12, -3.41, -3.96) for the test with a linear time trend. We choose the number of lags using the general-to-specific method recommended by Campbell and Perron (1991) and Ng and Perron (1995). *VWIV* is the value-weighted idiosyncratic volatility; *EWIV* is the equal-weighted idiosyncratic volatility; and *MV* is stock market volatility. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 3 Tests of Deterministic Trend

	Countries						
	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A. Value-Weighted Idiosyncratic Volatility							
PS^1-Statistic	0.018	0.008	0.015	0.003	0.012	0.007	0.012
LB	-0.012	-0.012	-0.042	-0.013	-0.014	-0.007	-0.008
UB	0.048	0.028	0.072	0.018	0.038	0.021	0.033
Panel B. Equal-Weighted Idiosyncratic Volatility							
PS^1-Statistic	0.268	0.038	0.040	0.008	0.028*	0.016	0.072*
LB	-0.085	-0.041	-0.786	-0.012	0.002*	-0.011	0.045*
UB	0.621	0.116	0.867	0.028	0.054*	0.043	0.099*
Panel C. Stock Market Volatility							
PS^1-Statistic	0.000	0.000	0.007*	-0.002	0.009*	-0.001	0.002
LB	-0.007	-0.007	0.000*	-0.010	0.004*	-0.008	-0.002
UB	0.007	0.007	0.014*	0.006	0.015*	0.005	0.006

Note: The table reports the PS^1 test for a deterministic trend proposed by Vogelsang (1998). LB and UB are lower and upper bounds, respectively, of the 90% confidence interval. * Denotes significance at the 10% level. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 4 Forecasting International Stock Returns Using Equal-Weighted Idiosyncratic Volatility

	Countries						
	Canada	France	Germany	Italy	Japan	U.K.	U.S.
			Panel A. Country-Specific *EWIV*				
EWIV(-1)	0.023	-0.188	-0.568	0.220	0.770	-0.084	0.162
	(0.202)	(-0.407)	(-1.308)	(0.236)	(1.178)	(-0.155)	(0.643)
Adjusted R^2	-0.011	-0.016	-0.004	-0.014	-0.004	-0.011	-0.008
			Panel B. Country-Specific *MV*				
MV(-1)	12.599	-0.115	-0.985	0.881	1.030	-0.808	1.844
	(0.556)	(-0.043)	(-1.251)	(0.370)	(1.054)	(-0.397)	(0.694)
Adjusted R^2	-0.003	0.000	0.003	-0.005	0.008	0.012	0.011
			Panel C. Country-Specific *MV* and *EWIV*				
MV(-1)	1.313	2.298*	3.582**	0.833	3.004**	2.907***	2.674*
	(0.608)	(1.734)	(2.009)	(0.828)	(2.549)	(4.265)	(1.737)
EWIV(-1)	0.022	-0.789	-1.143*	-0.094	0.140	-0.954**	-0.044
	(0.198)	(-1.189)	(-1.919)	(-0.099)	(0.170)	(-2.347)	(-0.191)
Adjusted R^2	-0.015	-0.009	0.020	-0.020	0.009	0.017	-0.001

Note: The table reports the OLS forecast regression results of stock market returns on the equal-weighted idiosyncratic volatility (*EWIV*) and stock market volatility (*MV*). A linear time trend is included in Panels A and C for all countries and in Panel B for Germany and Japan. Newey and West (1987) corrected t-statistics are reported in parentheses, with 4 lags. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 5 Forecasting International Stock Returns Using Value-Weighted Idiosyncratic Volatility

	Countries						
	Canada	France	Germany	Italy	Japan	U.K.	U.S.
			Panel A. Country-Specific *VWIV*				
VWIV_L(-1)	0.874	-0.059	-0.443	0.561	0.397	-0.390	0.469
	(0.786)	(-0.042)	(-0.426)	(0.385)	(0.431)	(-0.451)	(0.652)
Adjusted R^2	-0.003	0.011	-0.008	-0.007	-0.008	-0.006	0.001
			Panel B. Country-Specific *MV* and *VWIV*				
MV-*L*(-1)	0.962	0.157	2.836**	0.739	2.895***	2.220***	8.085***
	(0.363)	(0.142)	(2.085)	(0.651)	(2.777)	(3.271)	(4.280)
VWIV-*L*(-1)	0.279	1.625	-1.063	-0.007	-0.798	-0.944**	-2.480***
	(0.314)	(1.296)	(-1.224)	(-0.007)	(-1.141)	(-2.157)	(-5.393)
Adjusted R^2	-0.010	0.003	0.001	-0.014	0.007	0.013	0.080
			Panel C. U.S. *MV* and *VWIV*				
MV(-1)	4.433**	4.460	4.393*	5.644	3.121	4.051*	8.085***
	(0.025)	(1.585)	(1.824)	(1.611)	(1.248)	(1.708)	(4.280)
VWIV(-1)	-1.183	-1.559**	-1.544***	-1.565*	-0.982	-1.451***	-2.480***
	(-1.484)	(-2.083)	(-2.638)	(-1.781)	(-1.364)	(-3.635)	(-5.393)
Adjusted R^2	0.017	0.003	0.009	0.003	-0.005	0.007	0.080
			Panel D. Country-Specific and U.S. *MV* and *VWIV*				
MV-*L*(-1)	1.596	-2.374	0.064	-0.186	3.435***	1.594**	
	(0.539)	(-1.173)	(0.022)	(-0.178)	(2.895)	(2.238)	
VWIV-*L*(-1)	2.603**	6.084***	1.991	1.146	-0.123	0.827	
	(2.195)	(4.485)	(1.046)	(0.803)	(-0.119)	(0.721)	
MV-*US*(-1)	3.433	5.682	3.659	6.255*	0.812	1.786	
	(1.345)	(1.132)	(0.658)	(1.744)	(0.364)	(0.673)	
VWIV-*US*(-1)	-3.075***	-4.382***	-2.723**	-1.980**	-0.704	-1.746**	
	(-2.902)	(-4.514)	(-2.367)	(-2.313)	(-0.603)	(-2.149)	
Adjusted R^2	0.035	0.065	0.001	-0.009	-0.002	0.010	

Note: The table reports the OLS forecast regression results of stock market returns on the value-weighted idiosyncratic volatility (*VWIV*) and stock market volatility (*MV*). Newey and West (1987) corrected t-statistics are reported in parentheses, with 4 lags. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 6 Forecasting U.S. Stock Returns

	Countries					
	Canada	France	Germany	Italy	Japan	U.K.
	Panel A. Country-Specific *MV* and *VWIV*					
MV-L(-1)	1.185	1.072	2.997***	0.542	2.397**	1.990***
	(0.482)	(1.132)	(2.749)	(0.727)	(2.299)	(4.056)
VWIV-L(-2)	-0.654	-1.337**	-2.575***	-1.892**	-1.857***	-1.271**
	(-0.858)	(-2.038)	(-3.606)	(-2.569)	(-3.339)	(-2.537)
Adjusted R^2	-0.011	0.006	0.046	0.018	0.044	0.031
	Panel B. Country-Specific and U.S. *MV* and *VWIV*					
MV-L(-1)	-0.393	-2.358	-0.373	-0.232	1.140	0.442
	(-0.099)	(-1.673)	(-0.173)	(-0.291)	(0.828)	(0.473)
VWIV-L(-2)	0.141	-1.043	-2.220**	-1.117	-1.067	-0.880
	(0.149)	(-1.583)	(-2.340)	(-1.262)	(-1.255)	(-1.201)
MV-US(-1)	7.244***	10.793***	8.494**	6.933***	5.997**	7.397***
	(2.633)	(3.629)	(2.117)	(3.482)	(2.522)	(3.280)
VWIV-US(-1)	-2.364***	-2.267***	-2.122***	-1.921***	-2.031**	-1.879***
	(-3.177)	(-4.022)	(-2.888)	(-3.412)	(-2.393)	(-3.001)
Adjusted R^2	0.050	0.075	0.087	0.066	0.073	0.069

Note: The table reports the OLS forecast regression results of U.S. stock market returns on the value-weighted idiosyncratic volatility (*VWIV*) and stock market volatility (*MV*). Newey and West (1987) corrected t-statistics are reported in parentheses, with 4 lags. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 7 Forecasting the Value Premium

	Countries						
	Canada	France	Germany	Italy	Japan	U.K.	U.S.
MV(-1)	2.768	0.034	-3.380**	-1.855*	-1.018	-0.197	-3.838**
	(0.632)	(0.031)	(-2.605)	(-1.818)	(-0.755)	(-0.233)	(-2.400)
VWIV(-1)	0.069	1.469	2.384**	-0.352	1.455**	0.975**	1.493**
	(0.045)	(1.552)	(2.474)	(-0.220)	(2.183)	(2.256)	(2.094)
Adjusted R^2	-0.001	0.014	0.055	0.030	0.016	0.006	0.047

Note: The table reports the OLS forecast regression results of the value premium on the value-weighted idiosyncratic volatility (*VWIV*) and stock market volatility (*MV*). Newey and West (1987) corrected t-statistics are reported in parentheses, with 4 lags. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 8 Bootstrapped P-Values

	Countries						
	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A. Forecasting Stock Market Returns							
MV(-1)	0.962	0.157	2.836	0.739	2.895	2.220	8.085
	(0.363)	(0.142)	(2.085)	(0.651)	(2.777)	(3.271)	(4.280)
	<0.397>	<0.499>	<0.054>	<0.315>	<0.019>	<0.013>	<0.000>
VWIV(-1)	0.279	1.625	-1.063	-0.007	-0.798	-0.944	-2.480
	(0.314)	(1.296)	(-1.224)	(-0.007)	-1.141	(-2.157)	(-5.393)
	<0.397>	<0.119>	<0.145>	<0.537>	<0.192>	<0.034>	<0.000>
Panel B. Forecasting Value Premium							
MV(-1)	2.768	0.034	-3.380	-1.855	-1.018	-0.197	-3.838
	(0.632)	(0.031)	(-2.605)	(-1.818)	(-0.755)	(-0.233)	(-2.400)
	<0.302>	<0.478>	<0.028>	<0.066>	<0.262>	<0.418>	<0.023>
VWIV(-1)	0.069	1.469	2.384	-0.352	1.455	0.975	1.493
	(0.045)	(1.552)	(2.474)	(-0.220)	(2.183)	(2.256)	(2.094)
	<0.502>	<0.125>	<0.014>	<0.384>	<0.048>	<0.040>	<0.043>

Note: The table reports the OLS forecast regression results of the stock market return (Panel A) and the value premium (Panel B) on the value-weighted idiosyncratic volatility (*VWIV*) and stock market volatility (*MV*). Newey and West (1987) corrected t-statistics are reported in parentheses, with 4 lags. We also report the bootstrapped p-values in angle brackets, as discussed in subsection III.C. We use the CRSP data for the U.S. over the period 1962:Q4 to 2003:Q4. The Datastream data are used for the U.K. over the period 1965:Q2 to 2003:Q4 and for Canada, France, Germany, Italy, and Japan over the period 1973:Q2 to 2003:Q4.

Table 9 Relation between Scaled Stock Market Prices and Stock Volatilities

Dependent Variables	*IV*(t)	*MV*(t)	R^2
	Panel A. 1963:Q4-2004:Q4		
BM(t)	-1.463***	5.582***	0.864
	(-2.764)	(3.181)	
PE(t)	0.563*	-1.335***	0.930
	(1.789)	(-2.712)	
DY(t)	-4.277**	15.079**	0.971
	(-2.089)	(2.401)	
	Panel B. 1963:Q4-1983:Q4		
BM(t)	-1.774	17.376**	0.837
	(-0.493)	(2.381)	
PE(t)	1.070**	-1.916**	0.949
	(2.240)	(-2.130)	
DY(t)	-19.460	40.926	0.937
	(-1.522)	(1.648)	
	Panel C. 1984:Q1-2004:Q4		
BM(t)	-0.755*	4.464***	0.972
	(-1.735)	(4.292)	
PE(t)	0.553	-1.354**	0.892
	(1.555)	(-2.334)	
DY(t)	-1.459	15.525***	0.983
	(-1.120)	(2.820)	

Note: The table reports the OLS regression results of scaled stock market prices on contemporaneous stock market volatility (*MV*) and the value-weighted idiosyncratic volatility (*IV*). We also include 2 lags of the dependent variable as regressors; however, for brevity, their point estimates are not reported here. *BM* is the aggregate book-to-market ratio; *PE* is the price-to-earning ratio; and *DY* is the dividend yield. Newey and West (1987) corrected t-statistics are reported in parentheses, with 4 lags. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. The point estimates for PE are scaled by 1/100.

Table 10 Idiosyncratic Volatility and Volatility of the Value Premium in U.S. Data

	V_HML	*BM*	*PE*	*DY*	*MV*	*IV*	R^2
			Panel A: *V_HML*				
1	-3.949						0.007
	(-1.011)						
2	-12.725***				5.959***		0.088
	(-3.087)				(3.852)		
3	-1.690				6.954***	-2.593*	0.106
	(-0.201)				(4.193)	(-1.814)	
			Panel B: *BM*				
4		0.058					0.020
		(1.594)					
5		0.053			3.120**		0.052
		(1.523)			(2.559)		
6		0.026			6.636***	-2.683***	0.110
		(0.717)			(3.932)	(-4.275)	
			Panel C: *PE*				
7			-0.001				0.010
			(-1.124)				
8			-0.002*		3.905***		0.057
			(-1.774)		(3.183)		
9			-0.001		6.891***	-2.638***	0.109
			(-0.589)		(4.116)	(-3.952)	
			Panel D: *DY*				
10				0.007			0.009
				(1.112)			
11				0.010	3.695***		0.053
				(1.619)	(3.056)		
12				0.003	6.870***	-2.690***	0.108
				(0.543)	(4.125)	(-4.175)	

Note: The table reports the OLS forecast regression results of stock market returns on some predetermined variables. *V_HML* is realized volatility of the value premium; *BM* is the aggregate book-to-market ratio; *PE* is the price-earning ratio, *DY* is the dividend yield; *MV* is realized stock market volatility; and *IV* is the value-weighted idiosyncratic volatility. Newey and West (1987) corrected t-statistics are in parentheses, with 4 lags. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. The sample spans the period 1963:Q4 to 2004:Q4.

Table 11 Cross-Sectional Regressions Using 25 Fama and French Portfolios

	S1(smallest)	S2	S3	S4	S5(largest)
			Panel A Sample Average Excess Returns		
BM1(lowest)	0.011	0.015	0.015	0.018	0.014
BM2	0.028	0.022	0.024	0.017	0.015
BM3	0.029	0.030	0.023	0.023	0.015
BM4	0.035	0.031	0.028	0.027	0.017
BM5(highest)	0.039	0.034	0.033	0.029	0.018
			Panel B Parameter Estimates *MV*		
BM1(lowest)	11.694***	10.929***	10.373***	8.767***	6.815***
BM2	9.180***	8.617***	7.232***	6.776***	5.567***
BM3	7.273***	5.947***	5.497***	5.423***	4.351***
BM4	6.368***	5.571***	5.373***	5.167***	4.675***
BM5(highest)	7.062***	5.313**	4.982**	6.114***	4.330***
			Panel C Parameter Estimates *IV*		
BM1(lowest)	-3.847**	-3.697***	-4.011***	-3.038**	-3.070***
BM2	-1.939*	-1.957**	-2.111***	-1.513**	-1.944***
BM3	-1.209	-1.467**	-1.433**	-1.378*	-1.384**
BM4	-0.732	-1.237*	-1.423*	-1.213*	-1.261*
BM5(highest)	-1.602	-1.243*	-0.782	-1.755**	-1.705***
			Panel D T-Statistics *MV*		
BM1(lowest)	3.585	3.971	4.087	3.546	3.286
BM2	3.527	3.486	3.541	3.714	3.171
BM3	3.138	3.135	3.127	3.252	3.157
BM4	2.973	2.767	2.809	3.112	3.013
BM5(highest)	2.851	2.334	2.343	3.039	2.907
			Panel E T-Statistics *IV*		
BM1(lowest)	-2.327	-3.302	-3.645	-2.600	-4.368
BM2	-1.753	-2.331	-3.270	-2.127	-3.263
BM3	-1.381	-2.104	-2.094	-1.667	-2.152
BM4	-0.866	-1.825	-1.708	-1.700	-1.752
BM5(highest)	-1.589	-1.690	-1.101	-2.147	-2.799
			Panel F R^2		
BM1(lowest)	0.073	0.082	0.093	0.080	0.093
BM2	0.065	0.075	0.065	0.070	0.067
BM3	0.057	0.045	0.048	0.052	0.051
BM4	0.053	0.042	0.046	0.048	0.058
BM5(highest)	0.046	0.033	0.036	0.052	0.041
			Panel G Fitted Average Excess Returns		
BM1(lowest)	0.016	0.015	0.011	0.017	0.012
BM2	0.029	0.027	0.022	0.027	0.020
BM3	0.032	0.026	0.025	0.025	0.023
BM4	0.034	0.027	0.025	0.027	0.025
BM5(highest)	0.027	0.027	0.030	0.023	0.019
			Panel H Cross-Section Regressions		
Constant	*IV*	*MV*	*V_HML*		R^2
0.026***	0.010**	0.002			0.582
(3.830)	(3.269)	(1.318)			
[2.702]	[2.346]	[0.940]			
0.024**		0.002	0.002**		0.453
(3.642)		(1.331)	(3.253)		
[2.546]		[0.940]	[2.311]		
0.027***	0.010**	0.002	0.001		0.472
(4.011)	(3.140)	(1.144)	(2.060)		
[2.683]	[2.140]	[0.774]	[1.408]		

Note: Panel A reports the sample average of excess returns on 25 Fama and French (1993) portfolios. We also run the OLS forecast regression of the portfolio returns on stock market volatility (*MV*) and the value-weighted idiosyncratic volatility (*IV*). Panel B reports the point estimates of the coefficient on stock market volatility and Panel D reports the corresponding Newey and West (1987) corrected t-statistics. Panel C reports the point estimates of the coefficient on the value-weighted idiosyncratic volatility and Panel E reports the corresponding Newey and West (1987) corrected t-statistics; Panel F reports the R-squared. Panel H reports the cross-sectional regression results using the Fama and MacBeth (1973) method. The Fama and MacBeth t-statistics are reported in parentheses and the Shanken (1992) corrected t-statistics are reported in brackets. Panel G reports the fitted value using the model with the value-weighted idiosyncratic volatility and stock market volatility as risk factors. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. The sample spans the period 1963:Q4 to 2004:Q4.

Table 12 Cross-Sectional Regressions Using International Data

Panel A Forecasting Portfolio Returns

Country	Value Stocks						Growth Stocks					
	Mean	*MV*	T(*MV*)	*IV*	T(*IV*)	R^2	Mean	*MV*	T(*MV*)	*IV*	T(*IV*)	R^2
U.S.	0.027	3.566***	2.689	-0.615	-0.991	0.049	0.022	6.297**	2.555	-2.465***	-4.119	0.084
Japan	0.029	4.215	1.629	-1.259	-1.226	0.020	0.005	4.285*	1.816	-2.938***	-2.680	0.046
U.K.	0.040	4.945	1.348	-1.682**	-2.423	0.029	0.026	6.606*	1.814	-3.996***	-5.633	0.091
France	0.040	5.805	1.629	-2.443**	-2.087	0.031	0.019	5.660**	2.015	-3.526***	-3.782	0.071
Germany	0.031	2.831	1.333	-2.187**	-2.299	0.032	0.012	6.193**	2.249	-3.795***	-3.946	0.092
Italy	0.031	5.140	1.337	-2.913**	-2.379	0.028	0.006	7.369**	2.318	-3.888***	-3.439	0.069
Netherlands	0.023	6.528**	2.195	-3.035***	-2.887	0.034	0.024	4.162*	1.849	-2.897***	-4.799	0.069
Belgium	0.043	4.823**	2.437	-1.640**	-2.551	0.032	0.026	4.197**	2.146	-2.938***	-3.302	0.063
Switzerland	0.023	3.097	1.566	-3.071***	-4.333	0.055	0.021	1.777	0.681	-1.693**	-2.212	0.019
Sweden	0.039	6.259***	3.016	-2.156**	-2.376	0.038	0.027	9.341***	4.083	-4.992***	-2.968	0.103
Australia	0.040	3.870**	2.492	-1.357	-1.496	0.018	0.010	6.153***	3.766	-2.616***	-4.072	0.048
Hong Kong	0.051	7.707**	2.106	-2.767***	-3.301	0.035	0.035	5.263	1.542	-2.987***	-3.162	0.026
Singapore	0.033	11.922***	2.704	-2.890***	-2.630	0.095	0.016	8.015**	2.258	-3.068***	-2.925	0.053
World	0.029	4.949***	2.727	-1.884***	-3.597	0.051	0.011	5.356***	2.667	-3.188***	-4.762	0.099

Panel B Cross-Sectional Regressions

Constant	*MV*	*IV*	*V_HML*	*MKT*	*HML*	R^2
0.035***	0.002	0.007**				0.238
(4.212)	(1.121)	(2.357)				
[3.592]	[0.968]	[2.045]				
0.035***	0.002		0.001**			0.219
(4.284)	(1.210)		(2.339)			
[3.597]	[1.199]		[1.997]			
0.032***				-0.007	0.014**	0.238
(3.029)				(-0.473)	(2.436)	
[2.913]				[-0.462]	[2.400]	

Note: The value and growth portfolios are constructed according to the cash flows-to-prices ratio. For each country, the value portfolio includes stocks with the ratio in the top 30% and the growth portfolio includes stocks with the ratio in the bottom 30%. All the portfolio returns are denominated in the U.S. dollar. In panel A we use U.S. value-weighted idiosyncratic volatility (*IV*) and U.S. stock market volatility (*MV*) to forecast international portfolios returns and report the Newey and West (1987) corrected t-statistics. Panel B reports the cross-sectional regression results using the Fama and MacBeth (1973) method. The Fama and MacBeth t-statistics are reported in parentheses and the Shanken (1992) corrected t-statistics are reported in brackets. *V_HML* is realized volatility of the U.S. value premium; *MKT* is the world excess stock market return, and *HML* is the world value premium. * Denotes significance at the 10% level. ** Denotes significance at the 5% level. *** Denotes significance at the 1% level. The sample spans the period 1975:Q1 to 2004:Q4.

Figure 1 Stock Market Volatility

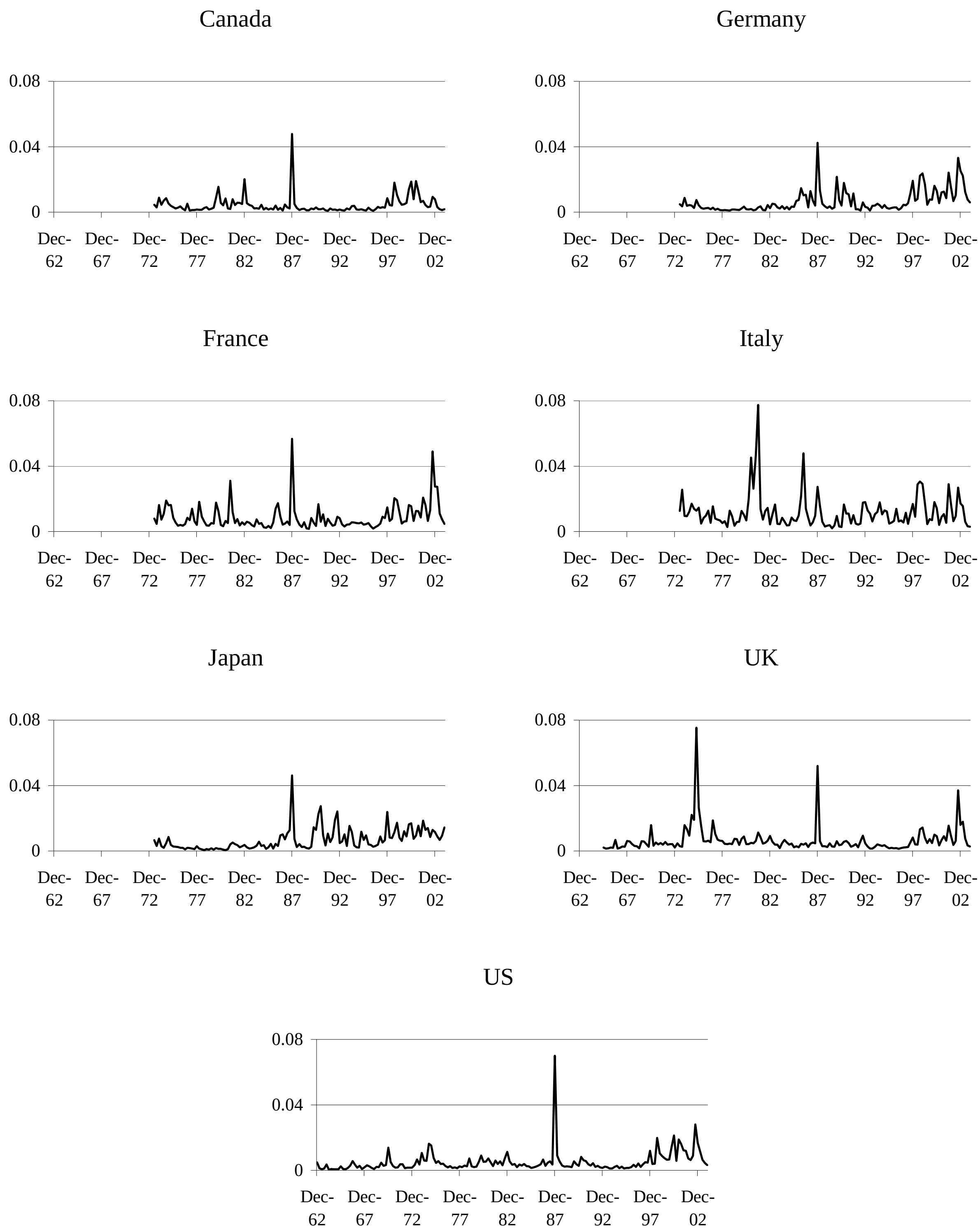

Figure 2 Value- (Thick Line) and Equal-Weighted Idiosyncratic Volatility (Thin Line) of All Stocks

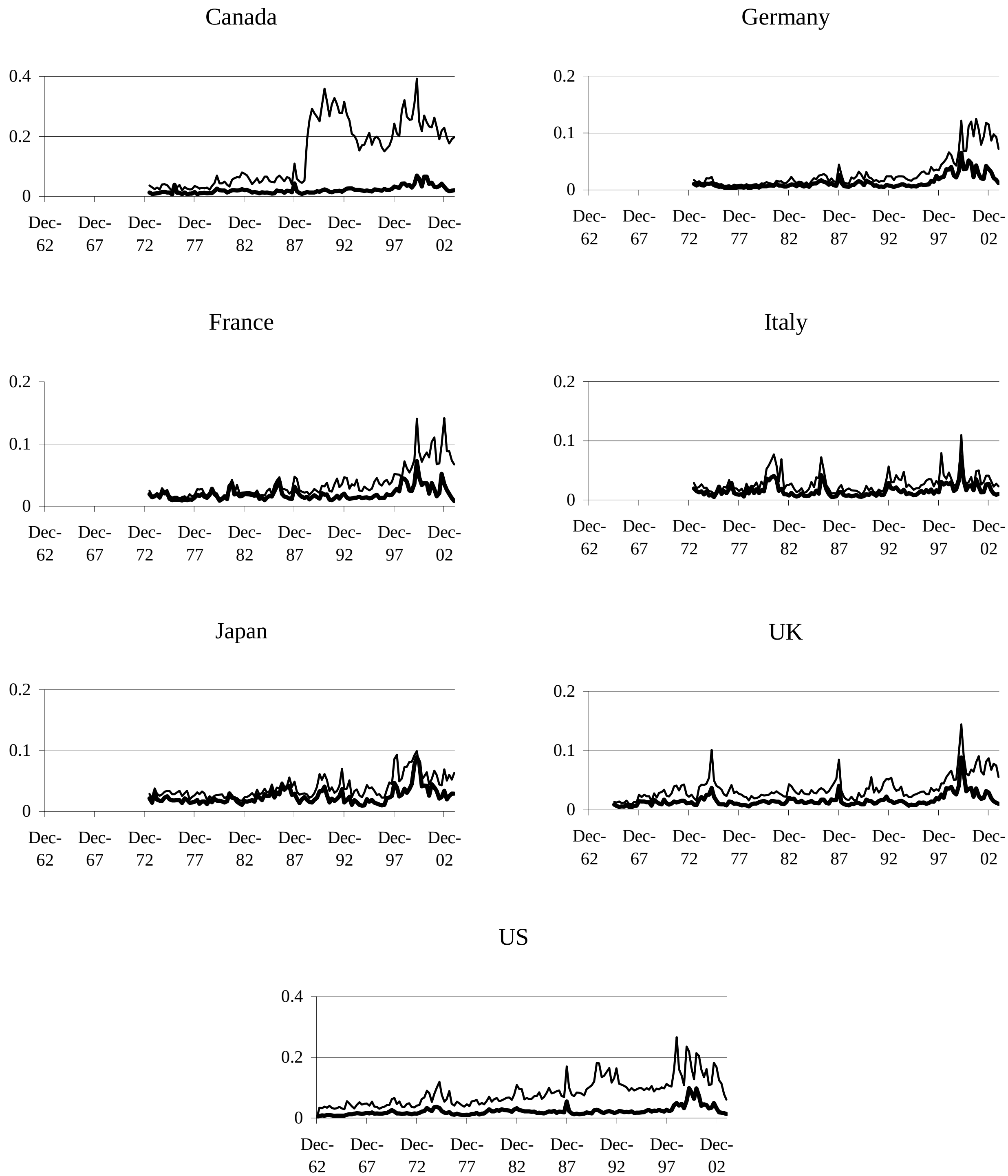

Figure 3 Fitted versus Realized Excess Portfolio Returns

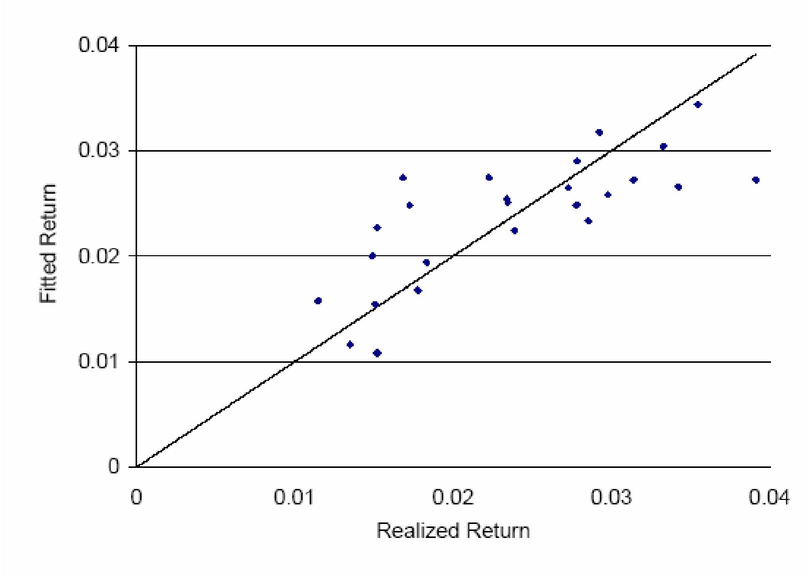

Figure A1: U.S. Value-Weighted Idiosyncratic Volatility of 500 Largest Stocks from Datastream (Solid Line) and CRSP (Dotted Line)