Return Reversals, Idiosyncratic Risk and Expected Returns

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ABSTRACT

We examine what causes a significant negative intertemporal relation between idiosyncratic risk and stock returns compiled by Ang et al. (2006a, 2006b). Our analyses of idiosyncratic volatility-sorted portfolios indicate that this negative relation is driven by monthly return reversals. 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 the "winners minus losers" portfolio returns added to the conventional three- or four-factor model as a control variable. The cross-sectional regressions confirm that no significant relation exists between ex ante idiosyncratic risk and expected returns in the context of asset pricing once we control for

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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 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 (2004)], or at the firm level [Malkiel and Xu (2002), Fu (2005), Spiegel and Wang (2005), Chua, Goh and Zhang (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. (2004) find that the positive relation documented by Goyal and Santa-Clara (2003) at the aggregate level is not robust.

In a recent study, Ang et al. (2006a) examine idiosyncratic risk at the firm 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

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high idiosyncratic volatility in the current month yield low returns in the following month and the difference between the return on the portfolio with the highest idiosyncratic risk and the return on the portfolio with the lowest idiosyncratic risk is -1.06% on average. In sharp contrast to the previous studies, they document a negative intertemporal relation between realized idiosyncratic risk and future stock returns, thereby raising a substantive "puzzle". 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.

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. These questions deserve 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 driven mostly by the highest idiosyncratic volatility portfolio and this relation is non-monotonic. 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, the first four quintile portfolios have positive average returns while only the fifth quintile portfolio with the highest idiosyncratic risk realizes "abysmally" low average returns in the following month. Thus, understanding the price behavior of the portfolio with the highest idiosyncratic risk seems to be the key to uncovering what drives the

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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 (1995), 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 [Fu (2005)]. Hence, determining whether the ex ante relation between idiosyncratic risk and expected returns is negative will offer significant insight into asset pricing model specifications.

Our objectives in this study are twofold. First, we investigate why the portfolio of common stocks with the highest idiosyncratic risk yields low future returns. In particular, we examine the role of short-horizon return reversals in explaining the negative intertemporal relation between idiosyncratic risk and stock returns in the framework of

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the portfolio-level analysis and time-series regressions. Second, we investigate the role of ex ante idiosyncratic risk in asset pricing with cross-sectional regression at the firm level.

Our key findings are summarized as follows. First, using extended sample-period data, we confirm Ang et al.'s (2006a) finding that the value-weighted (henceforth VW) average monthly return on the portfolio with the highest idiosyncratic volatility is significantly lower than that of the portfolio with the lowest idiosyncratic volatility. The difference is nearly 1% per month and is statistically significant. However, the difference disappears when we calculate equally-weighted (henceforth EW) portfolio returns. This fact has also been documented independently by Bali and Cakici (2006).[1] It suggests that the low return of the highest idiosyncratic volatility portfolio is explained by the lower returns of relatively larger cap stocks within the portfolio.

Second, we find high concentration of both "winners" and "losers" stocks in the portfolio with the highest idiosyncratic volatility. Because winner stocks are on average larger than loser stocks in market capitalization especially in the one-month portfolio formation period, we observe that their return reversals drive down the VW return on the portfolio in the one-month holding period. Specifically, winner (loser) stocks earn lower (higher) returns in the holding period than in the formation period. On average, winner stocks are larger than loser stocks; therefore past winner stocks have greater weight in the VW return on the highest idiosyncratic risk portfolio. Thus, their holding period portfolio returns are lower than those in lower idiosyncratic risk portfolios. Going beyond Bali and

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Cakici (2006), we illustrate why EW portfolios (sorted on idiosyncratic risk) exhibit no significant differences in average returns.

We further demonstrate that the negative relation between idiosyncratic risk and expected returns are driven by return reversals rather than idiosyncratic volatility itself. After controlling for both firm size and past returns, we find that the average return differences between the high and the low idiosyncratic volatility portfolios disappear. However, if we control for firm size and idiosyncratic volatility, significant differences still remain between average returns of formation period return-sorted quintile portfolios, highlighting the role of return reversals more 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 control variable to the conventional three- or four-factor model.

We further demonstrate that the negative relation between idiosyncratic risk and expected returns are driven by return reversals rather than idiosyncratic volatility itself. After controlling for both firm size and past returns, we find that the average return difference between the highest and the lowest idiosyncratic volatility portfolios disappears. We further examine the difference in returns on portfolios sorted by past returns after controlling for firm size and idiosyncratic volatility. Interestingly, the holding-month average return on the past winner portfolio is significantly lower than that

on the past loser portfolio. This evidence suggests a significant short term return reversal. We further conduct time series analysis. 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 the "winners minus losers" portfolio returns added to the conventional three- or four-factor model as a control variable.

Finally, we examine the ex ante relation between idiosyncratic risk and expected returns using cross-sectional regressions built on the framework of Fama-French (1992) and Fama-MacBeth (1973). When we control for return reversals, the relation between ex ante idiosyncratic risk and expected returns no longer exists. This finding is robust regardless of five different measures of ex ante idiosyncratic volatility measures introduced. This result is also robust after we control for momentum, liquidity and leverage. It suggests that ex ante idiosyncratic risk is irrelevant in explaining expected returns in asset pricing once short-horizon return reversals are taken into account.

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. 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 I, we examine why

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the portfolio with the highest idiosyncratic volatility has low return in the future one month holding period. In Section II, 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 III.

I. What Drives the Negative Relation between Idiosyncratic Risk and Expected Returns?

A.   Sample Data and Idiosyncratic Volatility Measure

Our data include NYSE, AMEX, and NASDAQ stock daily returns and monthly returns from July 1963 to December 2004. We obtain 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.

In general, one estimates idiosyncratic volatilities from the residuals of an asset pricing model. To facilitate comparison, however, we measure idiosyncratic risk following Ang et al. (2006a). For each month, we run the following regression for firms that have more than 17 daily return observations in that month:

$$r_{t,d}^i = \alpha_t^i + \beta_{MKT}^i \cdot MKT_{t,d} + \beta_{SMB}^i \cdot SMB_{t,d} + \beta_{HML}^i \cdot HML_{t,d} + \varepsilon_{t,d}^i \tag{1}$$

where, for day d in 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 $\varepsilon^i_{t,d}$ is the resulting residual relative to the Fama-French(1993) three-factor model.[2] We use the standard deviation of daily residuals in month t to measure the individual stock's idiosyncratic risk.[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.

B. Characteristics of Idiosyncratic Volatility-Sorted Portfolios

We first follow the methodology in Ang et al. (2006a) and conduct portfolio-level analyses. At the end of each month, we compute idiosyncratic volatility as the standard deviation of residuals from equation (1) using the daily stock returns over the past month. We construct value-weighted 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 their sample period stops in December 2000.

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In the second column of Table I, we report average value-weighted (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 with the highest idiosyncratic volatility portfolio, 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 Table I that on the average, stocks from the highest idiosyncratic volatility portfolio are much smaller, and have much lower prices. The market value of this portfolio accounts for only 2% of total market.

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[Insert Table I]

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 (month t+1); 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 equally- and value-weighted 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 in the highest idiosyncratic volatility portfolio.

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 the fourth column 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

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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.

C. 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 information [Stiglitz (1989), Summers and Summers (1989) and Jegadeesh and Titman (1995)].

If the high volatility portfolio is dominated by winner stocks in the month in

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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 future returns may be caused by return reversals rather than idiosyncratic volatility itself. 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 II reports the results.

[Insert Table II]

Consistent with previous literature, 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% to 1.92%. Furthermore, as shown in columns 6 and 7, the idiosyncratic volatilities are higher in two extreme loser/winner portfolios (P1 and P10), and lower in the middle portfolios (P5, P6, and P7), regardless of whether we use value- or equal-weighted average.[4] 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 5.7% to 5.8%. Figure 1 illustrates a U-shaped curve for EW idiosyncratic volatility of the ten portfolios sorted by

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the past returns. Finally, we observe from the last column of Table II that although past winner portfolio (P10) and loser portfolio (P1) have similar idiosyncratic volatility, the average size of the past winner stocks is larger than that of loser stocks, and the average price is also higher.

[Insert Figure 1]

D. Idiosyncratic Volatility-Sorted Portfolios after Controlling for Past Returns

To further examine the role of return reversal in the negative relation of idiosyncratic volatility and expected returns, we form two-pass independently sorted portfolios based on of each stock's performance and idiosyncratic volatility. We first sort all stocks into five portfolios based on idiosyncratic volatility, with portfolio IV1 (IV5) representing the lowest (highest) idiosyncratic volatility portfolio. We then allocate stocks to one of ten groups, P1 through P10, based on the rankings of one-month formation period returns, independent of their idiosyncratic volatility. P1 is the extreme losers portfolio and P10 is the extreme winners portfolio. This procedure creates 50 idiosyncratic volatility-past return portfolios as illustrated in Table III.

Panel A of Table III presents the number of stocks within each portfolio. The total number of common stocks assigned to the two extreme portfolios 1 and 10 amounts to 965. Only 29 (or three percent) of 965 of IV1 (the lowest idiosyncratic volatility) stocks are either past winners (P10) or past losers (P1). However, nearly one-half (456 out of 965) of IV5 (the highest idiosyncratic volatility) stocks are either past losers (222) or past

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winners (234). Interestingly, the number of winner stocks is roughly the same as the number of loser stocks in each idiosyncratic volatility-sorted portfolio. Panel A of Figure 2 shows a graphical illustration of the symmetric distribution of each quintile portfolio.

[Insert Table III and Figure 2]

Panels B and C of Table III 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. 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%. These results are consistent with Jegadeesh and Titman (1995) 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. However, high idiosyncratic volatility alone can not explain return reversals completely. For example, the return reversal of the highest idiosyncratic volatility stocks in portfolios P3, P4, and P5 are somewhat smaller than their lowest idiosyncratic volatility counterparts.

Panel C also shows that the EW returns on IV5 in the holding period are less than

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the returns on IV1 from P3 to P10,. In contrast, for the two losers 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 in not always lower than that on the lowest idiosyncratic volatility.

In Panel D, we report the average market capitalization for each of the 50 portfolios sorted by idiosyncratic volatility and returns in the portfolio formation period. The information gleaned from Panel D is important for our analyses to follow given the interrelation among firm size, idiosyncratic risk, and return reversals. We observe that a strong negative relation exists between firm size and idiosyncratic volatility within each of return-based ten decile portfolios: the highest idiosyncratic volatility portfolio dominated by small-sized stocks and the lowest idiocyncratic volatility portfolio associated with by large-sized stocks. In addition, within each of idiosyncratic volatility-sorted portfolio, 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). A graphical illustration is presented in Panel C of Figure 2. This indicates that the 'abysmally' low holding-month value weighted return on the highest idiosyncratic volatility portfolio is driven by the winner stocks in the portfolios, which have larger market values and lower returns in the holding period than the loser stocks in the portfolio.

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Combining the findings from Tables II and III, we can explain the difference in VW and EW returns reported in Table I. 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 loser stocks can compensate for the low returns of winner stocks. However, because the average size of winner stocks is larger than that of loser stocks in the portfolio formation period, winner stocks dominate the value-weighted high idiosyncratic volatility portfolio. The high idiosyncratic volatility portfolio will earn higher VW returns in the *formation* period but significantly lower value-weighted returns in the *holding* period due to the strong return reversal pattern. Therefore, as Table I shows, the VW high idiosyncratic volatility portfolios earn significantly lower return than the low idiosyncratic volatility portfolios in the portfolio holding period (month t), but the equally-weighted 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 (month t-1).

E. Portfolio Returns under Different Formation and Holding Periods

We have thus far found that the negative relation between idiosyncratic volatility

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and stock 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 an *L*-month period from month *t - L - M* to month *t - M*, and then we hold these portfolios from month t to month *t + N* for *N* months. To control for the short-term return reversals and thereby 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 one month and hold these EW or VW portfolios for the next 12 months. The portfolios are rebalanced each month. 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 IV, and plot the VW average monthly returns of all portfolios based on 1/1/12 strategy over 13 months portfolio post-formation period (including the waiting month) in Figure 3.

Table IV indicates that, when a one-month waiting period is imposed between the formation period and the holding period, the negative difference between return on IV5

portfolio and return on IV1 portfolio is no longer significant under the four strategies, regardless of whether the portfolio returns are computed using equal- or value-weighted methods.[5] The only exception is the case of value weighted return of 1/1/1 strategy, in which the negative difference between return on IV5 and return on IV1 is marginally significant. In fact, the negative return differences portfolios 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 average returns of idiosyncratic volatility portfolio 5 from 1/1/12, 12/1/1, and 12/1/12 are even higher than those of other portfolios, although the differences are insignificant. Figure 3 tracks the VW average returns on five IV sorted portfolios from the first month to 13 months after the portfolios are formed. Apparently, returns on IV5 portfolio are only low in the first one or two months after the portfolio is formed; they increase quickly afterwards. Returns on all five idiosyncratic volatility sorted portfolios tend to converge when the holding period gets longer. Overall, our evidence again supports that the negative relation between idiosyncratic volatility and stock returns is due to both short-term return reversals and the large firm size of the past winners in the highest idiosyncratic volatility portfolio. The evidence hence suggests the negative relation does not hold under different formation and holding periods that are longer than one month.

[Insert Table IV and Figure 3]

F. Sorting by Three Variables

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If return reversals are the driving force behind the return difference in idiosyncratic volatility-sorted portfolios, this negative relation between idiosyncratic volatility and future stock returns should disappear after controlling for past stock returns. Given that past returns and idiosyncratic volatility are correlated to many other variables such as firm size at the same time, we conduct a test to evaluate this negative relation using a triple sorting approach in this section.[6]

Each month, we first sort stocks into five portfolios based on each stock's first characteristic or control variable. Then, within each quintile we sort stocks into five subgroups based on the second variable. 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 the first and second characteristics are controlled for.

Under this triple sorting approach, there are many variables of firm characteristics that can potentially serve as good control variables, for example, size, book-to-market, beta, past returns, and price, since they are highly correlated with both idiosyncratic volatility and stock expected returns. Previous literature and our results in Table III suggest that, in particular, firm size and past returns are good candidates because: (i) firm size is highly correlated with expected stock returns [Fama and French (1992, 1993)]; (ii)

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firm size is negatively related to idiosyncratic volatility [Malkiel and Xu (2002)]; (iii) the previous month's return is negatively related to the current month's return [Jegadeesh (1990)]; and (iv) the previous month's return is positively related to idiosyncratic volatility [Duffee (1995) and Fu(2005)]. We therefore examine the relation between idiosyncratic volatility and expected stock returns by controlling for firm size and the previous one-month return simultaneously.

Table V reports the VW average returns for idiosyncratic volatility quintile portfolios after controlling for firm size and past returns. Although the quintile portfolios' VW idiosyncratic volatility increases from 3.84% in portfolio IV1 with the lowest idiosyncratic volatility to 13.27% in portfolio IV5 with the highest idiosyncratic volatility, the average return difference between these two 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% and is insignificant. This result indicates that the negative relation between idiosyncratic volatility and expected returns does not hold once we control for both the past returns and size.[7,8]

[Insert Table V]

If, indeed, it is the return reversal rather than idiosyncratic volatility that causes the return difference in idiosyncratic volatility-sorted portfolios, the return difference between the prior month's return-sorted portfolios should remain significant even after

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we control for firm size and idiosyncratic volatility. In Table VI, 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.

Table VI shows that 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 monthly return decreases monotonically from 1.24% in portfolio 1 (the portfolio of past loser stocks) to 0.66% in portfolio 5 (the portfolio of past winner stocks). The difference in monthly returns between portfolio 5 and portfolio 1 is -0.59%, which is significant. This finding again confirms that the negative relation between idiosyncratic volatility and expected returns are driven by return reversals rather than idiosyncratic volatility itself.

[Insert Table VI]

G. Time-Series Regression Approach

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 a investment strategy and run the time-series regressions of the excess returns on the

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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, that is, if the risk loadings of these three 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 difference between the return on IV5 portfolio and return on IV1 portfolio. To examine if this tradable return can be related to the past return, we add an easily constructed portfolio that takes a long (and short) position in the past winner stocks (and loser stocks) to the following time series regression:

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

where, $r_{p,t}$ is the excess return on portfolio that goes long the highest idiosyncratic portfolio and short the lowest idiosyncratic risk portfolio (IV5-1), *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

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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).

Table VII reports the results of time-series regressions of monthly returns on the "IV5-1" 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 IV5-1 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, we create a predictive variable based on the previous month's returns. For each month,

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we form ten portfolios based on the past one month's returns, with P1 containing past losers and P10 containing past winners. We then create a "winners minus losers" or "WML" return, which is the EW average return difference between the past winner portfolio and the past loser portfolio during the formation period.[9] We include the WML variable as additional explanatory variable in the three- and four-factor models and re-run the time-series regressions. The last two rows of Table VII show that both WML coefficients are negative and statistically significant, which indicates that the return of the idiosyncratic volatility investment strategy (IV5-1) 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 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. The larger the return difference between winner and loser stocks during the past month, the greater the return difference between high and low volatility portfolios in the subsequent month. Once again, the evidence indicates that the low return of high idiosyncratic volatility stocks is driven by the short-term return reversals.

[Insert Table VII]

II. Ex Ante Relation between Return and Idiosyncratic Risk: 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 is still mixed. There is also some theoretical and empirical evidence that 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, Goh and Zhang (2006)]. 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. Ideally, one would run a multiple regression with many explanatory variables on the right-hand side. 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 slopes. 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).

A. Constructing Ex Ante Idiosyncratic Volatility

To the extent that investors make decisions based on ex ante information, it is

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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.

A.1.   Estimating Idiosyncratic Volatility under the Martingale Assumption

Similar to Ang et al. (2006a, 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 $EIV1_{i,t} = IV_{i,t-1}$.

A.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. 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.

A.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 then 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.[10] 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.

A.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

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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.

B. Fama-MacBeth Cross-Sectional Regressions

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

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

(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.[11] $E I \hat{V}_{i,t}$ 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

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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 of t-1 based on last fiscal year information.[12]

In the above model, we use an individual stock's prior month return to control for return reversals. The idea is that if the stock's prior 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:

$$R_{i,t} = \alpha_t + \gamma_{1t}Beta_{i,t-1} + \gamma_{2t}Ln(Size)_{i,t-1} + \gamma_{3t}Ln(BE/ME)_{i,t-1} + \gamma_{4t}E\hat{IV}_{i,t} + \gamma_{5t}RR_{i,t-1} + e_{i,t}$$
(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 is a better proxy for return reversals than the raw

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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 VIII. 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. The *t*-statistics for the *Beta* coefficients are adjusted using Shanken (1992) correction factor and the *t*-statistics for all other estimated coefficients are Newey-West (1987) consistent. The results are for all NYSE/AMEX/NASDAQ stocks over the sample period from July 1963 to December 2004.

Panel A of Table VIII 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 VIII report the cross sectional regression results when various EIV measures are used. The results show that the coefficients of expected idiosyncratic volatility (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 1% 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 estimated by the EGARCH (1,1) model in Panel F or the ARIMA model based on individual stock-level idiosyncratic volatility in Panel C, the coefficient on expected volatility γ_{4t} is not significant.[13]

[Insert Table VIII]

It is noteworthy, however, none of the coefficients on expected idiosyncratic volatility γ_{4t} 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. The one-month formation period returns or demeaned returns take away all of the explaining power of idiosyncratic volatility. For example, in Panel B - where we use the previous month's idiosyncratic volatility as the expected idiosyncratic volatility - the volatility coefficient γ_{4t} is -0.02, 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 0.00, 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. Ang et al. (2006b) find negative relation between idiosyncratic volatility and expected returns after

controlling for the lagged return. However, note that the lagged return in their paper is a firm's return over the previous six months. Therefore the lagged return in their paper does not account for the short term return reversal.

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 evidence to support this argument. No matter what 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 II, 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

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VIII, but for every month we exclude from the sample the 50 winner stocks that have the highest prior-month return.[14] Table IX reports the average coefficients from the cross-sectional regressions with winner stocks excluded. As predicted, the negative relation between idiosyncratic volatility and expected returns disappears even before we control for the return reversals. In particular, the negative coefficients reported for idiosyncratic risks in Panels B, D, and E of Table VIII no longer exist in Table IX. 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.

[Insert Table IX]

C.   Robustness Checks

C.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 can use the CAPM model. Assume that the return of each stock i is driven by a common factor and a firm-specific shock ε_i:

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

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

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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 X. 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 X]

C.2.   NYSE/AMEX Stocks Only

Table X shows that our results still hold if we only include NYSE/AMEX stocks in our sample. 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. [15] The evidence confirms that our results are not driven by small-sized stocks or illiquid stocks listed on NASDAQ.

C.3. 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 X. 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

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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.

C.4. 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 from month t-7 to month t-2, assuming

that the current month is t.

The results in Table X suggest the existence of momentum since the coefficient

on *MOM* is positive and significant. However, the control for momentum does not

change the effect of idiosyncratic risk on average returns. In Table X, the coefficient on

past returns is still negatively significant, and the coefficient on idiosyncratic volatility is

still not significant.

C.5. 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)]. Pastor and Stambaugh (2003) also demonstrate that stocks with high liquidity betas have high average returns. According to Pastor and Stambaugh, 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 X 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 five per cent level, and the coefficient on the liquidity beta is very close to zero and insignificant.[16]

In summary, the negative relation between expected returns and past returns appears to be robust to the inclusion of other explanatory variables in the cross-sectional regressions, suggesting a persistent short term return reversal. More important, we do not find any relation between expected idiosyncratic volatility and expected returns once we control for past returns.

III. Conclusion

Empirical support for a positive relation between a stock's idiosyncratic volatility and expected returns has been mixed. Recently, Ang et al. (2006a, 2006b) document that portfolios with high monthly idiosyncratic volatility deliver low average returns in the next one month, suggesting a negative intertemporal relation between idiosyncratic risk and stock returns. While these results identify an interesting "puzzle," neither the cause of the negative relation nor the relation between ex ante idiosyncratic risk and expected returns is known.

In this paper, we demonstrate that the negative intertemporal relation between idiosyncratic risk and stock returns is 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. We observe that the winner stocks tend to be relatively larger cap stocks in the portfolio formation period and they experience significant return reversals, which drives down the value-weighted return on the portfolio in the next month. In contrast, there is no significant difference in the equally-weighted returns on the five portfolios sorted by idiosyncratic volatility. 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 evidence strongly indicate 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 difference between return on the highest idiosyncratic volatility portfolio and return on the lowest idiosyncratic volatility portfolio is driven by the short term return reversal.

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 no significant relation between ex ante idiosyncratic volatility and expected returns once we control for past returns. Our results

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are robust to the inclusion of other variables such as beta, size, book-to-market, momentum, liquidity, leverage and different measures of idiosyncratic volatility. Overall, our results contribute toward understanding of the role of idiosyncratic risk in asset pricing models and suggest that ex ante idiosyncratic risk does not matter in asset pricing once past returns are taken into account.

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 :

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

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

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

$$h_{i,t} = \omega_i + \delta_1^i h_{i,t-1} + \alpha_1^i \varepsilon_{i,t-1}^2 .$$ (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:

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

$$g(v_{i,t-1}) = \theta \cdot v_{i,t-1} + \gamma \cdot \left[|v_{i,t-1}| - (2/\pi)^{1/2} \right].$$ (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[17] 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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Endnotes

1 Bali and Cakici (2006) find that the negative relation between idiosyncratic risk and expected returns is not robust under different choices of data frequency, weighting scheme and breakpoints in the construction of idiosyncratic volatility sorted portfolios.

2 We thank Kenneth French for our use of data available on his website.

3 We also use the standard deviation of the residual from the capital asset pricing model (CAPM) and the return itself to measure idiosyncratic volatility and obtain qualitatively similar results.

4 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" refers to very positive returns or very negative returns, that is, to winners or to losers.

5 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 5 and portfolio 1 of the above four strategies. Our analysis are based on the value-weighted or equally-weighted return difference of portfolio 5 and portfolio 1 over the long run.

6 The same approach is adopted by Diether et al. (2002). This approach is useful in mitigating the weakness of the two-pass sorting. The conventional double sorting scheme may be vulnerable because both idiosyncratic volatility and stock returns are correlated with many other conditional variables or firm characteristics. If we control for only one factor, we cannot control for the effects of other factors at the same time.

7 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. This result is not reported but available upon request.

8 Note that Ang et al. (2006a) show that after controlling for past returns, the difference of Fama-French (1993) alphas of VW portfolios sorted on idiosyncratic volatility are still negatively significant. We replicate their two-pass sorting based on past return and idiosyncratic volatility and compute the return difference between IV5 and IV1. We find the difference is negative and significant, consistent with the result in the difference of Fama-French (1993) alphas. We conjecture that controlling for past return alone may not be able to simultaneously control for size.

9 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.

10 We also use a portfolio's previous 100 months' idiosyncratic volatility to predict expected idiosyncratic

volatility; the results are similar.

11 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.

12 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.

13 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 $1 \le p \le 3$, $1 \le q \le 3$, according to the Akaike Information Criterion to obtain each stock's forecast.

14 We also exclude portfolio P10, that is, all winner stocks, from our sample and obtain qualitatively similar results.

15 Our empirical analysis indicates that all robustness test results still hold when we use CAPM-based idiosyncratic volatility or raw return-based idiosyncratic volatility.

16 Spiegel and Wang (2005) confirm that stock returns decease with liquidity. They also find that the explanatory power of liquidity is weakened once idiosyncratic risk is included in the regression.