Return Reversals, Idiosyncratic Risk and Expected Returns

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ABSTRACT

Bali and Cakici (2006) find no relation between equally-weighted portfolio returns and idiosyncratic risk, whereas Ang et al. (2006a) report a negative relation between value-weighted portfolio returns and idiosyncratic risk. Our analyses demonstrate that both findings can be explained by short-term monthly return reversals. The abnormal positive returns from taking a long (short) position in the low (high) idiosyncratic risk portfolio are fully explained by an additional control variable, the "winners minus losers" portfolio returns, introduced to the conventional three- or four-factor time-series regression model. The cross-sectional regressions also confirm that no robust and significant relation exists between idiosyncratic risk and expected returns once we control for return reversals.

Whether idiosyncratic risk is priced in asset returns has been the subject of considerable attention in recent years due to its critical importance in asset pricing and portfolio allocation. This issue has gained further importance given the recent evidence that both firm-level volatility and the number of stocks needed to achieve a specific level of diversification have increased in the United States over time [Campbell et al. (2001)]. The empirical results reported so far are mixed. Consistent with earlier research such as Lehmann (1990a), Lintner (1965), Tinic and West (1986), and Merton (1987), a number of recent studies report a significant positive relation between idiosyncratic risk and expected stock returns, either at the aggregate level [Goyal and Santa-Clara (2003), Jiang and Lee (2005)], or at the firm or portfolio level [Malkiel and Xu (2002), Fu (2005), Spiegel and Wang (2005), Chua et el. (2006)]. Other studies, however, do not support this positive relation. For example, in their classic empirical asset pricing study, Fama and MacBeth (1973) document that the statistical significance of idiosyncratic risk is negligible. Bali et al. (2005) find that the positive relation documented by Goyal and Santa-Clara (2003) at the aggregate level is not robust. Guo and Savickas (2006) report a negative relation between aggregate stock market idiosyncratic volatility and the future quarterly stock market return.

In a recent study, Ang et al. (2006a) examine the relationship between idiosyncratic risk and the future stock return at the portfolio level. Specifically, they form portfolios sorted by idiosyncratic risk of individual stocks defined relative to the Fama and French (1993) three-factor model. They find that portfolios with high idiosyncratic volatility in the current month yield low returns in the following month and the difference between the value-weighted return on the portfolio with the highest idiosyncratic risk and the return on the portfolio with the lowest idiosyncratic risk is -1.06% per month on average. They therefore conclude that there is a negative intertemporal relation between realized idiosyncratic risk and future stock returns. Ang et al. (2006b) also confirm this negative relation in international markets and observe strong co-movement among stocks with high idiosyncratic risk across countries.

In a related study, however, Bali and Cakici (2006) find that the negative relation between idiosyncratic volatility and expected returns is not robust under different weight scheme to calculate average portfolio returns. They find that there is no significant difference between the equally-weighted quintile portfolio returns, when the idiosyncratic volatility sorted quintile portfolios are constructed using the same approach as in Ang et al. (2006a).

While raising an interesting puzzle, Ang et al. (2006a, 2006b) neither identify the determinants of this negative relation, nor do they characterize the ex ante relation between idiosyncratic risk and expected returns. In the presence of the seemingly conflicting evidence compiled by Bali and Cakici (2006), the relation between the two deserves further examination for the following three reasons. First, the negative relation between realized idiosyncratic risk and future stock returns in Ang et al. (2006a) is non-monotonic and driven mostly by the highest idiosyncratic volatility portfolio. For example, while the return on the lowest idiosyncratic risk portfolio is 1.04%, it is 1.20% for the medium idiosyncratic risk portfolio and -0.02% for the highest idiosyncratic risk portfolio; further, while the fifth quintile portfolio with the highest idiosyncratic risk realizes “abysmally” low average returns in the following month, the other four quintile portfolios have positive average returns. Thus, understanding the price behavior of the portfolio with the highest idiosyncratic risk seems to be the key to uncovering what drives the negative intertemporal relation between idiosyncratic risk and stock returns.

Second, to the extent that stock prices may overreact to firm-specific information as suggested by Jegadeesh and Titman (1995a), stocks with higher idiosyncratic risk and hence greater firm-specific information may experience larger short-horizon return reversals as documented in the previous literature [Jegadeesh (1990) and Lehmann (1990b)]. As a result, the role of short-horizon return reversals warrants a careful examination for a better understanding of the reported negative relation.

Third, while Ang et al. (2006a, 2006b) find that the cross-sectional negative relation between idiosyncratic risk and future stock returns cannot be explained by the common pricing factors, it remains unclear whether the negative relation between idiosyncratic risk and stock returns holds ex ante. Asset pricing models are ex ante in their very nature. Using past realized idiosyncratic volatility as the proxy for idiosyncratic risk implicitly assumes that stock volatility is a martingale, which contrasts with the evidence documented in other studies [e.g., Jiang and Lee (2005), Fu (2005)]. Hence, determining whether the ex ante relation between idiosyncratic risk and expected returns is negative will offer a significant insight into asset pricing model specifications.

Our objectives in this study are twofold. First, we investigate why the value-weighted (henceforth VW) portfolio of common stocks with the highest idiosyncratic risk yields low future returns, while there is no significant return difference between the equally-weighted (henceforth EW) quintile portfolios with different idiosyncratic volatilities. In particular, we examine the role of short-horizon return reversals in explaining the intertemporal relation between idiosyncratic risk and stock returns in the framework of the portfolio-level analysis and time-series regressions. Second, we investigate the role of ex ante idiosyncratic risk in asset pricing with cross-sectional regressions at the firm level. While so doing, we construct several measures of ex ante idiosyncratic risk to examine the robustness of the cross-sectional relation between expected stock returns and expected idiosyncratic volatilities conditioned on firm-specific variables.

In summary, we demonstrate why VW returns between the highest and lowest idiosyncratic volatility quintile portfolios are significantly different, while EW returns of the same portfolios exhibit no significant differences. Monthly return reversals of the stocks in the highest idiosyncratic risk portfolio lead to the "abysmally" lower VW portfolio return in the subsequent month. Because both "winners" and "losers" stocks are highly concentrated in the portfolio with the highest idiosyncratic volatility in the formation period and winner stocks are relatively larger than loser stocks, their return reversals drive down the VW returns on the highest idiosyncratic risk portfolio in the holding period. On the other hand, other portfolios with lower idiosyncratic volatility do not experience such dramatic return reversal, given the smaller percentage of winners and losers in those portfolios. As a result, the holding-month VW return on the highest idiosyncratic risk portfolio is significantly lower than that on the lowest idiosyncratic risk portfolio. In contrast, the return reversals of winner stocks and loser stocks cancel each other in an EW portfolio and therefore the EW returns on all idiosyncratic volatility sorted portfolios are very close.

More importantly, we further demonstrate that the negative relation between idiosyncratic risk and subsequent VW portfolio returns are driven by return reversals rather than idiosyncratic volatility. After controlling for both firm size and past returns using a triple sorting approach, we find that the VW average return differences between the high and the low idiosyncratic volatility portfolios disappear. However, after controlling for firm size and idiosyncratic volatility in the same triple sorting approach, VW return on the highest quintile portfolio sorted by formation-month return (past winners) is significantly lower than the return on the lowest quintile portfolio (past losers), which demonstrates that the negative relation between idiosyncratic risk and stock returns compiled by Ang et al. (2006a, 2006b) is attributed to return reversals, rather than idiosyncratic risk.

In addition, the time-series regression results indicate that the abnormal positive returns that arise from taking a long (short) position in the low (high) idiosyncratic risk portfolio can be fully explained by adding the “winners minus losers” portfolio returns as a conditioning variable in addition to the conventional three- or four-factor model.

Finally, we examine the ex ante relation between idiosyncratic risk and expected returns using cross-sectional regressions built on the framework of Fama-MacBeth (1973) and Fama-French (1992). When we control for return reversals, the relation between idiosyncratic risk and expected returns is no longer robust and significant. This finding holds regardless of five different measures of ex ante idiosyncratic volatility measures introduced. This result is also robust after we control for additional firm-specific variables such as momentum, liquidity, leverage, and sample selection.

Given the evidence above, we conclude that there exists no reliable relation between expected idiosyncratic volatility and expected return. The negative relation documented by Ang et al. (2006a) is driven by short-term return reversals and only applies to VW portfolio returns. In particular, the low future return of the high idiosyncratic volatility portfolio is attributed to return reversals of winner stocks rather than to high idiosyncratic volatility itself.

The remainder of our paper is organized as follows. In Section 1, using portfolio level analysis, we examine why the VW portfolio with the highest idiosyncratic volatility stocks has significantly lower return than the lowest idiosyncratic volatility portfolio in the future one month holding period, while the EW portfolio of the same group of stocks has similar return as the other quintile portfolios with different levels of idiosyncratic volatility. In Section 2, we conduct cross-sectional regressions to explore the ex ante relation between idiosyncratic risk and expected returns, and the role of idiosyncratic risk in asset pricing. We offer concluding remarks in Section 3.

1. What Drives the Negative Relation between Idiosyncratic Risk and Expected VW Portfolio Returns?

1.1 Data and Idiosyncratic Volatility Measure

Our data include NYSE, AMEX, and NASDAQ common stock daily returns and monthly returns from July 1963 to December 2004. We obtain daily and monthly returns data from the Center for Research in Security Prices (CRSP) and book values of individual stocks from COMPUSTAT. We use the NYSE/AMEX/NASDAQ index return as the market return and one-month Treasury bill rate as the proxy for the risk-free rate.

We measure idiosyncratic risk following Ang et al. (2006a) to facilitate comparison. For each month, we run the following regression for firms that have more than 17 daily return observations in that month:

$$r_{t,d}^{i} = \alpha_{t}^{i} + \beta_{MKT}^{i} \cdot MKT_{t,d} + \beta_{SMB}^{i} \cdot SMB_{t,d} + \beta_{HML}^{i} \cdot HML_{t,d} + \varepsilon_{t,d}^{i}, \quad (1)$$

where, for day *d* in the portfolio formation period month *t*, $r_{t,d}^{i}$ is stock *i*'s excess return, $MKT_{t,d}$ is the market excess return, $SMB_{t,d}$ and $HML_{t,d}$ represent the returns on portfolios formed to capture the size and book-to-market effects, respectively, and $\varepsilon_{t,d}^{i}$ is the resulting residual relative to the Fama-French(1993) three-factor model.[1] We use the standard deviation of daily residuals in month *t* to measure the individual stock's idiosyncratic risk.[2] [3]

1.2 Characteristics of Idiosyncratic Volatility-Sorted Portfolios

To conduct portfolio-level analysis, we construct quintile portfolios based on the ranking of the idiosyncratic volatility of each individual stock and hold these portfolios for one month. Portfolio IV1 (IV5) is the portfolio of stocks with the lowest (highest) volatility. The portfolios are rebalanced each month. Our procedure here is the same as that of Ang et al. (2006a) except that our sample extends from July 1963 to December 2004, whereas their sample period stops in December 2000.

In the second column of Table 1, we report average VW returns for five portfolios sorted by idiosyncratic volatility in the one-month holding period (month *t*+1) immediately following the portfolio formation month *t*. Average VW returns increase from 0.97% per month for portfolio IV1 (low volatility stocks) to 1.08% for portfolio IV2, and further to 1.12% per month for portfolio IV3. The differences in average returns across these three portfolios are not significant. However, as we move toward the higher volatility stocks, average returns drop substantially: portfolio IV5, which contains stocks with the highest idiosyncratic volatility, has an average return of only -0.03% per month.

The difference in monthly returns between portfolio IV5 and portfolio IV1 is -1.0% per month with a robust t-statistic of 2.95. The pattern for the average returns of idiosyncratic volatility-sorted portfolios is similar to that reported by Ang et al. (2006a, Table VI), which we show in column 4 for the purpose of comparison. A negative relation emerges between idiosyncratic volatility and expected stock returns if we focus only on the lowest and the highest idiosyncratic volatility portfolios. If we exclude portfolio IV5 containing the stocks with the highest idiosyncratic volatility, the return differences between the other four portfolios are not that large, which indicates that the negative relation is mostly driven by those stocks with extremely high idiosyncratic volatility. It can be also seen from the last three columns of Table 1 that the stocks from the highest idiosyncratic volatility portfolio are on average small cap and low priced. The market value of this portfolio accounts for only about 2% of total market.

[Insert Table 1]

Since portfolio IV5 largely contains small cap and low-priced stocks, we compute the EW average returns for each of the idiosyncratic volatility-sorted portfolios in the same holding period. The results are reported in the third column. The monthly return difference between portfolio IV5 and portfolio IV1 is not significant if we use EW average returns. The EW average monthly return of portfolio IV1 is 1.21%, while that of portfolio IV5 is 1.20%. In fact, the EW average returns of all five idiosyncratic volatility-sorted portfolios are close. We also find that there is a huge difference between the EW and VW returns of portfolio IV5: the former is 1.20% while the latter is only -0.03%. However, the differences between the EW and VW returns of the other four portfolios are not as large as that of portfolio IV5. This suggests that the VW return difference between portfolios IV5 and IV1 is likely to be driven by the stocks with *relatively* larger market capitalization rather than smaller-sized stocks within the highest idiosyncratic volatility portfolio, IV5.[4]

To verify how portfolio returns may have changed from the formation period to the holding period, we report each portfolio's VW average return in the portfolio formation month. The VW average returns during the portfolio formation month *t* reported in column 5 indicate that they increase monotonically from portfolios IV1 through IV5. Since the idiosyncratic volatility portfolio is constructed based on the daily returns in the portfolio formation month *t*, this result confirms that the contemporaneous relation between stock returns and idiosyncratic volatility is actually positive [Duffee (1995) and Fu (2005)]. The most important observation is that the VW average formation period return of portfolio IV5, which is at 8.06% per month, is in sharp contrast to the holding period return of -0.03%. This implies that some of the high idiosyncratic volatility stocks are likely to be winners in the portfolio formation period, but experience strong return reversals to become loser stocks in the holding period.

1.3 Short-Term Return Reversals

The empirical regularity that individual stock returns exhibit negative serial correlation has been well known for a long time. For example, Jegadeesh (1990) finds that the negative first-order correlation in monthly stock returns is highly significant; winner stocks with higher returns in the past month (formation period) tend to have lower returns in the current month (holding period) while loser stocks with lower returns in the past month tend to have higher returns in the current month. He reports profits of about 2% per month from a contrarian strategy that buys loser stocks and sells winner stocks based on their prior-month returns and holds them one month. Similarly, Lehmann (1990b) finds that the short-term contrarian strategy based on a stock's one-week return generates positive profits. The findings compiled by these studies are generally regarded as evidence that stock prices tend to overreact to firm-specific information [Stiglitz (1989), Summers and Summers (1989), Grossman and Miller (1988) and Jegadeesh and Titman (1995b)].

If the VW return on the highest volatility portfolio is dominated by winner stocks in the month in which the portfolio is formed, it will experience a low return in the next one-month holding period in the presence of return reversals. Thus, the negative relation between idiosyncratic volatility and subsequent VW portfolio returns should be caused by return reversals of winner stocks rather than idiosyncratic volatility itself. Loser stocks cannot have a role because loser stocks in the same highest idiosyncratic volatility portfolio will experience return reversals and hence have high returns in the holding month, which may partially offset this negative relation. To verify this possibility, we examine the characteristics of ten portfolios constructed by sorting stock returns in the same manner as Jegadeesh (1990). Specifically, we calculate the VW average returns for ten portfolios formed based on the rankings of formation period stock returns, with P1 containing past losers and P10 containing past winners. The portfolios are then rebalanced each month. Table 2 reports the results.

[Insert Table 2]

Consistent with Jegadeesh's (1990) findings, the average holding period returns exhibit a strong pattern of return reversals. P10, the past winners portfolio, becomes losers in the following month, with returns declining from 24.95% to -0.15%, while P1, the past losers portfolio, becomes winners, with returns increasing from -18.41% in the formation period to 1.92% in the holding period. Furthermore, as shown in columns 5 and 6, the idiosyncratic volatilities in the formation period are higher in two extreme loser/winner portfolios (P1 and P10), and lower in the middle portfolios (P5 and P6), regardless of whether we use VW or EW scheme to calculate idiosyncratic volatility.[5] For example, the VW average idiosyncratic volatilities of P1 and P10 are both over 13%, while the average idiosyncratic volatilities of P5 and P6 are only about 5.8% to 5.7%. Figure 1 illustrates U-shaped curves for both EW and VW idiosyncratic volatility of the ten portfolios sorted by the past returns. Clearly, both the "winners" and "losers" have significantly higher idiosyncratic volatilities in the portfolio formation month. Finally, we observe from the last two columns of Table 2 that although past winner portfolio (P10) and loser portfolio (P1) have similar idiosyncratic volatility, the average size and price of the past winner stocks are greater than those of loser stocks.

[Insert Figure 1]

1.4 Past Returns Distribution among Idiosyncratic Volatility-Sorted Portfolios

To highlight the role of return reversal in each of the five idiosyncratic volatility sorted portfolios, we form two-pass *independently* sorted portfolios based on each stock's performance and idiosyncratic volatility in the formation month. We first sort all stocks into five portfolios based on idiosyncratic volatility, with portfolio IV1 (IV5) representing the lowest (highest) idiosyncratic volatility portfolio (these portfolios are the same as in Table 1). We also sort stocks into ten portfolios based on returns in the one-month formation period, with portfolio P1 (P10) representing the extreme loser (winner) portfolio (these portfolios are the same as in Table 2). We then allocate stocks from each portfolio IV1 though IV5, to one of the ten groups, P1 through P10. The breakpoints for past stock returns sorting are independent of the idiosyncratic volatility sorting, and therefore the sequence of these two sortings does not matter. This procedure creates 50 idiosyncratic volatility-past return portfolios with unequal number of stocks as illustrated in Table 3.

Panel A of Table 3 presents the number of stocks within each portfolio. The total number of common stocks assigned to the two extreme portfolios P1 and P10 amounts to 965 (= 484 + 481). Only 29 (= 13 + 16) or three percent of 965 stocks are either past winners (P10) or past losers (P1) in the lowest idiosyncratic volatility portfolio (IV1). However, among these 965 past winners and losers, nearly one-half (456 = 222 + 234) of them are allocated to the highest idiosyncratic volatility portfolio (IV5).[6] Furthermore, winners and losers are also almost one-half of all the stocks within the highest idiosyncratic volatility portfolio, IV5 (the number of all the stocks in IV5 is 960). Interestingly, the number of winner stocks is roughly the same as that of loser stocks in each idiosyncratic volatility-sorted portfolio. Panel A of Figure 2 shows a graphical illustration of the symmetric distribution of past returns in each quintile portfolio.

[Insert Table 3 and Figure 2]

Panels B and C of Table 3 report the average monthly returns in the one-month formation period and in the holding period for each of the 50 portfolios sorted independently by idiosyncratic volatility and past return.[7] The two panels clearly illustrate the dramatic return reversals. Loser portfolio P1 and winner portfolio P10 have much stronger return reversals than other portfolios, especially for the highest idiosyncratic volatility portfolios. In particular, the return of the past loser (P1) with the highest idiosyncratic volatility changes from -24.29% to 4.30%, while the return of the past winner (P10) with the same highest idiosyncratic volatility changes from 38.24% to -0.79%. Panel B of Figure 2 illustrates the average return difference between the holding period and the formation period of these 50 portfolios. These results are consistent with Jegadeesh and Titman (1995a) in that higher idiosyncratic volatility stocks usually have more firm-specific information and hence stronger short-term return reversals if stock prices tend to overreact to firm-specific information.

Panel C also shows that the average returns on IV5 in the holding period are less than the returns on IV1 from P3 to P10. In contrast, for the two loser portfolios, P1 and P2, the return on IV5 is actually higher than the return on IV1. This indicates that the holding-month return on the highest idiosyncratic risk is not always lower than that on the lowest idiosyncratic volatility and the negative relation between idiosyncratic volatility and future returns does not hold for all portfolios.

In Panel D, we report the average market capitalization for each of the 50 portfolios. The information gleaned from Panel D is important for our analyses to follow given the interrelation among firm size, idiosyncratic risk, and return reversals. A strong negative relation exists between firm size and idiosyncratic volatility within each of return-based ten decile portfolios (P1 through P10): the highest idiosyncratic volatility portfolio dominated by small-sized stocks and the lowest idiosyncratic volatility portfolio associated with large-sized stocks. In addition, within each of the five idiosyncratic volatility-sorted portfolios (IV1 through IV5), the market capitalization of past winner stocks is much larger on average than that of loser stocks. In particular, in the highest idiosyncratic volatility portfolio, the market capitalization of winner stocks is 70% larger than that of loser stocks ($16.93 million vs. $9.98 million) although both of them are small-cap stocks among all stocks. A graphical illustration is presented in Panel C of Figure 2.

Combining the findings from Tables 2 and 3, we can now explain underlying reasons for the observed differences in VW and EW returns reported in Table 1. Both past winner and past loser stocks have high idiosyncratic volatility in the formation month, but the winner stocks earn low returns and the loser stocks earn high returns in the following month due to return reversals. Given that the number of winner stocks and the number of loser stocks are roughly equal in the high idiosyncratic volatility portfolio, the EW average return of the high idiosyncratic volatility portfolio will not be significantly lower than that of other portfolios since the high returns of past loser stocks can compensate for the low returns of past winner stocks in the holding month. However, because there is a large concentration of both winner stocks and loser stocks in the highest idiosyncratic volatility portfolio and the average size of winner stocks is substantially larger than that of loser stocks in the portfolio formation period, winner stocks dominate the VW high idiosyncratic volatility portfolio. The high idiosyncratic volatility portfolio will earn higher VW returns in the *formation* period but significantly lower VW returns in the *holding* period due to the strong return reversal pattern. Therefore, as Table 1 shows, the VW high idiosyncratic volatility portfolios earn significantly lower return than the low idiosyncratic volatility portfolios in the portfolio holding period, but the EW portfolio returns do not record this difference. Similarly, this return reversal can also be seen from the fact that the highest idiosyncratic volatility portfolio realizes the highest return during the portfolio formation period.

1.5 Portfolio Returns under Different Formation and Holding Periods

We have thus far found that the negative relation between idiosyncratic volatility and VW portfolio returns is driven by the short-term return reversals. Since the short-term return reversals may not be persistent (see Jegadeesh (1990)), an important question is whether this negative relation holds over the long run. To examine the performance of idiosyncratic volatility-sorted portfolios over the long run, we form four different trading strategies similar to Ang et al. (2006a). The trading strategies can be described by an *L*-month initial formation period, an *M*-month waiting period, and then an *N*-month holding period. At month *t*, we form portfolios based on the idiosyncratic volatility over a *L*-month period from the end of month $t - L - M$ to the end of month $t - M$, and then we hold these portfolios from month t to month $t + N$ for *N* months. To control for microstructure noises and ensure that we only use the information available at time *t* to form portfolios, we skip *M* (>0) months between the formation period and the holding period. For example, for the 12/1/12 strategy, we sort stocks into quintile portfolios based on their idiosyncratic volatility over the past 12 months; we skip 1 month and hold these EW or VW portfolios for the next 12 months. The portfolios are rebalanced each month.[8] Using this procedure, we form four trading strategies, namely, 1/1/1, 1/1/12, 12/1/1, and 12/1/12. We report the EW or VW average returns on these portfolios in Table 4.

Table 4 indicates that, when a one-month waiting period is imposed between the formation period and the holding period, the return difference between portfolio IV5 and portfolio IV1 is no longer significant under all four strategies, regardless of whether the portfolio returns are computed using EW or VW methods.[9] The only exception is the case of VW return of 1/1/1 strategy, in which the negative difference between return on IV5 and return on IV1 is marginally significant at the 10% level. In fact, the negative return differences between IV5 and IV1 decline when the holding period increases. For example, the return difference declines from -0.61% for 1/1/1 strategy to -0.27% for 1/1/12 strategy. The EW returns of idiosyncratic volatility portfolio IV5 from 1/1/12, 12/1/1, and 12/1/12 even have the highest returns among the five IV sorted quintile portfolios, although the differences are insignificant.

We also examine the long-run performance of the IV sorted quintile portfolios constructed in Table 1. We compare the EW and VW returns of these five portfolios in the following 12 months after they are formed. The difference from L/M/N strategy is that we do not rebalance the portfolios in the holding period once they are formed, i.e., the components of the portfolios are unchanged over the holding period. Statistical tests indicate that the EW return difference between IV5 and IV1 are insignificant in any of the 12 months. For brevity, we only report VW returns of IV sorted portfolios in Table V. We find that the return difference between IV5 and IV1 is not significant from month 2 to month 12, and is significant only in the first month of holding period after the portfolios are formed. For example, in month 2, the return difference between IV 5 and IV1 is -0.51% with a t-statistic of -1.38. Returns on all five idiosyncratic volatility sorted VW portfolios are very close in magnitude when the holding period gets longer than five months.

Overall, our evidence again suggests the negative relation between idiosyncratic volatility and expected returns does not hold under different formation and holding periods that are longer than one month. The negative relation between idiosyncratic volatility and VW portfolio returns in the subsequent month is caused by both short-term return reversals and the larger firm size of the past winners in the highest idiosyncratic volatility portfolio.

[Insert Tables 4 and 5]

1.6 Interrelation among Size, Idiosyncratic Volatility and Past Returns

If return reversals are the driving force behind the return difference in idiosyncratic volatility-sorted VW portfolios, this negative relation between idiosyncratic volatility and future VW portfolio returns might disappear after controlling for past stock returns. However, Ang et al. (2006a) have shown that after controlling for past returns, the difference in alphas of value-weighted portfolios sorted on idiosyncratic volatility is still significantly negative. We follow their approach and conduct a dependent double sorting based on past return and idiosyncratic volatility. We first sort stocks based on the formation month return, then within each past return sorted portfolio, we sort stocks based on idiosyncratic volatility. The five idiosyncratic volatility sorted portfolios (IV1 through IV5) are then averaged over each of the five past return sorted portfolios. Panel A of Table 6 indicates that the EW return difference between IV5 and IV1 is insignificant, while VW return difference is significantly negative after controlling for previous-month stock returns.

To further examine return reversals, we run another dependent double sort in which we first rank stocks based on idiosyncratic volatility, then we sort each of the idiosyncratic volatility-sorted quintile portfolios into five portfolios based on past returns. We compute the average of the same past return ranked portfolio across five idiosyncratic risk portfolios. P1 (P5) stands for loser (winner) portfolio. We confirm with Panel B of Table 6 that the reversal effect remains after controlling for idiosyncratic volatility, regardless of whether they are VW or EW returns. In particular, both the EW and VW return differences between P5 and P1 are significantly negative.

We explore the interrelation among size, idiosyncratic volatility and past returns to evaluate the relative importance of the volatility effect and reversal effect. Since firm size plays a critical role in determining the VW returns, different size distribution may have an influence on the negative relation between idiosyncratic volatility and future VW portfolio returns, even after we control for past returns and have the similar past return distributions among all five idiosyncratic volatility sorted VW portfolios. The efficacy of the double sorting method can be limited when a third variable is strongly correlated with the two sorting variables. We therefore use a triple-sorting approach that simultaneously controls for firm size and the previous one-month return to evaluate this negative relation between idiosyncratic volatility and expected stock returns.[10]

Under this triple-sorting approach, we first sort stocks into five portfolios based on each stock's size each month. Then, within each quintile we sort stocks into five subgroups based on the previous one-month return of stocks. This two-way sorting yields 25 portfolios. Finally, within each of these 25 portfolios, we sort stocks based on idiosyncratic volatility. The five idiosyncratic volatility portfolios are then constructed by averaging over each of the 25 portfolios that have the same idiosyncratic volatility ranking. Hence, the resulting portfolios represent idiosyncratic volatility quintile portfolios after firm size and past returns are controlled for simultaneously.

Panel A of Table 7 reports the VW average returns for idiosyncratic volatility quintile portfolios after controlling for firm size and past returns. Although idiosyncratic volatility increases from portfolio IV1's 3.84% to portfolio IV5's 13.27%, the average return difference between these two extreme portfolios is very small. The VW average one-month holding period return on portfolio IV1 is 0.88%, while the return on portfolio IV5 is 0.71%. The return difference between portfolio IV5 and portfolio IV1 is only -0.18%, which is insignificant. This result indicates that the negative relation between idiosyncratic volatility and expected returns does not hold once we control for both firm size and past returns.[11] The results suggest that controlling for past returns alone cannot control for size simultaneously, i.e., it may lead to different size distributions among idiosyncratic volatility sorted portfolios. Although conventional two-way sorting indicates that the volatility effect remains after controlling for past returns, it does not reveal the real reason behind the negative relation and is insufficient in the current scenario since it ignores the important role of size in determining the VW portfolio returns.

[Insert Table 7]

If, indeed, it is the return reversal rather than idiosyncratic volatility that causes the VW return difference in idiosyncratic volatility-sorted portfolios, the return difference between the prior month's return-sorted portfolios should remain significant even after we control for firm size and idiosyncratic volatility. In Panel B of Table 7, we perform another triple-sorting based on firm size, past returns, and idiosyncratic volatility. We first control for firm size and idiosyncratic volatility, and then form VW quintile portfolios based on the previous month's return. The five past return-sorted portfolios are constructed from each of the 25 size- and idiosyncratic volatility-sorted portfolios that have the same ranking on the previous month's return.

Panel B of Table 7 shows the VW average returns for the five previous return-sorted portfolios after controlling for firm size and idiosyncratic volatility. Although firm size and idiosyncratic volatility are roughly the same across all five portfolios, the VW average holding month return decreases monotonically from 1.24% in portfolio P1 (the portfolio of past loser stocks) to 0.66% in portfolio P5 (the portfolio of past winner stocks). The difference in monthly returns between portfolio P5 and portfolio P1 is -0.59%, which is significant. This finding again confirms that the negative relation between idiosyncratic volatility and future VW portfolio returns are driven by return reversals rather than idiosyncratic volatility itself.

1.7 Time-Series Regression

Studies that propose a profitable investment strategy often examine whether the investment strategy earns abnormal returns relative to the Fama-French three-factor model (e.g., Fama and French (1996)). In particular, one can construct return series from an investment strategy and run the time-series regressions of the excess returns on the investment strategy against the Fama-French three factors and the momentum factor (Carhart (1997)) that captures the medium-term continuation of returns documented in Jegadeesh and Titman (1993). If the intercept (Jensen's alpha) of the regression is significantly different from zero, which implies that risk loadings of these three or four factors are not sufficient to explain the portfolio return, then this investment strategy can earn abnormal profits. Ang et al. (2006b) report a significant tradable return from portfolio that goes long in IV5 stocks and short in IV1 stocks after controlling for Fama and French three factors. Their time series regression results thus suggest the persistence of the negative return difference between IV5 portfolio and IV1 portfolio. To examine if this tradable return can be related to past returns, we add an additional variable, "WML" which is a “winners minus losers” returns by taking a long (and short) position in the past winner stocks (and loser stocks) to the following time series regression:

$$r_{p,t} = a_p + \beta^p_{MKT} \cdot MKT_t + \beta^p_{SMB} \cdot SMB_t + \beta^p_{HML} \cdot HML_t + \beta^p_{UMD} \cdot UMD_t + \beta^p_{WML} \cdot WML_{t-1} + \varepsilon_{p,t}, \quad (2)$$

where, $r_{p,t}$ is the excess return on VW portfolio that goes long the highest idiosyncratic portfolio and short the lowest idiosyncratic risk portfolio (IV5-IV1), MKT is the market excess return, *SMB* is the difference between the return on a portfolio of small-cap stocks and the return on a portfolio of large-cap stocks (the size premium), *HML* is the difference between the return on a portfolio comprised of high book-to-market stocks and the return on a portfolio comprised of low book-to-market stocks (the value premium), and *UMD* is the difference between the return on a portfolio comprised of stocks with high returns from *t* - 12 to *t* - 2 and the return on a portfolio comprised of stocks with low returns from *t* - 12 to *t* - 2 (the momentum premium). Finally, WML stands for returns on the portfolio of “winners minus losers”. For each month, we form ten portfolios based on the past one month returns, with P1 containing past losers and P10 containing past winners. WML is the EW average return difference between the past winner portfolio and the past loser portfolio during the formation period.

Table 8 reports the results of time-series regressions of monthly returns on the “IV5-IV1” strategy against the three or four factors with (the last two rows) or without (the first two rows) controlling for the return on the past winner minus past losers. The estimated intercepts in the first two rows indicate that both the three- and four-factor models leave a large negative unexplained return for the investment strategy. The intercept on the three-factor model is -1.34%, with a t-statistic of -6.79; after we include the momentum factor, the intercept is still as large as -1.07%, with a t-statistic of -5.40.

The loadings also indicate that the IV5-IV1 strategy portfolio behaves like small, growth stocks since it loads positively and heavily on SMB but negatively on HML. Overall, consistent with Ang et al. (2006b), the strategy based on idiosyncratic volatility can have significant tradable return even after adjusting for the conventional four factors.

If low returns of high volatility stocks are really driven by their short-run return reversals, the investment strategy based on idiosyncratic volatility could show strong co-movement with the investment strategy based on stocks' previous month returns. In particular, the abnormal return of the IV-based investment strategy should be explained by the difference in returns on past winner and loser stocks. To examine this hypothesis, the WML variable is introduced as an additional explanatory variable in the three- and four-factor models and we re-run the time-series regressions.[12] The last two rows of Table 8 show that both WML coefficients are negative and statistically significant, which indicates that the return of the idiosyncratic volatility investment strategy (IV5-IV1) experiences reversals in the holding period. More important, none of the intercepts is significantly different from zero with WML added to the regression. This suggests that the VW return difference between the high idiosyncratic volatility portfolio and the low idiosyncratic volatility portfolio can be explained by the return reversals of the prior winner and loser stocks, while controlling for other factors. Once again, the evidence indicates that the low return of high idiosyncratic volatility portfolio is driven by the short-term return reversals.

[Insert Table 8]

2. Relation between Idiosyncratic Risk and Expected Return: Cross-Sectional Evidence

Ang et al. (2006b) report the negative relationship between idiosyncratic volatility and expected return in the framework of Fama-MacBeth cross-sectional regressions. In particular, they use past idiosyncratic volatility as the predictor of future idiosyncratic volatility and confirm that there is a negative relationship between expected idiosyncratic volatility and expected returns. However, empirical evidence remains mixed. Some theoretical and empirical evidence suggests a positive relation between expected idiosyncratic volatility and future returns [Merton (1987), Barberis and Huang (2001), Malkiel and Xu (2002), Fu (2005), Spiegel and Wang (2005), Chua et al. (2006)]. Bali and Cakici (2006) report no robust, significant relation between idiosyncratic volatility and expected returns in contrast to the findings of Ang et al. (2006a).

In this section, we investigate whether the predicted idiosyncratic volatility, a proxy for expected idiosyncratic risk, is positively or negatively related to expected returns after return reversals are accounted for. The use of cross-sectional regressions allows us to control for multiple variables at the same time when those variables are correlated. The coefficients in the regression indicate the effect of each explanatory variable on the dependent variable when other variables are kept fixed. For this purpose, we run Fama-MacBeth regressions of the cross-section of stock returns on expected idiosyncratic volatility and other variables month-by-month and calculate time-series averages of the coefficients. Using these regressions, we evaluate the explanatory power of expected idiosyncratic volatility and the previous month's return on the expected stock return, in addition to beta, book equity to market equity ratio, and firm size as identified by Fama and French (1992).

2.1 Constructing Expected Idiosyncratic Volatility

To the extent that investors make decisions based on ex ante information, it is expected idiosyncratic risk, rather than realized idiosyncratic risk that affects equilibrium expected returns. In this study, we use five different methods to estimate expected idiosyncratic volatility.

2.1.1 Estimating Idiosyncratic Volatility under the Martingale Assumption

Similar to Ang et al. (2006b) approach, we use stock *i*'s realized idiosyncratic volatility at month t-1, $IV_{i,t-1}$, as the forecast of its idiosyncratic volatility at month t, which we denote as $EIV1_{i,t}$. This method implicitly assumes that the idiosyncratic volatility series follows a martingale. Thus, under the martingale assumption, stock *i*'s expected idiosyncratic volatility at month t is given by $EIV1_{i,t} = IV_{i,t-1}$.

2.1.2 Estimating Idiosyncratic Volatility using ARIMA

Given the time-series characteristics of the realized idiosyncratic volatility series, we employ the best-fit autoregressive integrated moving average (ARIMA) model to estimate expected idiosyncratic volatility over a rolling window.[13] In particular, for each month, we use the best-fit ARIMA model to predict a stock's idiosyncratic volatility next month based on the individual stock's realized idiosyncratic volatility in the previous 24 months. We denote the resulting estimate as *EIV2*. Appendix A provides a description of the model selection procedure for finding the best-fit ARIMA model.

2.1.3 Estimating Idiosyncratic Volatility using Portfolios

Like beta estimates for individual stocks, idiosyncratic volatility estimates for individual stocks can suffer from the errors-in-variables problem. To mitigate this problem, we calculate portfolio idiosyncratic volatility in the spirit of Fama and French (1992). For each month, we form 100 portfolios based on a stock's realized idiosyncratic volatility level, where portfolio 1 (100) contains stocks with the lowest (highest) idiosyncratic volatility. We compute a portfolio's idiosyncratic volatility as the VW average idiosyncratic volatility of its component stocks. We rebalance the portfolios every month and create each portfolio's idiosyncratic volatility time series. Next, for each month, we use the best-fit ARIMA model to obtain the portfolio's expected idiosyncratic volatility based on portfolio idiosyncratic risk over the previous 36 months.[14] Finally, again for each month, we assign a portfolio expected idiosyncratic volatility to individual stocks according to their realized idiosyncratic volatility rankings, which we use as the proxy for the expected idiosyncratic volatility of each stock in the portfolio. We therefore obtain the expected idiosyncratic volatility *EIV3*, which we use in the Fama-MacBeth cross-sectional regressions for individual stocks.

2.1.4 Estimating Idiosyncratic Volatility using GARCH and EGARCH

In the last two decades, the autoregressive conditional heteroskedasticity (ARCH) model of Engel (1982) has been increasingly used to capture the volatility of financial time series. The ARCH model estimates the mean and variance jointly and captures the serial correlation of volatility by expressing conditional variance as a distributed lag of past squared innovations. Building upon Engel (1982), Bollerslev (1986) presents a generalized autoregressive conditional heteroskedasticity (GARCH) model that provides a more flexible framework to capture the persistent movements in volatility. More recently, Nelson (1991) develops an exponential GARCH (EGARCH) model that accommodates the asymmetric property of volatility, that is, the leverage effect, whereby negative surprises increase volatility more than positive surprises. Following this literature, we employ two widely used generalized ARCH models, GARCH (1, 1) and

EGARCH (1, 1), to capture the conditional volatility of individual stocks. The details are provided in Appendix B. The forecasts thus obtained comprise our fourth and fifth expected idiosyncratic volatility measure, *EIV4* and *EIV5*, respectively.

2.2 Fama-MacBeth Cross-Sectional Regressions

Our model is very similar to Fama and MacBeth (1973) and Fama and French (1992) except that we include the expected idiosyncratic volatility and prior month returns of individual stocks. Specifically, we regress

$$R_{i,t} = \alpha_t + \gamma_{1t} Beta_{i,t-1} + \gamma_{2t} Ln(Size)_{i,t-1} + \gamma_{3t} Ln(BE/ME)_{i,t-1} + \gamma_{4t} EIV_{i,t} + \gamma_{5t} R_{i,t-1} + e_{i,t}, \qquad (3)$$

where $R_{i,t}$ is stock *i*'s return at month *t*, $R_{i,t-1}$ is stock *i*'s return at month *t*-1, $Beta_{i,t-1}$ is the stock's beta estimate at month *t*-1.[15] $EIV_{i,t}$ is the predicted idiosyncratic volatility for stock *i* at month *t* conditioning on the information available at the end of month *t*-1. We use five different methods to predict the expected volatility as specified above. In addition, $Ln(Size)_{i,t-1}$ is the stock's log market capitalization at the end of month *t*-1, and $Ln(BE/ME)_{i,t-1}$ is the log of the ratio of book value to market value based at the end of month *t*-1 based on last fiscal year information.[16]

In the above model, we use prior month returns of individual stocks to control for return reversals. The idea is that if the stock's previous month return is too high (low), it will tend to reverse next month and earn a low (high) return. However, the prior month return could be a noisy proxy for return reversals. Some small-sized stocks or value stocks earn higher returns and these high return stocks do not necessarily tend to reverse in the future; similarly, some large stocks and growth stocks that earn low returns in the past do not necessarily have high returns in the next month. To distinguish whether the high (low) returns of winner (loser) stocks are due to the overreaction to market information or to their fundamental risk, we also use the previous month's demeaned return $RR_{i,t-1}$ to proxy for the return reversal. We therefore also run the following regression:

$$R_{i,t} = \alpha_t + \gamma_{1t} Beta_{i,t-1} + \gamma_{2t} Ln(Size)_{i,t-1} + \gamma_{3t} Ln(BE/ME)_{i,t-1} + \gamma_{4t} EIV_{i,t} + \gamma_{5t} RR_{i,t-1} + e_{i,t}, \quad (4)$$

where $RR_{i,t-1} = R_{i,t-1} - \sum_{j=t-36}^{t-1} R_{i,j} / 36$, is stock i's return at month t-1 minus the mean of the stock i's return over the past 36 months. The intuition behind this measure is that if the stock's return is higher or lower than its long-term mean return, it will tend to reverse next month. Thus, the demeaned return might be a better proxy for return reversals than the raw return since it accounts for long-term return level.

We run cross-sectional regressions for equations (3) and (4) for each month and then report the time-series averages of the coefficients' estimates in Table 9. Panel A summarizes the regression results without the idiosyncratic volatility variable introduced and the remaining five panels report the results when five forecasts of idiosyncratic volatility are introduced. Panel A shows that the coefficients on monthly returns or demeaned returns in the portfolio formation period are negative and significant with conventional explanatory variables such as beta, firm size, and book-to-market introduced, which is consistent with Jegadeesh (1990). The rest of Table 9 reports the cross sectional regression results when various expected idiosyncratic volatility (EIV) measures are used. The results show that the coefficients of EIV are not consistent. Specifically, in Panel B when we use the previous month's idiosyncratic volatility as the expected idiosyncratic volatility, the coefficient on expected volatility, γ_{4t}, is negatively significant at the 5% level, which implies that stocks with higher idiosyncratic volatility earn lower returns in the following month. Similar results are reported by Ang et al. (2006b). The same result also holds in Panel D and Panel E when the expected idiosyncratic volatility is estimated from the ARIMA model on portfolio idiosyncratic volatility and from the GARCH (1, 1) model, respectively. However, this negative relation is not very robust. When idiosyncratic risk is estimated by the ARIMA model based on individual stock-level idiosyncratic volatility in Panel C, the coefficient on expected volatility is not significant, confirming the prediction in Bali and Cakici (2006). The coefficient on expected volatility from the EGARCH (1, 1) model in Panel F is not significant either.[17]

[Insert Table 9]

However, none of the coefficients on expected idiosyncratic volatility is significant after return reversal is controlled for. This result holds no matter which forecast of idiosyncratic volatility is used. We also find that the magnitude of the coefficients on expected idiosyncratic volatility become much smaller for most of the regressions. The one-month formation period returns or demeaned returns take away all of the explanatory power of idiosyncratic volatility. The results of Panel B where we use the previous month's idiosyncratic volatility as the expected idiosyncratic volatility indicates that the volatility coefficient γ_{4t} is -0.019, with a *t*-statistic of -2.44, without controlling for the previous month's return. However, when we add the formation period return (formation month demeaned return) to the regressions, the coefficient γ_{4t} is 0.001 (-0.004), with a t-statistic of 0.15 (-0.51). The evidence here once again indicates that the negative relation between idiosyncratic volatility and expected returns is driven by return reversals.[18]

Early theories, such as Merton (1987), argue that since investors are not able to totally diversify idiosyncratic risk, they will demand a premium for holding stocks with high idiosyncratic risk, and thus stocks with higher expected idiosyncratic risk should deliver higher expected returns. We do not find reliable empirical evidence to support this argument. No matter which method we use to forecast expected idiosyncratic volatility, we do not find a significantly positive coefficient on expected idiosyncratic volatility. Furthermore, after we control for return reversals, we never obtain significant coefficients on expected idiosyncratic volatility.

From Table 2, we notice that both winner stocks and loser stocks have high idiosyncratic risk in the formation month, but winners earn lower returns and losers earn higher returns in the holding-period month. If we observe a negative relation between idiosyncratic volatility and expected returns, it can only be driven by winner stocks, since loser stocks with high idiosyncratic volatility will earn high expected returns due to their return reversals. Therefore, we expect that this negative relation between idiosyncratic volatility and expected returns will disappear if we exclude the winner stocks from our sample.

To test this hypothesis, we run the same cross-sectional regressions as in Table 9, but for every month we exclude from the sample the 50 winner stocks that have the highest prior-month return.[19] Table 10 reports the average coefficients from the cross-sectional regressions with 50 winner stocks (about 1% of all stocks) excluded. As predicted, the negative relation between idiosyncratic volatility and expected returns disappears even before we control for the return reversals and none of the coefficients on idiosyncratic risks is significant in all panels. Another interesting finding is that the significance of one-month portfolio formation period returns or demeaned returns are not affected by the exclusion of winner stocks from the sample. The evidence here therefore suggests that the negative relation between idiosyncratic volatility and expected returns is driven in particular by the return reversals of winner stocks.[20]

[Insert Table 10]

2.3 Robustness Checks

2.3.1 Estimates of Idiosyncratic Volatility

Since idiosyncratic volatilities are unobservable, we require estimates of idiosyncratic volatility in order to perform empirical tests. Usually these estimates can be obtained from the residuals of an asset pricing model. Because different asset pricing models call for different approaches to measure an individual stock's idiosyncratic risk, the relation between idiosyncratic volatility and expected returns reported above could be driven by a particular model used. Therefore, we use different idiosyncratic volatility estimates to verify the robustness of our results.

Besides using the Fama-French three-factor model (1993) given in equation (1) to calculate idiosyncratic volatility, we also use the CAPM model. Assume that the return of each stock *i* is driven by a common factor and a firm-specific shock:

$$r_{t,d}^{i} = \alpha_{t}^{i} + \beta_{MKT}^{i} \cdot MKT_{t,d} + \varepsilon_{t,d}^{i}, \tag{5}$$

where, for each day d in month t, $r_{t,d}^{i}$ is stock i's excess return, $MKT_{t,d}$ is the market excess return as in equation (1), and $\varepsilon_{t,d}^{i}$ is the idiosyncratic return (relative to the CAPM model). Again, we use the standard deviation of the daily residuals to measure stock i's month t idiosyncratic volatility relative to the CAPM model.

Theoretically idiosyncratic risk has to be estimated from the residuals of an asset pricing model; empirically, however, it is very difficult to interpret the residuals estimated from the CAPM or from a multifactor model as solely the idiosyncratic risk. One can always argue that these residuals simply represent omitted factors and thus are not really "idiosyncratic." Jiang and Lee (2004) suggest that most of the return volatility (about 85%) is idiosyncratic volatility. More importantly, since we do not know which asset pricing model is correct; we can use total risk to proxy for idiosyncratic volatility. This method is essentially model-free. We therefore calculate stock *i*'s standard deviation of daily returns within month *t* and use this statistic to proxy for idiosyncratic volatility.

We use the previous month CAPM-based idiosyncratic volatility or the raw return-based idiosyncratic volatility as the expected idiosyncratic volatility and run cross-sectional regressions. The time-series averages of the coefficients' estimates are reported in Table 11. The results show that the role of idiosyncratic volatility is not significant when we control for return reversals, and our results are not driven by any particular approach to measure idiosyncratic volatility.

[Insert Table 11]

2.3.2 NYSE/AMEX Stocks Only

Table 11 shows that our results still hold if we only include NYSE/AMEX stocks in our sample. The evidence confirms that our results are not driven by small-sized stocks or illiquid stocks listed on NASDAQ. To save space, in our remaining robustness test discussions, we use only the previous month's idiosyncratic volatility relative to the Fama-French model's (1993) idiosyncratic volatility to proxy for expected idiosyncratic volatility. Our empirical analysis indicates that all robustness test results still hold when we use CAPM-based idiosyncratic volatility or raw return-based idiosyncratic volatility.[21]

2.3.3 Excluding Stocks with Extremely High Idiosyncratic Volatility

Idiosyncratic volatility estimates for individual stocks suffer not only from the errors-in-variables problem, but also sampling errors. A small percentage of outliers with exceptionally large or small returns (winners or losers) may have extremely high idiosyncratic volatilities in a month, but never experience similar moves before and after. Outliers can also occur because of a data error. To take this into account, we divide the highest idiosyncratic volatility portfolio, IV5, which we have used in our portfolio level analysis into ten sub-portfolios with the same number of stocks based on their past return performance. The first and the last sub-portfolios include the winners and losers with extremely high idiosyncratic volatilities. Most of them are penny stocks (with prices less than $5). We exclude them (about $20\% \times 20\% = 4\%$ of all stocks) from our cross-sectional regressions. Table 11 indicated that the volatility coefficient is -0.024, with an insignificant *t*-statistic of -1.55. The coefficient on previous monthly returns is -0.063, with a strongly significant *t*-statistic of -12.65. Therefore, our results are not driven by a very small fraction of outliers.

2.3.4 Controlling for Leverage

Leverage is related to both past returns and volatility. Past winners have a smaller ratio of book assets to market equity, or smaller market leverage; while an increase in leverage produces an increase in stock volatility. We use the natural log of the ratio of the total book value assets to book value of equity to measure book leverage in Table 11. Consistent with Fama and French (1992), there is a negative relation between book leverage and expected returns. Controlling for leverage does not change the effect of idiosyncratic risk and past returns on average returns - the coefficient on past returns is negatively significant, and that of idiosyncratic volatility is insignificant from zero.

2.3.5 Controlling for Momentum

Jegadeesh and Titman (1993) show that the stocks that perform the best (worst) over the previous 3- to 12-month period tend to continue to perform well (poorly) over the subsequent 3 to 12 months. This phenomenon is referred to as the momentum effect. If the loser stocks during the previous month are the stocks with good historic performance and the winner stocks are the stocks with poor historic performance, the role of return reversals may simply proxy for the momentum effect. To examine the role of idiosyncratic risk on expected returns after taking the momentum effect into account, we construct the momentum variable *MOM* and include it in the cross-sectional regressions. This variable is equal to the cumulative returns for six months from month t-7 to month t-2, assuming that the current month is t.

The results in Table 11 suggest the existence of momentum since the coefficient on *MOM* is positive and significant. However, controlling for momentum does not change the effect of idiosyncratic risk on expected returns. In Table 11, the coefficient on past returns is still significantly negative, while the coefficient on idiosyncratic volatility is not significant.

2.3.6 Controlling for Liquidity

Liquidity measures the degree to which one can trade a large amount of stocks without changing their prices. Many theoretical and empirical papers confirm the role of liquidity in cross-sectional returns and document a negative relation between liquidity and expected stock returns [Amihud and Mendelson (1986), Constantinides (1986), Brennan and Subrahmanyam (1996), Heaton and Lucas (1996), Brennan et al. (1998), Datar et al.

(1998), and Huang (2002), Spiegel and Wang (2005)]. Pastor and Stambaugh (2003) also demonstrate that stocks with high liquidity betas have high average returns. According to them, liquidity is a systematic risk and thus assets with higher liquidity risk should have lower prices, other things being equal, in order to compensate investors for assuming the risk. Hence, if liquidity is indeed priced, our idiosyncratic volatility measure constructed based on residuals from the CAPM, the Fama-French three-factor model, or total risk could potentially capture the liquidity factor. We use two measures of liquidity to control for liquidity risk. The first liquidity measure is the turnover ratio, which is the ratio between share volume and shares outstanding; this metric can also be regarded as the relative volume. Specifically, we use the previous 36 months' average turnover rate to proxy for liquidity in the cross-sectional regressions. Our second liquidity measure is the historical Pastor-Stambaugh (2003) liquidity beta that measures exposure to liquidity risk.

Table 11 shows that our results are robust to liquidity risk. When idiosyncratic volatility, past returns, and liquidity risk are included, the sign and significance of the coefficients of past returns are unchanged, and the coefficients on idiosyncratic volatility are very small and insignificant. The ability of liquidity to explain expected returns seems to be limited; the coefficient on the turnover ratio is negative as the previous literature suggests, but not significant or marginally significant at the 5% level, and the coefficient on the liquidity beta is very close to zero and insignificant. This is consistent with Spiegel and Wang (2005), who documents that the explanatory power of liquidity is weakened once idiosyncratic risk is included in the regression.[22]

In summary, the negative relation between current-month returns and past one-month returns is very robust to the inclusion of other explanatory variables in the cross-sectional regressions, suggesting a significant short-term return reversal. On the other hand, the negative relation between idiosyncratic volatility and cross-sectional expected returns is not robust. In most of the regressions, no discernable relation exists between expected idiosyncratic volatility and expected returns once we control for past returns. Once some winner stocks are excluded from the sample, the coefficients on expected idiosyncratic volatility are consistently insignificant whether we control for return reversals or not. Our results are not depending on a very small fraction of outliers in the sample.

3. Conclusion

Empirical support for the relation between idiosyncratic volatility and expected stock returns has been mixed. Recently, Ang et al. (2006a, 2006b) document that portfolio with high monthly idiosyncratic volatility delivers low VW average return in the next one month, suggesting a negative intertemporal relation between idiosyncratic risk and stock returns. Bali and Cakici (2006), however, find no robust, significant relation between idiosyncratic volatility and expected portfolio returns. Most important, they find that the relation is not consistent under different choices of weight schemes in computing portfolio returns. While these results identify an interesting “puzzle,” neither the cause of the negative relation in Ang et al. (2006a) nor the reason in Bali and Cakici (2006) is known. Furthermore, there is no understanding of the relation between ex ante idiosyncratic risk and expected return.

In this paper, we demonstrate that the negative intertemporal relation between idiosyncratic risk and VW portfolio returns and no relation between idiosyncratic risk and EW portfolio returns are driven by short-term return reversals. In particular, we observe that nearly half of the stocks in the portfolio with the highest idiosyncratic volatility are either winner stocks or loser stocks. The winner stocks tend to be relatively larger cap stocks than the loser stocks in the portfolio formation period and they experience significant return reversals, which drive down the VW return on the portfolio in the next month and cause the negative relation to appear. In contrast, there is no significant difference in the EW returns on the five portfolios sorted by idiosyncratic volatility because return reversals experienced by winner and loser stocks offset each other. In the absence of return reversals for longer holding periods, no negative relation is observed between idiosyncratic volatility and stock returns, regardless of VW or EW portfolio return. This result provides further supportive evidence that return reversals are the driving force of the negative relation. Our evidence from idiosyncratic volatility-sorted portfolios that control for both size and past returns also suggest that negative VW return difference between the highest idiosyncratic volatility portfolio and the lowest idiosyncratic volatility portfolio is driven by the short term return reversal, rather than idiosyncratic volatility itself.

The time-series regression results indicate that the seemingly abnormal positive return from taking a long position in the lowest idiosyncratic risk portfolio and a short position in the highest idiosyncratic risk portfolio can be fully explained by adding the "winners minus losers" return to the conventional three- or four-factor model.

Finally, we use five different approaches to form ex ante idiosyncratic risk and conduct cross-sectional tests. Once again, we find that there is no robust, significant relation between ex ante idiosyncratic volatility and expected returns. There is a significantly negative relation between current-month returns and past one-month returns, indicating a strong return reversal effect. In all of the regressions with the full sample of all common stocks, the relation between expected idiosyncratic volatility and expected returns is flat once we control for past returns. Our results are robust to the inclusion of other variables such as beta, size, book-to-market, momentum, liquidity, leverage, different measures of idiosyncratic volatility, and excluding a small percentage of extremely high idiosyncratic volatility stocks from the sample. Overall, our results suggest that return reversal is the underlying reason behind the negative relation between idiosyncratic risk and subsequent stock returns. The role of idiosyncratic risk is significantly weakened when past return is used as a conditional variable. Our study thus contributes toward understanding of the role of idiosyncratic risk in asset pricing.

Appendix A: Forecasting Idiosyncratic Volatility using ARIMA

To obtain the best-fit ARIMA model, we first de-trend the data using a linear trend model, then take the residuals and compute autocovariances for the number of lags it takes for the autocorrelation to be not significantly different from zero. We run a regression of the current values against the lags, using the autocovariances in a Yule-Walker framework.

We do not admit any autoregressive parameter that is not significant and find the autoregressive parameter that is the least significant and exclude it from the model. We continue this process until only significant autoregressive parameters remain. With this, we generate forecasts using the estimated model.

Appendix B: Forecasting Idiosyncratic Volatility using GARCH and EGARCH

Using GARCH (1, 1), we have the following process for each stock i at month t:

$$r_{i,t} = \alpha_i + \beta^i_{MKT} \cdot MKT_t + \beta^i_{SMB} \cdot SMB_t + \beta^i_{HML} \cdot HML_t + \varepsilon_{i,t}, \tag{6}$$

$$\varepsilon_{i,t} = \sqrt{h_{i,t}} \cdot \nu_{i,t},$$

where $\nu_{i,t}$ is independently and identically distributed (i.i.d.) with standard normal distribution and $h_{i,t}$ can be expressed as

$$h_{i,t} = \omega_i + \delta^i_1 h_{i,t-1} + \alpha^i_1 \varepsilon^2_{i,t-1}. \tag{7}$$

The equation for the mean of the GARCH (1, 1) model is the Fama-French three-factor model as given in equation (6). The conditional (on time t-1 information) distribution of the residual $\varepsilon_{i,t}$ is assumed to be normal with mean zero and variance $h_{i,t}$.

We estimate the idiosyncratic risk of individual stocks as the square root of the conditional variance $h_{i,t}$, which is a function of the past one month's residual variance and the shock as specified in equation (7). For each month and each stock, we run the GARCH (1, 1) model using the monthly returns in the previous 30 months (if available) and the forecasts thus obtained for the next month comprise our fourth expected idiosyncratic volatility measure, *EIV4*.

To arrive at our fifth expected idiosyncratic volatility measure, *EIV5*, we employ the EGARCH (1, 1) model to estimate idiosyncratic volatility. The EGARCH model is similar to the GARCH model, except that we use the following equation in the place of equation (3) to capture the leverage effect:

$$\log h_{i,t} = \omega_i + \delta_1^i \log h_{i,t-1} + \alpha_1^i g(v_{i,t-1}),$$

$$g(v_{i,t-1}) = \theta \cdot v_{i,t-1} + \gamma \cdot \left[\left| v_{i,t-1} \right| - (2/\pi)^{1/2} \right]. \tag{8}$$

As in the case of the GARCH (1, 1) process, for each month and each stock, we run the EGARCH (1, 1) model by using the monthly returns in the previous 30 months (if available) to estimate and predict the monthly standard deviation. The rolling forecasts thus obtained form our fifth expected idiosyncratic volatility measure, *EIV5*.

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Footnotes

1 We thank Kenneth French for making the data available on his website.

2 We also use the standard deviation of the residuals from the capital asset pricing model (CAPM) and the returns to measure idiosyncratic volatility and obtain qualitatively similar results.

3 To measure the monthly idiosyncratic volatility of stock *i*, we follow French et al. (1987) and multiply the standard deviation of daily residuals in month *t* ($STD_{i,t}$) by $\sqrt{n_{i,t}}$, where $n_{i,t}$ is the number of trading days during month *t*. Therefore $IV_{i,t} = \sqrt{n_{i,t}} STD_{i,t}$ is stock *i*'s realized idiosyncratic volatility in month *t*.

4 Bali and Cakici (2006) call the largest stocks in the tenth sub-quintile of the highest idiosyncratic volatility quintile portfolio as "biggest of small stocks" and find that their returns are much lower than those of the "smallest of small stocks" in the first sub-quintile of the same quintile portfolio.

5 This is more obvious if we use total volatility as the measure of idiosyncratic volatility. In this case, idiosyncratic volatility is simply the standard deviation of stock returns and "high volatility" means very positive returns or very negative returns, that is, winners or losers.

6 Jiang and Lee (2004) find that on average, idiosyncratic volatility is about 85% of total stock return volatility. Since winner and loser stocks often have larger total volatility, it is not surprising to find the large presence of both of them in the highest idiosyncratic volatility portfolio.

7 We report the simple (equally-weighted) average monthly returns in Panels B and C. This implies that we treat the stocks within each of the 50 idiosyncratic volatility-past return sorted portfolios as homogeneous, and stocks from different portfolios as heterogeneous.

8 For the 12/1/12 strategy, each quintile portfolio changes $1/12^{th}$ of its composition each month, where each $1/12^{th}$ part of the portfolio consists of a value-weighted portfolio or equally-weighted portfolio. The first (fifth) quintile portfolio consists of $1/12^{th}$ of the lowest (highest) idiosyncratic stocks from 1 month ago until from 12 months ago.

9 Ang et al. (2006a) document that the negative relation between past idiosyncratic volatility and future returns still holds for a long horizon when they compare the difference in Fama-French three-factor (FF-3) alphas between value-weighted portfolio IV5 and portfolio IV1 of the above four strategies. Our analysis is based on the value-weighted or equally-weighted return difference of portfolio IV5 and portfolio IV1 over

the long run.

10 The same approach is adopted by Diether et al. (2002). Sorting portfolios on more than two dimensions is useful in controlling for the effects of multiple factors at the same time.

11 We also conduct a triple sort based on stock price, past returns, and idiosyncratic volatility, and find qualitatively similar results, that is, the average return difference between portfolio 5 and portfolio 1 remains insignificant. This is not surprising given the high correlation (0.76) between stock price and firm size. These results are not reported but available upon request.

12 Strictly speaking, WML here is not a trading strategy since we are calculating its return during the formation period. However, we use the formation period to capture the lead-lag relation between this portfolio and the idiosyncratic volatility-based portfolio. We also construct WML by using the EW or VW average return difference between P10 and P1 during the holding period and the Short-Term Reversal Factor taken from Professor Kenneth French's website. These WMLs can be thought of as risk factors since they are evaluated in the same period as the dependent variables, the IV portfolio spread. However, none of these factors could explain the IV portfolio return spread because the intercepts are all significantly negative. These results are available upon request.

13 Bali and Cakici (2006) show that the realized idiosyncratic volatility measure obtained from monthly data is a more accurate proxy for the expected idiosyncratic volatility than that based on daily data within the same month. Under this new measure, they find that the cross-sectional relation between the realized idiosyncratic volatility and expected (VW or EW) portfolio returns is flat.

14 We also use a portfolio's previous 100 months' idiosyncratic volatility to predict expected idiosyncratic volatility; the results are similar.

15 To reduce errors-in-variables problems, we assign individual stock betas based upon 100 portfolios, sorted using the Fama and French (1992) methodology. In particular, each month, all stocks are sorted into 10 groups by market capitalization. Within each size group, stocks are sorted again by their betas into ten equal-numbered groups. The beta of each stock is estimated from a market model using the previous 24 to 60 months of returns, as available. The 100 portfolios thus obtained are rebalanced every month. We use NYSE-listed stocks to determine the cutoff value for each size group to ensure that the ranking is not dominated by many small-cap stocks on NASDAQ. For each portfolio, we compute its return in each

month and then regress the return series against the market return and the one-month lagged market return. The portfolio betas therefore equal the sum of these two beta coefficients. Finally, we assign the portfolio betas to individual stocks according to their size-beta ranking in each month.

16 To ensure that accounting data are known before they are used to explain the cross-section of stock returns, we use a firm's market equity at the end of December of year t-1 to compute its year t-1 book-to-market ratio, and then match the book-to-market ratio for calendar year t-1 with the returns from July of year t to June of t+1.

17 Fu (2005) runs a similar cross-sectional regression and finds that the coefficient on expected idiosyncratic volatility is significantly positive. Although he also uses an EGARCH model to estimate expected idiosyncratic volatility, he chooses the best-fit EGARCH model among nine EGARCH (p, q) models, with $1 \leq p \leq 3$, $1 \leq q \leq 3$, according to the Akaike Information Criterion to obtain the expected idiosyncratic volatility for each individual stock.

18 Ang et al. (2006b) find the negative relation between idiosyncratic volatility and expected returns after controlling for the lagged return. However, the lagged returns in their paper are a firm's returns over the previous six months. Therefore it takes account of both short term return reversals and the momentum effect.

19 We also conduct analysis by excluding portfolio P10. By excluding all winner stocks from our sample, we obtain qualitatively similar results.

20 On the contrary, if we exclude 50 loser stocks from the sample and use daily standard deviation in the previous month to predict expected idiosyncratic volatility, we find that the coefficient on the expected idiosyncratic risk is negatively significant, even after past returns are controlled for. The coefficient on past returns is still highly significant and negative. Consistent with Bali and Cakici (2006), this shows that the relation between idiosyncratic volatility and cross-section expected returns is not robust and easily affected if we exclude only the extreme winners or losers in the sample.

21 When we exclude penny stocks (stock prices less than $5) from NYSE/AMEX universe, there is a negative relation between idiosyncratic volatility and future returns if we use raw return-based idiosyncratic volatility, even after past returns are controlled for. The reason is that more losers than winners are excluded from the sample because of their relatively lower prices, which leads to the negative significance

of idiosyncratic volatility in some of the cross-sectional regressions. The coefficients on past returns are still significantly negative in all regressions.

22 The difference from our result is that Spiegel and Wang (2005) find a positive relation between idiosyncratic volatility and expected returns by using monthly data to measure idiosyncratic volatility, following Fu (2005).

Table 1
Characteristics of Portfolios Sorted by Idiosyncratic Volatility

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Portfolio	VW Return	EW Return	Ang et al. (2006a) [1963.07-2000.12]	Formation Period Return	VW-IV	Size	MKT Share Percentage	Average Price
IV1	0.969	1.207	1.04	1.126	4.179	4.985	48.26	44.05
IV2	1.075	1.439	1.16	1.603	6.967	4.932	30.41	28.79
IV3	1.120	1.466	1.20	2.157	10.289	4.265	13.40	19.20
IV4	0.746	1.300	0.87	3.016	14.341	3.600	5.95	12.85
IV5	-0.026	1.202	-0.02	8.061	24.576	2.643	2.09	7.02
IV5-IV1	-1.000	-0.005	-1.06	6.935				
	(-2.95)	(-0.01)	(-3.10)	(9.74)				

This table reports the characteristics of five portfolios sorted by idiosyncratic volatility relative to the Fama and French (1993) model. Portfolios are formed every month based on idiosyncratic volatility computed using daily data over the previous month. Portfolio IV1 (IV5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. VW (EW) Return is the value (equally)-weighted average monthly return measured in percentage terms in the month following the portfolio formation period. Formation Period Return is the value-weighted average monthly portfolio return during the previous one-month formation period. The VW-IV is the value-weighted average idiosyncratic volatilities of the portfolio in the formation period. The weights are based upon the stock's market capitalization at the end of the previous month. For comparison, we report Ang et al.'s (2006a) Table VI Panel B in column 4; their sample period extends from 1963.07 to 2000.12. Size is the simple average of the log market capitalization of firms within the portfolio and B/M is the simple average book-to-market ratio. Market share percentage measures the market value of a portfolio relative to total market value of all stocks. Price is the simple average price at the end of previous month. The row "IV5-IV1" refers to the difference in monthly returns between portfolio IV5 and portfolio IV1. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

Table 2
Characteristics of Portfolios Sorted by Past One month Returns

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio	Rank	Formation Period VW Return	Holding Period VW Return	VW-IV (%)	EW-IV (%)	Size	Price
Loser	1	-18.409	1.915	13.073	20.395	2.990	9.34
	2	-10.279	1.767	8.438	13.336	3.737	15.45
	3	-6.2467	1.616	6.835	11.108	4.048	21.39
	4	-3.3758	1.253	6.111	10.034	4.246	22.02
	5	-1.0167	1.203	5.767	9.443	4.393	25.31
	6	1.2353	1.001	5.729	9.311	4.465	26.82
	7	3.7483	0.837	5.895	9.766	4.516	28.26
	8	7.0133	0.706	6.495	10.833	4.476	25.49
	9	12.0148	0.310	7.925	13.115	4.262	22.90
Winner	10	24.9501	-0.154	13.085	21.764	3.593	15.65

This table reports the characteristics of ten portfolios sorted by the previous one-month stock returns in the formation period. Portfolios are formed at the end of each month and held for next one month. P1 through P10 represent winners/losers portfolios, with P1 containing past losers and P10 containing past winners. Formation Period VW Returns are the value-weighted average returns during the formation period. Holding Period VW Returns are the value-weighted average returns during the following one-month holding period. Both are measured in monthly percentage terms. VW (EW)-IV is the value (equally)-weighted idiosyncratic volatility of the portfolio in the formation period. The weights are based upon the stock's market capitalization at the end of the formation month. The idiosyncratic volatility is relative to the Fama and French (1993) model. We calculate the individual stock's idiosyncratic volatility using daily data in the formation month. Size is the simple average log market capitalization of firms within the portfolio. Price is the simple average price at the end of the formation month. The sample period is from July 1963 to December 2004.

Table 3
Portfolios Sorted by Idiosyncratic Volatility and Past One Month Returns

Portfolio	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Panel A: The Average Number of Stocks within Each Portfolio										
IV1	13	56	108	146	156	162	142	108	60	16
IV2	35	94	114	119	114	118	118	116	97	36
IV3	77	117	109	99	87	89	93	104	115	71
IV4	137	121	95	79	67	67	72	86	115	124
IV5	222	98	67	54	45	43	47	58	92	234
Total	484	486	493	497	469	479	472	472	479	481
Panel B: The EW Average Monthly Returns During Formation Periods										
IV1	-14.793	-9.844	-6.059	-3.271	-0.954	1.303	3.798	6.889	11.287	18.183
IV2	-16.489	-10.210	-6.212	-3.343	-0.971	1.319	3.851	7.057	11.877	20.189
IV3	-17.699	-10.430	-6.258	-3.357	-0.958	1.337	3.892	7.130	12.218	22.273
IV4	-19.497	-10.534	-6.266	-3.326	-0.948	1.367	3.926	7.201	12.443	25.355
IV5	-24.294	-10.601	-6.311	-3.324	-0.918	1.421	3.984	7.268	12.599	38.237
Panel C: The EW Average Monthly Returns During Holding Periods										
IV1	2.882	1.641	1.358	1.288	1.211	1.174	1.086	0.922	0.678	0.035
IV2	2.177	1.844	1.735	1.625	1.464	1.456	1.274	1.115	0.941	0.368
IV3	2.509	1.938	1.724	1.481	1.628	1.332	1.227	1.195	0.952	0.775
IV4	2.673	1.649	1.377	1.363	1.364	1.024	1.071	0.928	0.743	0.504
IV5	4.295	1.807	1.017	0.872	0.658	0.231	0.404	0.042	-0.180	-0.791
Panel D: The Average Market Capitalization During Formation Periods										
IV1	94.349	127.996	136.047	141.034	149.008	168.679	199.737	249.635	273.144	227.466
IV2	65.957	86.056	104.585	117.331	127.613	135.368	149.157	163.041	170.545	152.018
IV3	39.291	50.958	56.940	62.427	67.222	71.307	75.189	82.765	88.943	89.121
IV4	23.571	28.905	30.478	32.525	34.536	36.053	37.600	40.731	43.904	47.040
IV5	9.984	12.466	13.027	14.354	15.196	15.705	15.565	16.379	16.330	16.929

This table reports the characteristics of 50 portfolios sorted independently by idiosyncratic volatility and previous one month stock returns. At the beginning of each month, we sort all of stocks into five portfolios based on idiosyncratic volatility computed using daily data over the previous one month. Portfolio IV1 (IV5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. The stocks are also independently allocated to ten portfolios based on their previous one-month returns. P1 through P10 represent winners/losers portfolios, with P1 containing past losers and P10 containing past winners. The intersections of the idiosyncratic volatility-sorted portfolios and previous month return-sorted portfolios are then used to create 50 idiosyncratic volatility- and past return-sorted portfolios. Panel A reports the average number of stocks in each of the 50 portfolios and the total number of stocks in each past return sorted portfolios. Panel B shows the simple average monthly returns measured in percentage terms in the portfolio formation period. Panel C reports the simple average monthly returns measured in percentage terms in the one-month holding period. Panel D reports the average of market capitalization (in million dollars) of firms within the portfolio in the portfolio formation period. The sample period is from July 1963 to December 2004.

Table 4
Portfolios Sorted by Idiosyncratic Volatility for *L/M/N* Strategies

		Ranking on Idiosyncratic Volatility					
Strategy		IV1	IV2	IV3	IV4	IV5	IV5-IV1
1/1/1	VW	0.964	1.025	1.087	0.820	0.359	-0.605 (-1.75)
	EW	1.310	1.364	1.397	1.223	1.284	-0.025 (-0.07)
1/1/12	VW	0.990	1.008	1.025	0.942	0.724	-0.266 (-0.80)
	EW	1.303	1.331	1.336	1.323	1.614	0.311 (0.91)
12/1/1	VW	0.967	1.062	1.089	0.901	0.727	-0.240 (-0.58)
	EW	1.238	1.345	1.362	1.290	1.728	0.491 (1.16)
12/1/12	VW	0.968	1.046	1.048	0.891	0.874	-0.094 (-0.23)
	EW	1.234	1.299	1.358	1.369	1.842	0.608 (1.48)

The table reports EW and VW average returns of five idiosyncratic volatility portfolios under *L/M/N* strategies described in Section I.E. At month *t*, we form quintile portfolios based on the idiosyncratic volatility over the *L*-month period from month *t-L-M* to month *t-M*, then hold these portfolios for *N* months from month *t*. To take short-term return reversals into account, we skip the middle *M* months. The column "IV5-IV1" refers to the difference in monthly returns between portfolio IV5 and portfolio IV1. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

Table 5
Post-Formation Returns of Portfolios Sorted by Idiosyncratic Volatility

Portfolio	1st Month	2nd Month	3rd Month	4th Month	5th Month	6th Month	7th Month	8th Month	9th Month	10th Month	11th Month	12th Month
IV1	0.969	1.03	0.97	0.94	0.87	0.94	0.88	0.90	1.01	0.91	0.94	0.81
IV2	1.075	1.02	1.13	1.03	1.06	0.99	1.07	0.99	1.04	1.04	1.07	1.16
IV3	1.120	1.11	1.04	1.18	1.09	1.05	1.16	1.04	1.04	0.96	0.94	1.05
IV4	0.746	0.88	0.93	1.05	0.91	0.92	1.07	1.08	0.82	0.99	1.07	1.04
IV5	-0.026	0.52	0.58	0.41	0.52	0.89	0.92	0.78	0.83	0.94	1.12	1.01
IV5-IV1	-1.000	-0.51	-0.39	-0.53	-0.35	-0.05	0.04	-0.12	-0.18	0.03	0.18	0.20
	(-2.95)	(-1.38)	(-1.11)	(-1.46)	(-1.01)	(-0.16)	(0.10)	(-0.39)	(-0.56)	(0.07)	(0.50)	(0.59)

This table reports the value-weighted monthly returns during the 12-month post formation period of five portfolios sorted by idiosyncratic volatility relative to the Fama and French (1993) model. Portfolios are formed every month based on idiosyncratic volatility computed using daily data over the previous month and held for 12 months after formation. Portfolio IV1 (IV5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. The weights are based upon a stock's market capitalization at the end of the formation period. The row "IV5-IV1" refers to the difference in monthly returns between portfolio IV5 and portfolio IV1. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

Table 6
Characteristics of Portfolios Sorted by Idiosyncratic Volatility (Past Returns) Controlling for Past Returns (Idiosyncratic Volatility)

Portfolios	VW Holding Period Return	EW Holding Period Return	VW Formation Period Return	EW Formation Period Return	Size
Panel A. Idiosyncratic risk sorted portfolios (IV1: Lowest IV portfolio, IV5: Highest IV portfolio)					
IV1	0.94	1.22	1.95	0.57	4.84
IV2	1.02	1.38	1.37	0.69	4.76
IV3	0.98	1.37	1.36	0.89	4.29
IV4	0.83	1.25	1.76	1.34	3.70
IV5	0.21	1.05	3.88	3.11	2.77
IV5－IV1	-0.73 (-2.44)	-0.07 (-0.44)			
Panel B. Past Return Sorted Portfolio (P1: Lowest return portfolio, P5: Highest return portfolio)					
P1	1.23	2.40	1.23	-14.30	3.74
P2	1.11	1.48	1.11	-5.11	3.87
P3	0.75	0.99	0.75	0.43	4.00
P4	0.90	0.87	0.90	6.51	4.21
P5	0.69	0.51	0.69	19.74	4.35
P5－P1	-0.53 (-3.77)	-1.91 (-8.65)			

In Panel A (Panel B), we first sort stocks each month based on the formation-month return (formation-month idiosyncratic volatility), then within each past return (idiosyncratic volatility) sorted portfolio, we sort stocks based on formation-month idiosyncratic volatility (formation-month return). The five idiosyncratic volatility sorted (past return-sorted) portfolios are then averaged over each of the five past return sorted (idiosyncratic volatility sorted) portfolios. VW (EW) Holding Period Return denotes value (equally)-weighted average monthly returns measured in percentage terms during the holding period. VW (EW) Formation Period Return denotes value (equally)-weighted average monthly returns measured in percentage terms during the formation period. The weights are based upon a stock's market capitalization at the end of the previous month. Size is the average of log market capitalizations of firms within the portfolio in the formation month. The row "IV5-IV1" ("P5-P1") refers to the difference in monthly returns between portfolio IV5 (P5) and portfolio IV1 (P1). Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

Table 7
Characteristics of Portfolios Sorted by Idiosyncratic Volatility (Past Returns) Controlling for Size and Past Returns (Size and Idiosyncratic Risk)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
IV Sorted Portfolio	VW Holding Period Returns	VW Formation Period Return	EW Formation Period Return	VW-IV	EW-IV	Size
Panel A: Idiosyncratic risk sorted portfolios (IV1: Lowest IV portfolio, IV5: Highest IV portfolio)						
IV1	0.884	1.815	0.444	3.837	5.334	4.093
IV2	1.135	1.518	0.755	5.366	8.454	4.157
IV3	0.944	1.476	0.960	6.732	11.065	4.066
IV4	0.998	1.563	1.406	8.589	14.570	4.000
IV5	0.706	2.259	3.075	13.273	23.979	3.886
IV5－IV1	-0.178 (-0.83)					
Panel B: Past return sorted portfolios (P1: Lowest return portfolio, P5: Highest return portfolio)						
P1	1.243	-7.989	-13.781	6.784	13.035	3.937
P2	1.102	-2.416	-5.014	6.436	12.433	3.968
P3	0.828	1.117	0.494	6.473	12.780	4.061
P4	0.860	4.907	6.623	6.440	12.795	4.138
P5	0.657	11.344	19.431	6.651	13.909	4.093
P5－P1	-0.585 (-4.56)					

In Panel A (Panel B), we first sort stocks based on size and then, within each size quintile, we sort stocks into five portfolios based on the formation month return (idiosyncratic volatility). This yields 25 size-past return (size-IV) portfolios. Finally, within each size-past return (size-IV) portfolio, we sort stocks based on idiosyncratic volatility (formation month returns). The five idiosyncratic volatility (past return-sorted) portfolios are then averaged over each of the 25 size-past return (size-IV) portfolios. VW Holding Period Returns denote VW average monthly returns measured in percentage terms during the holding period. VW (EW) Formation Period Return statistics are VW (EW) average formation month returns. The VW (EW)-IV is the value (equally)-weighted idiosyncratic volatility of the portfolio in the formation period. The weights are based upon the stock's market capitalization at the end of the previous month. Size is the average of log market capitalizations of firms within the portfolio in the formation month. The row "IV5-IV1" ("P5-P1") refers to the difference in monthly returns between portfolio IV5 and portfolio IV1 (portfolio P5 and portfolio P1). Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

Table 8
The Time-Series Regression

Regression Models	Constant	RM-RF	SMB	HML	UMD	WML	Adjusted R-squares
1	-1.339	0.353	1.447	-0.400			0.66
	(-6.79)	(7.33)	(23.12)	(-5.51)			
2	-1.065	0.317	1.454	-0.469	-0.266		0.68
	(-5.40)	(6.74)	(23.96)	(-6.58)	(-5.71)		
3	0.112	0.357	1.455	-0.386		-0.028	0.66
	(0.16)	(7.46)	(23.30)	(-5.33)		(-2.19)	
4	0.272	0.322	1.461	-0.460	-0.263	-0.026	0.68
	(0.41)	(6.86)	(24.12)	(-6.39)	(-5.66)	(-2.08)	

This table reports results from the time-series regressions. The dependent variable is the time-series return on the strategy (IV5-IV1) that takes a long position in the highest idiosyncratic risk portfolio and a short position in the lowest idiosyncratic risk portfolio. The independent variables include the Fama and French (1993) three factors (*RM-RF*, *SMB*, and *HML*), the momentum factor (*UMD*), and a time-series return on a strategy that takes a long position in the winner portfolio and a short position in the loser portfolio (*WML*). Winner and loser portfolios are formed based on past one month returns. Specifically, ten portfolios are formed based on the past one month returns, with P1 containing past losers and P10 containing past winners. "*WML*" is the difference between the equally-weighted average return of the past winners (P10) and the past losers (P1) during the formation period. Adjusted R-squares are reported in the last column. Newey-West (1987) robust *t*-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

Table 9
Relation between Idiosyncratic Risk and Expected Return: Cross-Sectional Evidence

Intercept	Beta	Size	B/M	EIV	R_{t-1}	RR_{t-1}
Panel A: Regression without Expected Idiosyncratic Volatility						
2.289	-0.004	-0.147	0.381		-0.068	
(7.66)	(-0.01)	(-3.23)	(4.90)		(-14.02)	
2.288	0.005	-0.160	0.386			-0.907
(7.61)	(0.02)	(-3.75)	(5.11)			(-15.92)
Panel B: Regression with Expected Idiosyncratic Volatility EIV1						
2.505	0.018	-0.188	0.301	-0.019		
(8.29)	(0.08)	(-4.79)	(4.25)	(-2.44)		
2.044	-0.007	-0.109	0.384	0.001	-0.070	
(6.75)	(-0.03)	(-2.83)	(5.22)	(0.15)	(-14.57)	
2.123	0.009	-0.132	0.387	-0.004		-0.912
(6.81)	(0.04)	(-3.57)	(5.40)	(-0.51)		(-16.74)
Panel C: Regression with Expected Idiosyncratic Volatility EIV2						
2.469	-0.090	-0.183	0.313	-0.003		
(7.95)	(-0.43)	(-4.92)	(4.22)	(-0.25)		
2.153	-0.040	-0.123	0.386	0.002	-0.072	
(6.70)	(-0.173)	(-3.24)	(5.03)	(0.18)	(-14.87)	
2.161	-0.044	-0.138	0.393	0.004		-0.944
(6.57)	(-0.19)	(-3.79)	(5.25)	(0.29)		(-16.57)
Panel D: Regression with Expected Idiosyncratic Volatility EIV3						
2.809	-0.065	-0.212	0.298	-0.027		
(9.21)	(-0.29)	(-5.43)	(3.95)	(-3.25)		
2.281	-0.064	-0.124	0.384	-0.006	-0.072	
(7.39)	(-0.26)	(-3.22)	(4.91)	(-0.63)	(-14.68)	
2.346	-0.068	-0.143	0.391	-0.009		-0.945
(7.36)	(-0.28)	(-3.85)	(5.17)	(-1.00)		(-16.60)
Panel E: Regression with Expected Idiosyncratic Volatility EIV4						
2.678	0.053	-0.214	0.279	-0.024		
(9.53)	(0.24)	(-5.48)	(4.11)	(-2.89)		
2.139	0.0219	-0.130	0.385	0.003	-0.071	
(7.43)	(0.09)	(-3.35)	(5.42)	(0.37)	(-14.50)	
2.310	0.025	-0.162	0.378	-0.006		-0.904
(7.78)	(0.10)	(-4.25)	(5.38)	(-0.69)		(-16.38)
Panel F: Regression with Expected Idiosyncratic Volatility EIV5						
2.444	-0.032	-0.188	0.307	0.000		
(8.55)	(-0.13)	(-4.39)	(4.21)	(0.10)		

2.200	0.036	-0.139	0.378	0.002	-0.069	
(7.56)	(0.14)	(-3.24)	(5.02)	(0.54)	(-14.32)	
2.262	0.013	-0.157	0.384	0.001		-0.905
(7.69)	(0.05)	(-3.87)	(5.18)	(0.11)		(-15.90)

This table reports the average coefficients of the Fama-MacBeth cross-sectional regressions for all NYSE/AMEX/NASDAQ individual stocks over the period from July 1963 to December 2004. Panel A reports the cross-sectional regressions without expected idiosyncratic volatility as the explanatory variable. In Panel B, the expected idiosyncratic volatilities (EIV1) are the realized idiosyncratic volatility in the previous month. In Panel C, the expected idiosyncratic volatility (EIV2) is estimated by the best-fit ARIMA model based on an individual stock's realized idiosyncratic volatility over the previous 24-month period. In Panel D, the expected idiosyncratic volatilities (EIV3) is estimated by the ARIMA model based on portfolio's realized idiosyncratic volatility over the previous 36-month period where 100 portfolios are formed based on the idiosyncratic volatility of a stock in the previous month. In Panel E, the expected idiosyncratic volatility (EIV4) is estimated by the GARCH (1, 1) model based on an individual stock's idiosyncratic volatility over the previous 30-month period. In Panel F, the expected idiosyncratic volatility (EIV5) is estimated by the EGARCH (1, 1) model based on an individual stock's realized idiosyncratic volatility over the previous 30-month period. Beta is estimated using the 100 size/beta sorted portfolio following Fama and French (1992). Size is the log of market capitalization and B/M is the log of book-to-market in the previous month as defined by Fama and French (1992). R_{t-1} is an individual stock's previous one-month return. RR_{t-1} is the stock's demeaned return during the previous month. The demeaned return is the difference between an individual stock's return at month *t*-1 and the average of the stock's return over the period from *t*-36 to *t*-1. All returns and idiosyncratic volatilities are in percentages. We run the cross-sectional regression every month and report the time-series averages of the coefficients. The *t*-statistics are reported in the parentheses. The *t*-statistics for the betas are adjusted using the Shanken (1992) correction factor. The *t*-statistics for the other variables are Newey and West (1987) consistent.

Table 10
Relation between Idiosyncratic Risk and Expected Return: Cross-Sectional Evidence with Winner Stocks Excluded

Intercept	Beta	Size	B/M	EIV	R_{t-1}	RR_{t-1}
Panel A: Regression without Expected Idiosyncratic Volatility						
2.240	-0.001	-0.139	0.379		-0.076	
(7.47)	(-0.003)	(-3.08)	(4.88)		(-14.59)	
2.300	0.006	-0.166	0.373			-0.903
(7.59)	(0.02)	(-3.91)	(4.929)			(-15.60)
Panel B: Regression with Expected Idiosyncratic Volatility EIV1						
2.404	-0.014	-0.179	0.302	-0.010		
(7.84)	(-0.07)	(-4.62)	(4.27)	(-1.14)		
2.028	0.008	-0.105	0.378	-0.002	-0.078	
(6.57)	(0.03)	(-2.74)	(5.17)	(-0.23)	(-15.42)	
2.057	-0.007	-0.128	0.379	-0.001		-0.909
(6.42)	(-0.03)	(-3.46)	(5.30)	(-0.06)		(-17.03)
Panel C: Regression with Expected Idiosyncratic Volatility EIV2						
2.409	-0.108	-0.181	0.308	0.005		
(7.66)	(-0.51)	(-4.84)	(4.13)	(0.37)		
2.103	-0.051	-0.115	0.385	0.003	-0.080	
(6.45)	(-0.22)	(-3.01)	(4.99)	(0.21)	(-15.19)	
2.109	-0.060	-0.136	0.384	0.007		-0.939
(6.30)	(-0.26)	(-3.72)	(5.12)	(0.57)		(-16.66)
Panel D: Regression with Expected Idiosyncratic Volatility EIV3						
2.688	-0.092	-0.201	0.297	-0.017		
(8.72)	(-0.41)	(-5.18)	(3.94)	(-1.84)		
2.276	-0.059	-0.122	0.380	-0.009	-0.08	
(7.27)	(-0.24)	(-3.15)	(4.84)	(-0.93)	(-15.23)	
2.286	-0.083	-0.140	0.384	-0.005		-0.945
(7.03)	(-0.34)	(-3.76)	(5.06)	(-0.55)		(-16.90)
Panel E: Regression with Expected Idiosyncratic Volatility EIV4						
2.520	-0.018	-0.200	0.293	-0.004		
(8.94)	(-0.09)	(-5.33)	(4.40)	(-0.41)		
2.19	0.019	-0.132	0.370	-0.002	-0.0780	
(7.51)	(0.083)	(-3.49)	(5.28)	(-0.20)	(-15.16)	
2.240	-0.018	-0.156	0.376	0.002		-0.909
(7.42)	(-0.08)	(-4.26)	(5.43)	(0.16)		(-16.67)
Panel F: Regression with Expected Idiosyncratic Volatility EIV5						

2.46	-0.036	-0.196	0.300	0.005		
(8.64)	(-0.15)	(-4.60)	(4.10)	(1.33)		
2.17	0.024	-0.133	0.373	0.003	-0.077	
(7.41)	(0.09)	(-3.17)	(4.94)	(0.75)	(-14.66)	
2.253	0.004	-0.160	0.375	0.002		-0.901
(7.64)	(0.016)	(-3.97)	(5.05)	(0.47)		(-16.01)

This table reports the average coefficients of the Fama-MacBeth cross-sectional regressions for all individual NYSE/AMEX/NASDAQ stocks over the period from July 1963 to December 2004. Each month, we exclude the 50 winner stocks that have the highest returns over the previous one month. All variables are the same as those in Table 9. We run the cross-sectional regression every month and report the time-series averages of the coefficients. The *t*-statistics are reported in the parentheses. The *t*-statistics for the betas are adjusted using the Shanken (1992) correction factor. The *t*-statistics for the other variables are Newey and West (1987) consistent.

Table 11
Robustness Test

	NYSE/AMEX Stocks only	Excluding Extremely High IV Stocks	All Stocks							
Intercept	1.963	2.086	1.909	1.869	2.170	2.139	1.862	1.999	2.037	2.166
	(7.12)	(6.76)	(5.66)	(5.52)	(8.18)	(7.24)	(6.75)	(6.35)	(8.36)	(8.05)
Beta	0.020	0.134	-0.007	-0.007	-0.030	-0.060	0.175	0.012	0.108	-0.063
	(0.01)	(0.64)	(-0.03)	(-0.03)	(-0.14)	(-0.27)	(0.85)	(0.05)	(0.55)	(-0.27)
Size	-0.083	-0.112	-0.114	-0.110	-0.107	-0.128	-0.090	-0.106	-0.105	-0.118
	(-2.38)	(-3.02)	(-3.01)	(-2.86)	(-2.76)	(-3.32)	(-2.37)	(-2.70)	(-2.73)	(-2.98)
B/M	0.295	0.360	0.384	0.384	0.372	0.360	0.330	0.375	0.294	0.344
	(4.03)	(5.05)	(5.18)	(5.23)	(4.93)	(4.84)	(4.68)	(5.04)	(3.99)	(4.49)
R_{t-1}	-0.067	-0.063	-0.070	-0.070	-0.071	-0.071	-0.074	-0.073	-0.083	-0.081
	(-12.25)	(-12.65)	(-14.52)	(-14.54)	(-14.97)	(-14.82)	(-15.52)	(-14.78)	(-19.42)	(-18.57)
FF-IV	-0.014	-0.024			0.003	-0.002	-0.000	0.003	0.001	0.002
	(-1.50)	(-1.55)			(0.34)	(-0.24)	(-0.00)	(0.34)	(0.08)	(0.23)
CAPM-IV			-0.184							
			(-0.21)							
Total-IV				0.090						
				(0.10)						
Leverage					-0.135				-0.113	-0.110
					(-2.03)				(-1.78)	(-1.65)
MOM						0.005			0.007	0.007
						(3.15)			(3.91)	(3.80)
TURN							-1.960		-2.827	
							(-1.451)		(-1.99)	
L-Beta								0.007		-0.005
								(0.09)		(-0.08)

This table reports the average coefficients of the Fama-MacBeth cross-sectional regressions. Column 2 is for the sample without NASDAQ stocks. Column 3 is for the sample without winners and losers that have extremely high idiosyncratic volatilities. Other columns are for all NYSE/AMEX/NASDAQ individual stocks over the period of July 1963 to December 2004. The variables Beta, Size, B/M, R_{t-1} are the same as explained in Table 9. FF-IV is the idiosyncratic volatility relative to the Fama-French (1993) model. CAPM-IV is the idiosyncratic volatility relative to the CAPM model. Total-IV is computed from standard deviation of the daily raw returns. We calculate the idiosyncratic volatility using daily data over the previous month. Leverage is the log of the ratio of total book value of assets to book value of equity. MOM is the cumulative return from month *t*-7 to *t*-2, where *t* is the current month. The returns of the immediate prior month (*t*-1) are excluded to avoid any spurious association between the prior month return and the current month return caused by thin trading or bid-ask spread effects (Jegadeesh (1990)). TURN is the average share turnover in the past 36 months. L-Beta represents the Pastor and Stambaugh (2003) historical liquidity beta. The *t*-statistics are reported in parentheses. The *t*-statistics for betas are adjusted using the Shanken (1992) correction factor. The *t*-statistics for other variables are Newey and West (1987) consistent.

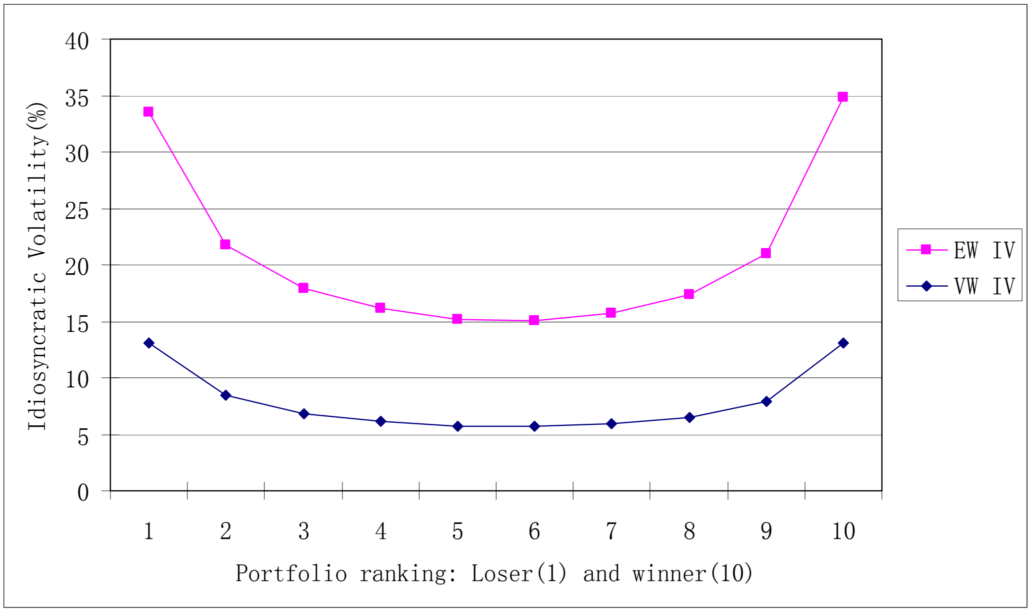
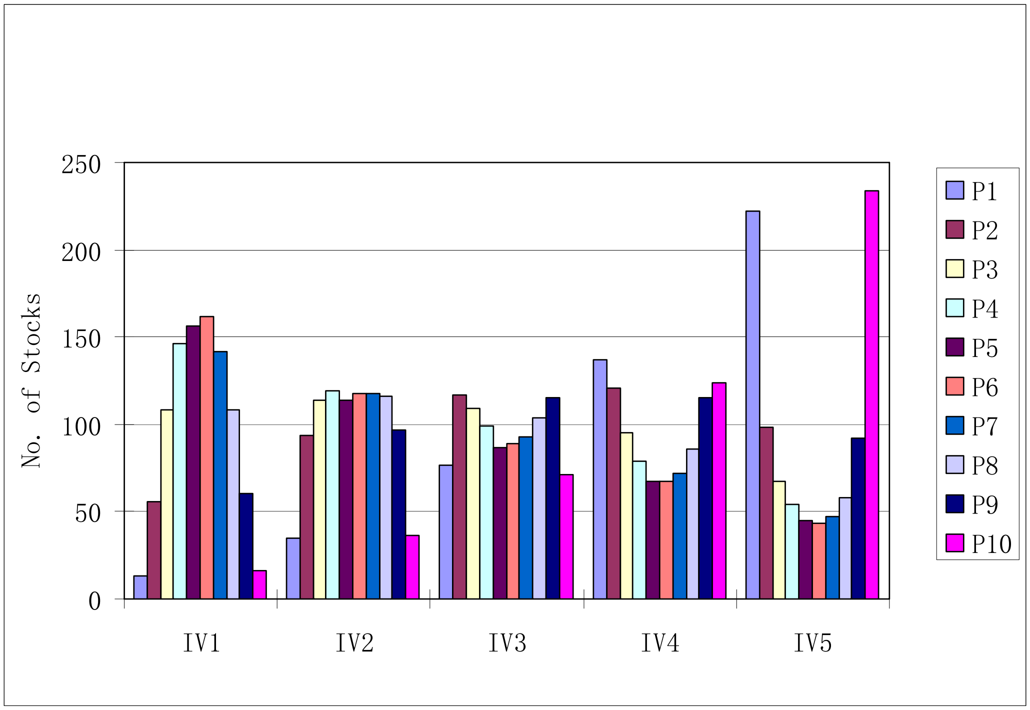


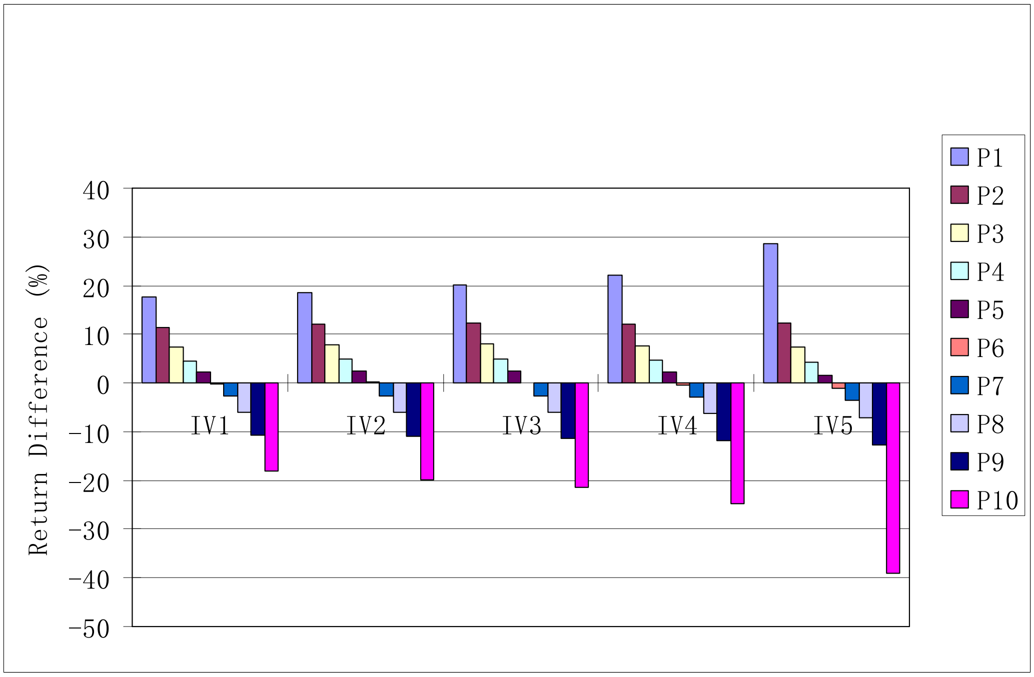
Figure 1. Idiosyncratic Volatility for Past Performance Sorted Portfolios

This figure plots the EW (VW) average percentage level of the idiosyncratic volatility for the portfolios sorted by return performance in the previous one-month formation period. Portfolio 1 (10) is the loser (winner) portfolio. The idiosyncratic volatility of a portfolio is the EW（VW）average of the idiosyncratic volatilities of all the stocks within the portfolio.

Panel A: The Number of Stocks in 50 Portfolios Sorted on Idiosyncratic Volatility and the Previous One Month Return



Panel B: Return Difference between Formation Period and Holding Period for 50 Portfolios Sorted by Idiosyncratic Volatility and Previous One-Month Formation Period Return



Panel C: The Average Market Capitalization (in Million Dollars) of 50 Portfolios Sorted by Idiosyncratic Volatility and the Previous One-Month Formation Period Return

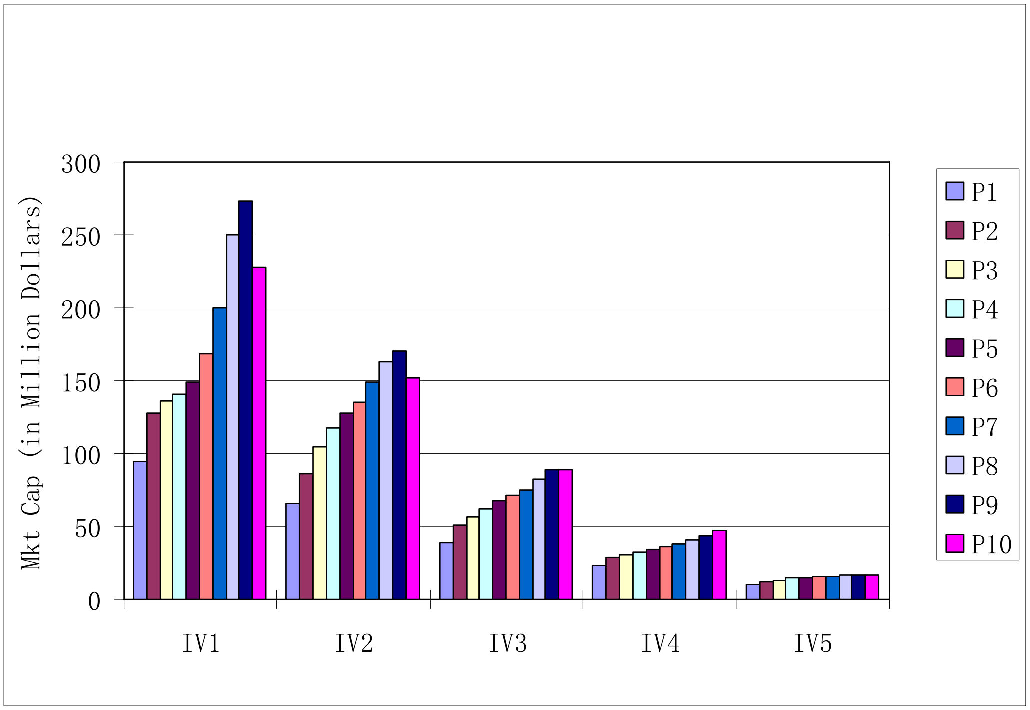


Figure 2. The Characteristics of Idiosyncratic Volatility-Sorted Portfolio and Past One Month Return-Sorted Portfolios

This figure shows the average number of stocks (Panel A), the difference between the average one-month holding period return and the average one-month formation period return (Panel B), and the average market capitalization (Panel C) for each of the 50 portfolios sorted independently by idiosyncratic volatility and the previous one month (formation period) returns.