Return Reversals, Idiosyncratic Risk, and Expected Returns

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The empirical evidence on the cross-sectional relation between idiosyncratic risk and expected stock returns is mixed. We demonstrate that the omission of the previous month's stock returns can lead to a negatively biased estimate of the relation. The magnitude of the omitted variable bias depends on the approach to estimating the conditional idiosyncratic volatility. Although a negative relation exists when the estimate is based on daily returns, it disappears after return reversals are controlled for. Return reversals can explain both the negative relation between value-weighted portfolio returns and idiosyncratic volatility and the insignificant relation between equal-weighted portfolio returns and idiosyncratic volatility. In contrast, there is a significantly positive relation between the conditional idiosyncratic volatility estimated from monthly data and expected returns. This relation remains robust after controlling for return reversals. (*JEL* G12, C13)

Whether idiosyncratic risk is priced in asset returns has been the subject of considerable attention in the finance literature. The Capital Asset Pricing Model (CAPM) suggests that idiosyncratic risk should not be priced because it can be eliminated through diversification. Theoretical work by Merton (1987) predicts a positive relation between idiosyncratic risk and stock returns to the extent that

investors do not fully diversify their portfolios due to market imperfections.[1] The empirical results so far are mixed. For instance, Malkiel and Xu (2002); Spiegel and Wang (2006); Chua, Goh, and Zhang (2008); and Fu (2009) find positive relation at the firm or portfolio level using monthly returns to estimate conditional idiosyncratic volatility. Ang et al. (2006, 2009), on the other hand, find a negative relation between the monthly realized idiosyncratic volatility estimated with daily returns in the previous month and the value-weighted (henceforth VW) portfolio return in the subsequent month. Bali and Cakici (2008), however, do not find such a negative relation in the equal-weighted (henceforth EW) returns. Baker and Wurgler (2006) and Boehme et al. (forthcoming) show that conditional on investor sentiment or short-sale constraints, idiosyncratic risk can be positively or negatively correlated with expected returns. The empirical evidence at the market level is also mixed.[2] The inconsistent findings warrant further examination given the rising difficulty in achieving portfolio diversification due to the ever increasing firm-level volatility (Campbell et al. 2001), and the important role of idiosyncratic risk relative to liquidity risk in explaining cross-sectional stock returns (Spiegel and Wang 2006).

In this article, we investigate the relation between idiosyncratic risk and expected returns with a particular interest in understanding the contrasting results between idiosyncratic risk estimated by daily data and monthly data. We show that two well-known empirical facts can explain the different findings: (i) the negative serial correlation in monthly returns of individual stocks, which implies short-term return reversals (Jegadeesh 1990; Lehmann 1990b); and (ii) the positive contemporaneous relation between realized monthly idiosyncratic volatility and stock returns (Duffee 1995; Fu 2009). These two effects combined point to an omitted variable bias when stock returns during the previous month are not explicitly controlled for in studying the relation between idiosyncratic risk and expected returns. In particular, the coefficient on idiosyncratic risk is negatively biased and inconsistent when the estimate for conditional idiosyncratic volatility is based on the realized idiosyncratic volatility of the previous month.[3] The negative bias arises because the coefficient incorporates part of the return reversal that should have been captured by the stock returns of the previous month.

The magnitude of the omitted variable bias depends on the approach to estimating idiosyncratic risk. We construct four estimates of the conditional idiosyncratic volatility in our cross-sectional analysis to quantify the bias. Among them, the first three are constructed from the realized monthly idiosyncratic

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[1] The positive relation is also suggested in other early studies such as Lintner (1965); Levy (1978); Tinic and West (1986); and Lehmann (1990a).

[2] Goyal and Santa-Clara (2003) and Jiang and Lee (2006) report a significant positive relation between idiosyncratic risk and expected monthly stock market returns, while Bali et al. (2005) find that the positive relation documented by Goyal and Santa-Clara (2003) is not robust. Guo and Savickas (2006) report a negative relation between aggregate stock market idiosyncratic volatility and future quarterly stock market returns.

[3] In this article we use the term "volatility" to refer to standard deviation rather than variance.

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volatility series using daily data, while the last estimate is based on monthly data. We then examine how the relation between returns and idiosyncratic volatility varies for different estimates of idiosyncratic risk, particularly before and after the omitted variable bias is corrected. We are especially interested in whether the contrasting findings reported in previous studies continue to exist when short-term return reversals are taken into account.

Our empirical results demonstrate that a negative relation exists between idiosyncratic risk and expected monthly returns in cross-sectional regressions when the estimates of conditional idiosyncratic volatility are based on the time series of realized monthly idiosyncratic volatilities from daily returns. This result is consistent with Ang et al. (2006, 2009). However, after controlling for return reversals, the negative relation is no longer significant. Following Fu (2009), we estimate conditional idiosyncratic volatility with an exponential GARCH (EGARCH) model using monthly returns. We confirm the significantly positive relation between this proxy for idiosyncratic risk and expected returns. More importantly, this relation is still significantly positive after return reversals are controlled for. These findings hold for residuals generated from different asset pricing models and different sample selections. The results are also robust to the inclusion of additional firm characteristics, such as momentum, liquidity, and leverage.

We further conduct portfolio analysis and find that in the presence of short-term return reversals, all else being equal, expected VW portfolio returns are less than expected EW portfolio returns. The difference arises because winner stocks in the VW portfolio have greater weight than loser stocks, and, due to short-term return reversals, they also have lower expected returns. Although the difference is typically small for most portfolios, it is magnified in the portfolio with very high realized idiosyncratic volatility. This is the portfolio with a high concentration of both winner stocks and loser stocks. Since the VW portfolio returns are based on market capitalization in the portfolio formation period, winner stocks receive much larger weight than loser stocks. Their return reversals in the following month dictate a significant difference in the VW returns between high and low idiosyncratic volatility-sorted quintile portfolios, while their EW returns exhibit a very little difference as returns on winners and losers cancel each other out. The reversal effect therefore explains the different results in Ang et al. (2006) and Bali and Cakici (2008). Moreover, our time-series regressions indicate that the abnormal returns that arise from taking a long (short) position in the high (low) idiosyncratic volatility portfolio are fully explained by adding the "winners minus losers" (WML) portfolio return as an additional factor to proxy for return reversals in the conventional three- or four-factor model.

The remainder of the article is organized as follows. In Section 1, we construct four measures of conditional idiosyncratic volatility from daily or monthly returns, which we use to estimate idiosyncratic risk and examine the potential bias caused by omission of previous month stock returns in cross-sectional

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regressions. Section 2 presents empirical evidence on the cross-sectional relation between idiosyncratic risk and expected returns, and its robustness after we control for return reversals. In Section 3, we present an in-depth analysis of the relation between return reversals and realized idiosyncratic volatility and its implications for portfolio returns. Section 4 offers concluding remarks.

1. The Relation between Idiosyncratic Risk and Expected Returns: Cross-Sectional Regressions

1.1 Framework

In this section, we investigate whether idiosyncratic risk is related to expected returns at the firm level in cross-sectional regressions. We employ Fama and MacBeth (1973) regressions of the cross-section of stock returns on idiosyncratic volatility and other firm characteristic variables on a monthly basis and calculate the time-series averages of the coefficients. Our aim is to test whether the coefficient on idiosyncratic volatility is significantly different from zero.

Specifically, we run the following cross-sectional regression each month:

$$R_{i,t+1} = X_{i,t}\beta_t + \gamma_t \sigma_t(\varepsilon_{i,t+1}) + \varepsilon_{i,t+1}, \tag{1}$$

where $R_{i,t+1}$ is stock i's return in month $t + 1$, and $X_{i,t}$ is a vector of firm characteristics that are observable or measurable in month t. The first element in this vector is a constant. We include other variables known to explain the cross-sectional variation in stock returns, such as estimates of beta, size, and book-to-market ratios. $\varepsilon_{i,t+1}$ is the model residual, and $\sigma_t(\varepsilon_{i,t+1})$ is conditional idiosyncratic volatility, given as the standard deviation of the residual for stock i in month $t + 1$ conditioned on the information available in month t. We use the conditional idiosyncratic volatility as our proxy for idiosyncratic risk.

Note that direct estimation of Equation (1) is impossible because conditional idiosyncratic volatility is unobservable. Thus, in practice we estimate

$$R_{i,t+1} = X_{i,t}\beta_t + \gamma_t \hat{\sigma}(\varepsilon_{i,t+1}|\Omega_t) + \varepsilon_{i,t+1}, \tag{2}$$

where $\hat{\sigma}(\varepsilon_{i,t+1}|\Omega_t)$ is the estimate of the idiosyncratic volatility that is conditioned on the information set known at time t, Ω_t.

1.2 Estimates of idiosyncratic volatility

The information set Ω_t typically includes some measure of realized idiosyncratic volatility for month t and prior months. In this study, we define realized monthly idiosyncratic volatility for a stock as the standard deviation of the daily return residuals relative to the Fama and French (1993) three-factor model for a given month. We construct three estimates to extract the information from Ω_t in estimating conditional idiosyncratic volatility at month $t + 1$, which use different weighting schemes of lagged realized volatilities. In addition, to evaluate

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the effect of the data frequency on the accuracy of the estimate of idiosyncratic risk, we also construct an estimate from monthly returns. These four estimates enable us to examine the robustness of the cross-sectional relation between expected stock returns and idiosyncratic volatility after controlling for other firm characteristic variables.

1.2.1 Estimating idiosyncratic volatility under the martingale assumption. We first use stock i's realized idiosyncratic volatility in month t, $RIV_{i,t}$, as the forecast of its idiosyncratic volatility in month $t + 1$. This method implicitly assumes that the idiosyncratic volatility series follows a martingale.[4] Under the martingale assumption, $RIV_{i,t}$ is the conditional expectation of stock i's idiosyncratic volatility in month $t + 1$.

1.2.2 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 monthly 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 over the previous twenty-four months.[5] This method gives us our second idiosyncratic volatility estimate.

1.2.3 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 one hundred portfolios based on a stock's realized idiosyncratic volatility that month. We compute a portfolio's monthly idiosyncratic volatility as the VW average idiosyncratic volatility of its component stocks. We rebalance the portfolios each 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 conditional idiosyncratic volatility based on its realized values over the previous thirty-six months.[6] Finally, we assign the predicted value of a portfolio to individual stocks according to their realized idiosyncratic volatility ranking each month. This measure serves as our third proxy for the idiosyncratic volatility of each stock.

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[4] Although this assumption contrasts with the evidence documented in other studies (e.g., Jiang and Lee 2006; Fu 2009), we include the resulting estimate to compare with more sophisticated estimates and evaluate the effect of this assumption.

[5] To obtain the best-fit ARIMA model, we first de-trend the data using a linear trend model, and then take the residuals and compute autocovariances for the number of lags it takes for the autocorrelation to be insignificantly different from zero. We run a regression of the current values against the lags using the autocovariances in a Yule-Walker framework. This process is repeated until only significant parameters remain.

[6] We also use a portfolio's idiosyncratic volatility over the previous one hundred months to predict idiosyncratic volatility and find similar results.

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1.2.4 Estimating idiosyncratic volatility using EGARCH. Monthly idiosyncratic volatility can also be estimated from monthly returns. Bali and Cakici (2008) compare the estimates from different data frequency and find that the realized monthly idiosyncratic volatility from daily data is subject to market microstructure biases. Using the conditional idiosyncratic volatility estimates from GARCH (1, 1) and EGARCH (1, 1) models as benchmarks, they show that the idiosyncratic volatility based on past monthly returns provides a more accurate prediction of conditional idiosyncratic volatility both in sample and out of sample.

In our study, we use an EGARCH model to estimate conditional idiosyncratic volatility from monthly returns. Developed by Nelson (1991), this model is a generalization of the ARCH model of Engel (1982) and the GARCH model of Bollerslev (1986). These models estimate the mean and variance of returns jointly and capture volatility persistence from residual variance and past squared innovations. The EGARCH model accommodates the asymmetric property of volatility, that is, the leverage effect, whereby negative surprises increase volatility more than positive surprises. Foster and Nelson (1996) show that the resulting conditional volatility estimate is a weighted average of the lagged realized idiosyncratic volatilities from monthly returns.

Following the approach in Fu (2009), we choose the best-fit EGARCH model among nine EGARCH (p, q) models (where $p = 1, 2, 3$, and $q = 1, 2, 3$) for each individual stock according to the Akaike Information Criterion. In each EGARCH model, we estimate mean returns using the Fama and French (1993) three-factor model. We then estimate conditional idiosyncratic volatility each month from the chosen model with a rolling window of the previous thirty months. The resulting forecast for the next month comprises our fourth idiosyncratic volatility measure. Fu (2009) indicates that this estimate is a better measure of idiosyncratic risk when compared with realized monthly idiosyncratic volatility from daily returns.

1.3 Omitted variable bias

The omitted variable bias in estimating the coefficient on idiosyncratic risk, γ_t, in Equation (2) arises when there is a missing variable in the set of predetermined explanatory variables such that the omitted variable is both a determinant of the dependent variable and correlated with one or more of the included explanatory variables.

An important explanatory variable in the context of this study is the previous month's stock return, which accounts for return reversals:

$$R_{i,t+1} = X_{i,t}\beta_t + \gamma_t \hat{\sigma}(\varepsilon_{i,t+1} \mid \Omega_t) + \lambda_t R_{i,t} + \varepsilon_{i,t+1}. \tag{3}$$

In the absence of this variable, the relation between idiosyncratic risk and expected returns may become distorted because of the negative first-order

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correlation in monthly stock returns, first documented by Jegadeesh (1990) and generally regarded as evidence of short-term return reversals of individual stocks, and the positive contemporaneous relation between realized idiosyncratic volatility and stock returns. Using the monthly idiosyncratic volatility constructed from daily residuals from the Fama and French (1993) three-factor model during the period 1963–2004, we find that the average cross-sectional correlation between realized idiosyncratic volatility and stock returns in the same month is 0.15, which is significantly positive. Thus, omission of the previous month's stock returns in Equation (3) can cause the estimated coefficient of idiosyncratic risk to suffer from the omitted variable bias.

To evaluate the effect of return reversals directly, we exclude firm characteristic variables in Equation (2) and obtain the OLS estimate of the coefficient on idiosyncratic risk as follows:[7]

$$\hat{\gamma}_t = (V'_t \cdot V_t)^{-1} V'_t R_{t+1}, \tag{4}$$

where $V_t = [\hat{\sigma}(\varepsilon_{1,t+1} \,|\, \Omega_t)...\hat{\sigma}(\varepsilon_{N,t+1} \,|\, \Omega_t)]'$, $R_{t+1} = [R_{1,t+1}...R_{N,t+1}]'$, and N is the number of stocks. V_t is the vector of each stock's conditional idiosyncratic volatility estimate, and R_{t+1} is the vector of stock returns in month $t+1$. Taking the expectation of Equation (3) and substituting it into Equation (4) yields

$$E(\hat{\gamma}_t \,|\, \Omega_t) = \gamma_t + (V'_t \cdot V_t)^{-1} V'_t R_t \cdot \lambda_t. \tag{5}$$

The second term on the right-hand side of Equation (5) is negative for two reasons. First, because of the positive contemporaneous correlation between realized idiosyncratic volatility and stock returns, the term $V'_t R_t$ is positive if the realized idiosyncratic volatility in month t is used as proxy for the estimate of conditional idiosyncratic volatility. More generally, this term is positive as long as the estimate of conditional idiosyncratic volatility (V_t) is positively correlated with stock returns (R_t). Second, λ_t is negative because of the return reversals. Therefore, by estimating Equation (2) instead of Equation (3), the coefficient on idiosyncratic volatility ($\hat{\gamma}_t$) is negatively biased because it includes the return reversal effect that should be captured by λ_t.[8]

Of course, different estimates put different weights on lagged realized idiosyncratic volatilities and therefore will produce different magnitudes of the omitted variable bias. The magnitude of the bias depends on the relation between the previous month stock returns (R_t) and the conditional idiosyncratic volatility estimates (V_t). Nevertheless, it is clear from Equation (5) that when

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[7] The constant term in the model will not affect the bias. In theory, the bias also depends on the relation between the omitted variable and other explanatory variables. Our empirical results indicate that the negative bias still exists when these firm characteristic variables are included.

[8] We are grateful to the referee for suggesting this comparison.

short-term return reversals are not taken into account, the negative bias will exist if there is a positive contemporaneous correlation between stock returns and the idiosyncratic volatility estimates.

2. Empirical Results

2.1 Data and realized idiosyncratic volatility measure

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

We measure realized idiosyncratic volatility following the approach in Ang et al. (2006, 2009) and Bali and Cakici (2008). Specifically, for each month, we run the following Fama and French (1993) three-factor regression for firms that have more than seventeen daily return observations in that month:

$$r_{t,d}^i = \alpha_t^i + \beta_{MKT}^i \cdot MKT_{t,d} + \beta_{SMB}^i \cdot SMB_{t,d} + \beta_{HML}^i \cdot HML_{t,d} + \varepsilon_{t,d}^i, \quad (6)$$

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 $HML_{t,d}$ are the returns on portfolios formed to capture size and book-to-market effects, respectively, and $\varepsilon_{t,d}^i$ is the resulting residual.[9] We use the standard deviation of daily residuals in month t to measure the individual stock's idiosyncratic volatility for this month.[10]

2.2 Cross-Sectional regressions

Our models are similar to Fama and MacBeth (1973) and Fama and French (1992), with the exception that we include conditional idiosyncratic volatility and the prior month's individual stock returns. Specifically, $X_{i,t} = [1 Beta_{i,t} Ln(Size)_{i,t} Ln(BE/ME)_{i,t}]$ in Equations (2) and (3), where $Beta_{i,t}$ is the estimate of stock i's beta in month t, $Ln(Size)_{i,t}$ is the log of stock i's market capitalization at the end of month t, and $Ln(BE/ME)_{i,t}$ is the log of stock i's book-to-market ratio as of the end of month t based upon the last fiscal year's

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[9] We thank Kenneth French for making the data available on his website.

[10] Note that realized monthly idiosyncratic volatility for a stock is not constructed from the standard deviation of the monthly residuals in Equation (1). To measure the monthly idiosyncratic volatility of stock i, we follow French, Schwert, and Stambaugh (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.

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information.[11,12] We use the four measures described in Section 1.2 to estimate the conditional volatility $\hat{\sigma}(\varepsilon_{i,t+1} \mid \Omega_t)$ in both equations.

To estimate Equation (3), we use the returns of individual stocks in the prior month to control for return reversals. The idea is that if a stock's previous month return is too high (low), it will tend to reverse the following month and earn a low (high) return.[13] We run cross-sectional regressions with Equations (2) and (3) each month and then report the time-series averages of estimated coefficients in Table 1. Among all the models shown in Table 1, model 1 summarizes the regression results with idiosyncratic volatility excluded and the remaining models report the results with each of the four conditional idiosyncratic volatility estimates introduced. In all of the models with lagged monthly returns included, the coefficient on this variable is significantly negative, consistent with Jegadeesh (1990). The coefficient on idiosyncratic volatility is not consistent across the four measures. Specifically, in model 2, where we use the previous month's realized idiosyncratic volatility as the measure of conditional idiosyncratic volatility, the coefficient estimate is significant and negative 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. (2009). The same result also appears in model 6, where conditional idiosyncratic volatility is estimated from the ARIMA model on portfolio idiosyncratic volatility. Nevertheless, this negative relation is not robust. When idiosyncratic volatility is estimated by the ARIMA model based on individual stocks in model 4, the coefficient on idiosyncratic volatility is negative, but insignificant. In model 8, when we estimate conditional idiosyncratic volatility with an EGARCH model from monthly returns, we observe a significantly positive relation between idiosyncratic risk and stock returns in the cross-section. The *t*-statistic of the coefficient on idiosyncratic volatility is as high as 15.31. This result is consistent with the relation documented in Spiegel and Wang (2006) and Fu (2009).

Note that for each of these estimates of conditional idiosyncratic volatility, the coefficient becomes larger after controlling for stock returns in the previous

[11] To reduce errors-in-variables problems, we follow Fama and French (1992) and assign portfolio betas to individual stocks. In particular, each month, all stocks are sorted into ten groups by market capitalization. Within each size group, stocks are sorted again by their betas into ten groups. The beta of each stock is estimated from a market model using the previous twenty-four to sixty months of returns, as available. The one hundred resulting portfolios 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 in 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 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 year $t + 1$.

[13] Returns in the prior month could be a noisy proxy for return reversals. Since the high (low) returns of winner (loser) stocks could be due to their fundamental risk, we also use the demeaned returns in the previous month to proxy for return reversals in the regressions, where the mean return of each stock is measured as its average return over the past thirty-six months. The empirical results are similar to those based on raw returns.

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Table 1
Relation between idiosyncratic risk and expected returns: cross-sectional evidence

Models	Beta	Size	B/M	Ret(−1)	IV1	IV2	IV3	IV4
1	−0.004	−0.147	0.381	−0.068				
	(−0.01)	(−3.23)	(4.90)	(−14.02)				
2	0.018	−0.188	0.301		−0.019			
	(0.08)	(−4.79)	(4.25)		(−2.44)			
3	−0.007	−0.109	0.384	−0.070	0.001			
	(−0.03)	(−2.83)	(5.22)	(−14.57)	(0.15)			
4		−0.179	0.332			−0.004		
		(−4.28)	(3.98)			(−0.28)		
5		−0.124	0.399	−0.068		0.002		
		(−2.86)	(4.63)	(−14.51)		(0.14)		
6		−0.217	0.312				−0.032	
		(−4.75)	(3.74)				(−3.35)	
7		−0.131	0.387	−0.063			−0.013	
		(−2.94)	(4.54)	(−13.18)			(−1.18)	
8		0.309	0.819					0.251
		(7.63)	(10.88)					(15.31)
9		0.346	0.877	−0.067				0.255
		(8.20)	(11.34)	(−15.82)				(15.07)

This table reports the average coefficients in the Fama and MacBeth cross-sectional regressions for all NYSE/AMEX/NASDAQ individual stocks over the period from July 1963 to December 2004. IV1 is the realized idiosyncratic volatility in the previous month. IV2 is estimated by the best-fit ARIMA model based on an individual stock's realized idiosyncratic volatility over the previous twenty-four-month period. IV3 is estimated by the ARIMA model based on a portfolio's realized idiosyncratic volatility over the previous thirty-six-month period, where one hundred portfolios are formed based on the idiosyncratic volatility of an individual stock in the previous month. IV4 is estimated by an EGARCH model following the approach in Fu (2009), based on monthly stock returns over the previous thirty months. Beta is estimated using the one hundred size/beta double-sorted portfolios 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 in Fama and French (1992). Ret(−1) is the individual stock return during the previous month. Returns and idiosyncratic volatilities are in percentages. We run cross-sectional regressions every month and report the time-series averages of the coefficients. The t-statistics are reported in 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.

month. This evidence indicates that a negative bias exists for all four estimates when the return reversal effect is not controlled for. However, the magnitude of the negative bias is much larger for the estimates based on realized idiosyncratic volatility using daily returns. In fact, two of these three estimates generate coefficients with positive signs. For instance, consider model 2, which reports the results from using the previous month's realized idiosyncratic volatility as the proxy for conditional idiosyncratic volatility. The volatility coefficient is −0.019 with a t-statistic of −2.44 when we do not control for return reversals, whereas the coefficient is 0.001 with a t-statistic of 0.15 when we add the prior month return to the regression in model 3, indicating that the negative relation between realized idiosyncratic volatility and expected returns is biased and indeed driven by return reversals.[14] The coefficient on idiosyncratic volatility changes from −0.004 in model 4 to 0.002 in model 5, with a smaller magnitude of the omitted variable bias when the ARIMA model is used to

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[14] Ang et al. (2009) find a negative relation between idiosyncratic volatility and expected returns after controlling for the lagged returns. However, the lagged returns in their paper are stock returns over the previous six months. Therefore, their measure takes into account both short-term return reversals and the momentum effect.

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estimate conditional idiosyncratic volatility for individual stocks. In addition, none of the coefficients on idiosyncratic volatility estimates from daily data are significant after controlling for return reversals, which suggests that the previous one-month return removes the explanatory power of daily return-based idiosyncratic volatility when it is included in cross-sectional regressions.

In contrast, for the conditional idiosyncratic volatility estimate based on monthly returns, the coefficient is still highly significant in model 9 when we control for return reversals. The coefficient increases very little from 0.251 to 0.255, with a *t*-statistic of 15.07. This result indicates that the positive relation between idiosyncratic volatility estimated from monthly returns and future stock returns is robust, confirming the findings in Spiegel and Wang (2006) and Fu (2009).

Early theories, such as those proposed in Merton (1987), suggest 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 idiosyncratic risk should deliver higher expected returns. Unlike the widely documented size effect, Merton (1987) also predicts that larger firms should have higher returns controlling for idiosyncratic risk. Both assertions are confirmed in model 8 when the conditional idiosyncratic volatility is estimated from an EGARCH model using monthly returns. Model 9 further shows that these findings are robust after controlling for the previous month's stock returns. It is also instructive to review the positive relation between idiosyncratic risk and expected returns from Equation (2). Since there is a positive relation between realized idiosyncratic volatility and stock returns in the same month, in principle an estimate of conditional idiosyncratic volatility should also be positively related to future stock returns if it is accurate enough. Moreover, Equation (5) implies that if the estimated coefficient on conditional idiosyncratic volatility is positive without controlling for short-term return reversals, it will be larger after the negative omitted variable bias is corrected, assuming that this idiosyncratic volatility estimate is positively related to stock returns contemporaneously. By controlling for stock returns in the previous month, our results support the positive relation between idiosyncratic risk and expected stock returns, and also suggest why the daily and monthly data produce contrasting results in previous studies.

2.3 Additional tests

We run cross-sectional regressions for different samples using realized idiosyncratic volatility as the proxy for idiosyncratic risk. First, we include only NYSE/AMEX stocks. The evidence in panel A of Table 2 confirms that our results are not driven by small or illiquid stocks listed on the NASDAQ.[15] Second, we exclude stocks with extremely high idiosyncratic volatility to avoid

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[15] When we exclude penny stocks (stock prices less than $5) from the NYSE/AMEX universe, a negative relation between idiosyncratic volatility and future returns arises if we use raw-return-based idiosyncratic volatility, even after past returns are controlled for. This happens because more losers than winners are excluded from the sample

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Table 2
Relation between idiosyncratic risk and expected returns: robustness test

Beta	Size	B/M	Ret(−1)	Total-IV	CAPM-IV	FF-IV	EGARCH-IV	Leverage	MOM	TURN	L-Beta
Panel A: NYSE/AMEX stocks only											
0.020 (0.01)	−0.083 (−2.38)	0.295 (4.03)	−0.067 (−12.25)			−0.014 (−1.50)					
Panel B: Excluding stocks with extremely high idiosyncratic volatility											
0.134 (0.64)	−0.112 (−3.02)	0.360 (5.05)	−0.063 (−12.65)			−0.024 (−1.55)					
Panel C: All stocks											
−0.007 (−0.03)	−0.110 (−2.86)	0.384 (5.23)	−0.070 (−14.54)								
−0.007 (−0.03)	−0.114 (−3.01)	0.384 (5.18)	−0.070 (−14.52)	0.090 (0.10)							
−0.003 (−0.03)	−0.107 (−2.76)	0.372 (4.93)	−0.071 (−14.97)		−0.184 (−0.21)						
−0.003 (−0.14)	−0.128 (−3.32)	0.360 (4.84)	−0.071 (−14.82)			0.003 (0.34)					
−0.060 (−0.27)	−0.090 (−2.37)	0.330 (4.68)	−0.074 (−15.52)			−0.002 (−0.24)		−0.135 (−2.03)			
0.175 (0.85)	−0.106 (−2.70)	0.375 (5.04)	−0.073 (−14.78)			−0.000 (−0.00)			0.531 (3.15)		
0.012 (0.05)	−0.105 (−2.73)	0.294 (3.99)	−0.083 (−19.42)			0.003 (0.34)				−1.960 (−1.45)	
0.108 (0.55)	−0.118 (−2.98)	0.344 (4.49)	−0.081 (−18.57)			0.001 (0.08)		−0.113 (−1.78)	0.740 (3.91)	−2.827 (−1.99)	0.007 (0.09)
−0.063 (−0.27)	0.354	0.887	−0.070			0.002 (0.23)		−0.110 (−1.65)	0.711 (3.80)		−0.005 (−0.08)
							0.262	0.012			

0.345	0.906	−0.075	0.260		0.634							−10.708		0.108	
(8.21)	(11.05)	(−16.47)	(14.97)	(0.016)	(3.39)							(−6.60)		(1.46)	
0.400	0.719	−0.074	0.295												
(8.21)	(11.39)	(−19.40)	(14.89)												
0.397	0.925	−0.072	0.289												
(8.94)	(10.10)	(−17.64)	(15.43)												
0.373	0.689	−0.080	0.292	−0.073	0.524							−11.124			
(9.34)	(11.88)	(−16.33)	(14.78)	(−1.14)	(2.83)							(−6.30)			
0.372	9.49	−0.078	0.284	0.003	0.502									0.092	
(8.43)	(−20.84)	(15.22)	(0.04)	(2.67)									(1.35)		
0.883															
(9.00)	(11.62)	(−19.88)	(14.64)												

This table reports the average coefficients in the Fama and MacBeth cross-sectional regressions. Panel A reports the results for the sample without NASDAQ stocks. Panel B corresponds to the sample without the top 10% winner stocks and the top 10% loser stocks in the highest idiosyncratic volatility quintile portfolio. Panel C corresponds to all NYSE/AMEX/NASDAQ individual stocks over the period from July 1963 to December 2004. The variables *Beta, Size, B/M,* and *Ret*(−1) are the same as in Table 1. Total-IV is the idiosyncratic volatility estimated by the standard deviation of daily raw returns over the previous month. CAPM-IV is the idiosyncratic volatility relative to the CAPM model. FF-IV is the idiosyncratic volatility relative to the Fama and French (1993) model. These three monthly idiosyncratic volatility estimates are based on daily returns in the previous month. EGARCH-IV is the idiosyncratic volatility estimated by an EGARCH model using monthly returns in the previous thirty months, following the approach in Fu (2009). Leverage is the log of the ratio of book value of assets to book value of equity. MOM is the cumulative return from month $t − 6$ to $t − 1$, with $t + 1$ representing the current month. TURN is the average share turnover in the past thirty-six months. L-Beta represents the Pastor and Stambaugh (2003) 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.

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sampling error caused by possible outliers.[16] Panel B indicates that the coeffi-
cient on idiosyncratic risk is not significant once we control for return reversals,
the same as in the full sample case.

Because realized idiosyncratic volatilities are constructed from the residuals,
the relation between idiosyncratic volatility and expected returns reported above
could be driven by the particular model (i.e., Fama and French 1993) used.
Therefore, we also use different estimates of realized idiosyncratic volatility to
verify the robustness of our results.

Instead of using the Fama and French (1993) three-factor model given in
Equation (6), we use the standard deviation of the daily residuals obtained
from the CAPM model to measure realized idiosyncratic volatility. We also
use the standard deviation of the daily stock returns within a month as an
estimate of realized idiosyncratic volatility. Jiang and Lee (2006) suggest that
most of the stock return volatility (approximately 85%) is idiosyncratic. The
time-series averages of the coefficient estimates in panel C of Table 2 show that
for these estimates based on daily data, the role of idiosyncratic volatility is
not significant when we control for return reversals and hence that our results
are not driven by any particular approach to measuring realized idiosyncratic
volatility.[17]

Next, we control for several explanatory variables that might be related to
past returns or idiosyncratic volatility in our cross-sectional regressions. We
first control for leverage, where book leverage is measured as the natural log
of the ratio of the book value of assets to book value of equity. Consistent with
Fama and French (1992), we find a negative relation between book leverage
and expected returns in most of the regressions. Controlling for leverage does
not change the effect of idiosyncratic risk and prior monthly returns on stock
returns in the next month; the coefficient on prior monthly returns is still
significantly negative, while the coefficient on idiosyncratic volatility depends
on the data frequency, which we use to estimate idiosyncratic risk. If we use
realized idiosyncratic volatility constructed from daily returns, the coefficient
becomes insignificant once we include stock returns in the previous month.
However, it is significantly positive when we use the EGARCH model based
on monthly returns to estimate conditional idiosyncratic volatility. The leverage
effect is also weaker for the latter estimate.

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with the relatively lower prices of loser stocks. The negative relation is driven in particular by the return reversals
of winner stocks, due to their positive contemporaneous correlation with realized idiosyncratic volatility. The
coefficients on past returns are still significantly negative in all regressions. These results are available upon
request.

[16] We divide the highest idiosyncratic volatility portfolio in Ang et al. (2006) into ten subportfolios with the same
number of stocks based on their past return performance. The first and last subportfolios include the winners and
losers with extremely high idiosyncratic volatilities. Most are penny stocks (with prices less than $5). We thus
exclude around 4% of all stocks from our cross-sectional regressions.

[17] For the sake of brevity, the remaining robustness tests reported in Table 2 are based on residuals generated from
the Fama and French three-factor model. Unreported empirical results are consistent when we use CAPM-based
idiosyncratic volatility or raw-return-based idiosyncratic volatility.

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Our second variable of interest is momentum, where momentum is measured as the cumulative returns over the six months from month $t - 6$ to month $t - 1$, with the previous month being t and the current month being $t + 1$. Consistent with Jegadeesh and Titman (1993), our results indicate that the coefficient on momentum is positive and significant in all of the models. However, controlling for momentum does not change the effect of idiosyncratic risk on expected returns. Once again, we document a robust positive relation between idiosyncratic risk and expected returns when the estimate is generated from the EGARCH model based on monthly returns, while the negative relation becomes insignificant for the daily return-based realized idiosyncratic volatility in the previous month once we control for return reversals.

Lastly, we control for the liquidity effect because idiosyncratic volatility measures could simply be capturing liquidity risk. We use both the average turnover ratio (the ratio of share volume to shares outstanding) in the previous thirty-six months and the Pastor and Stambaugh (2003) liquidity beta as proxies for liquidity. Our results are robust to liquidity risk since the sign and significance of the coefficients on past returns are unchanged, and the coefficients on idiosyncratic volatility are significantly positive for the EGARCH volatility estimate using monthly returns, but small and insignificant for realized idiosyncratic volatility estimated with daily returns. Consistent with previous studies, we find that less liquid stocks are expected to have higher future returns. However, Spiegel and Wang (2006) show that the explanatory power of liquidity is weakened once idiosyncratic volatility is included in the regression. Our results are consistent with their findings from monthly return-based conditional idiosyncratic volatility estimates. We also find that the coefficient on the turnover ratio is only marginally negative at most, and the coefficient on liquidity beta is very close to zero and insignificant, when idiosyncratic volatility is estimated based on daily returns.

3. Return Reversals and Realized Idiosyncratic Volatility: Portfolio Analysis

3.1 VW and EW portfolio returns
In this section, we further examine how the omission of lagged returns can affect the relation between idiosyncratic volatility and expected returns in a portfolio analysis. Return reversals imply that, all else being equal, expected VW portfolio returns will be less than expected EW portfolio returns, given that the portfolio weights are dependent on the market capitalization of the component stocks in the portfolio formation month.[18]

The portfolio return difference caused by the two different weighting schemes is much larger for the portfolio with very high idiosyncratic volatility.

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[18] The short-term return reversals might be due to the lead-lag effects in stock returns (Lo and MacKinlay 1990) or corrections of prior stock price overreactions (Jegadeesh and Titman 1995). However, the omitted variable bias does not depend on the source of return reversals.

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Table 3
Returns of portfolios sorted by idiosyncratic volatility

Portfolio	$VW_t(t+1)$	$EW(t+1)$	$VW_t(t)$	$VW_t(t+2)$
IV1	0.969	1.207	1.126	1.028
IV2	1.075	1.439	1.603	1.021
IV3	1.120	1.466	2.157	1.112
IV4	0.746	1.300	3.016	0.877
IV5	−0.026	1.202	8.061	0.523
IV5-IV1	−1.000	−0.005	6.935	−0.505
	(−2.95)	(−0.01)	(9.74)	(−1.38)

This table reports the returns 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 returns over the previous month. Portfolio IV1 (IV5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. Returns are measured in monthly percentages. $EW(t+1)$ is the EW average monthly return in the month $(t+1)$ following the portfolio formation period (t). $VW_i(j)$ denotes the VW average monthly returns in month j, where the weights are based upon market capitalization at the end of month i. In this table, we assume that all portfolios are formed at the end of month t; therefore, the component stocks are the same in all columns. The row "IV5-IV1" refers to the difference in monthly returns between portfolio IV5 and portfolio IV1. Newey and West (1987) robust t-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

The difference arises due to the high concentration of winner and loser stocks in this portfolio and their strong short-term return reversals. Indeed, using the sample from July 1963 to December 2004, we observe a high contemporaneous cross-sectional correlation (0.51) between realized idiosyncratic volatility and absolute stock returns. We also document significantly negative (−0.06) and positive (0.02) correlations between realized idiosyncratic volatility in the previous month (t) and stock returns in the following month $(t+1)$, conditioning on whether stock returns are positive or negative in the previous month (t). VW portfolios, where the portfolio weights are determined by stock market capitalization at the end of the portfolio formation month, place greater weight on winner stocks. These stocks are also the stocks that realize lower expected returns, owing to the presence of short-term return reversals. In contrast, equal weighting puts the same weight on all stocks, and thus the reversal effect on winners and losers cancels out. Hence, EW expected returns should be larger than VW expected returns.

We provide evidence in support of this argument in Table 3. We construct quintile portfolios based on the idiosyncratic volatility ranking 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. The second column reports the VW average returns for five portfolios sorted by idiosyncratic volatility in the holding month $(t+1)$, where the weights are based on market capitalization at the end of the portfolio formation month (t). Consistent with Ang et al. (2006), the return on portfolio IV5, which contains stocks with the highest idiosyncratic volatility, is significantly lower than the returns on the other four portfolios, although the returns across the first four portfolios are very close. The difference in monthly

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returns between portfolio IV5 and portfolio IV1 is -1.0% per month, with a t-statistic of -2.95.

Note that the return difference between IV5 and IV1 depends upon the weighting scheme used in the portfolios. In the third column of Table 3, we confirm the finding of Bali and Cakici (2008) that the monthly return difference between these two portfolios 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%. The EW average returns on all five idiosyncratic volatility-sorted portfolios are quite similar. This result arises because both winner and loser stocks experience return reversals, and the high returns of loser stocks offset the low returns of winner stocks in the holding month.

Column 4 of Table 3 reports the VW returns on the five portfolios in the portfolio formation month t, where the portfolio weights are again based on market capitalization at the end of month t, as in column 2. Clearly, there is a significantly positive contemporaneous relationship between idiosyncratic volatility and portfolio returns. The VW average return on portfolio IV5 in portfolio formation month t is significantly higher than that on portfolio IV1. The return on portfolio IV5 is 8.06% per month, which is in sharp contrast to the holding period $(t + 1)$ return of -0.03%. This large difference arises because of the greater weights placed on winner stocks in the portfolio formation month for both VW returns. However, these stocks experience strong return reversals and become loser stocks in the holding period.

The last column of Table 3 shows the VW returns on the IV-sorted quintile portfolios two months after they are formed, with the weights still being based upon the market capitalization in formation month t. To facilitate comparison with column 2, we retain the same component stocks in each of the portfolios for two months. The return difference between IV5 and IV1 in month $t + 2$ is -0.51%, with a t-statistic of -1.38, which is not statistically significant.[19] This result again emphasizes the role of short-term return reversals. Winner stocks turn into loser stocks in the first holding month after the portfolio is formed, but the VW average returns in the second holding month are not so low because some of the loser stocks might become winners again, and these stocks still retain their larger weights from formation month t.

3.2 Time-series regressions

In this section, we examine whether the abnormal profits earned on an investment strategy with IV-sorted portfolios are caused by short-term return reversals. Ang et al. (2009) report significant tradable returns from a portfolio

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[19] We examine the EW and VW returns of the five IV portfolios in the twelve months after they are formed, with the weights depending on market capitalization in the formation month. Once portfolios are formed, their components are unchanged over the holding period. Statistical tests indicate that the EW return difference between IV5 and IV1 is insignificant over all twelve months; in contrast, the VW return difference between IV5 and IV1 is not significant from months 2 to 12, and it is significant only in the first holding month. VW returns on all five idiosyncratic volatility-sorted portfolios are very close in magnitude when the holding period is longer than five months. These results are available upon request.

that is long in IV5 stocks and short in IV1 stocks after controlling for the Fama and French three factors. Their time-series regression results suggest persistence of the negative return difference between the IV5 portfolio and the IV1 portfolio. To investigate if the return patterns of this trading strategy can be related to stock returns in the previous month, we add an additional factor, the "winners minus losers" return denoted by WML that is formed by taking a long (short) position in past winner (loser) stocks, to the following time-series regression:

$$r_{p,t} = a_p + \beta^p_{MKT} \cdot MKT_t + \beta^p_{SMB} \cdot SMB_t + \beta^p_{HML} \cdot HML_t$$
$$+ \beta^p_{UMD} \cdot UMD_t + \beta^p_{WML} \cdot WML_{t-1} + \varepsilon_{p,t}, \qquad (7)$$

where $r_{p,t}$ is the excess return on the VW portfolio that is long the highest idiosyncratic volatility portfolio and short the lowest idiosyncratic volatility portfolio (IV5-IV1); $MKT, SMB,$ and HML are the Fama and French three factors, namely, the market excess return, the size premium, and the value premium, respectively; and UMD is the momentum factor of Carhart (1997). Following Jegadeesh (1990), we form ten portfolios based on the past one-month returns in each month with the two extreme deciles being the past losers and past winners. WML is the EW average return difference between the past winner portfolio and the past loser portfolio during the formation period.[20] If low returns on high idiosyncratic volatility stocks in the holding month are really driven by their short-term return reversals, we would expect that an investment strategy based on idiosyncratic volatility could show strong comovement with the investment strategy based on the previous month's stock returns. In particular, the abnormal return on the IV5-IV1 strategy may be explained by the difference in returns on past winner and loser stocks (WML).[21]

Table 4 reports the results of the time-series regressions of monthly returns on the "IV5-IV1" strategy against the three or four factors, where the first two rows do not control for the return difference between past winners and losers (WML) and the last two rows do control for this difference. If the intercept (Jensen's alpha) of the regression is significantly different from zero, this investment strategy can earn abnormal profits since the risk loadings on the factors are not sufficient to explain the portfolio's returns.

The intercepts in the first two rows of Table 4 indicate that the IV5-IV1 strategy is associated with a large negative unexplained return in both the three- and

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[20] We find similar empirical results when we calculate the WML return as the VW average return difference between past winners and losers in the formation period.

[21] Strictly speaking, WML here is not a trading strategy since we calculate its return during the formation period. 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 the 10% best and worst performing stocks during the holding period and the Short-Term Reversal Factor constructed by Kenneth French. These WMLs are evaluated in the same period as the dependent variable, the IV portfolio return 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.

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Table 4
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 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*). "*UMD*" is the difference between the return on a portfolio comprising stocks with high returns from $t − 12$ to $t − 2$ and the return on a portfolio comprising stocks with low returns from $t − 12$ to $t − 2$. Winner and loser portfolios are formed based on past one-month returns. Specifically, ten portfolios are formed based on the past one-month returns as in Jegadeesh (1990). "*WML*" is the difference between the EW average return of the past winners (the 10% best performing stocks) and the past losers (the 10% worst performing stocks) during the formation period. Adjusted R-squares are reported in the last column. Newey and West (1987) robust *t*-statistics are reported in parentheses. The sample period is from July 1963 to December 2004.

four-factor models; the intercepts are as large as −1.34% and −1.07%, respectively, on a monthly basis, and both are statistically significant. 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. Thus, consistent with Ang et al. (2009), we find that the strategy based on idiosyncratic volatility can have significant tradable returns even after adjusting for the conventional three or four factors.

The last two rows of Table 4, where we control for the return difference between past winners and losers, show that the coefficient on WML is negative and statistically significant in both the three- and four-factor models, indicating that the return on the idiosyncratic volatility investment strategy (IV5-IV1) experiences reversals in the holding period. More importantly, none of the intercepts is significantly different from zero after WML is added to the regression. This result 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 prior winner and loser stocks, while controlling for other factors. Once again, the evidence indicates that the low VW return of the high idiosyncratic volatility portfolio is driven by short-term return reversals.

4. Conclusion

The empirical evidence on the cross-sectional relation between monthly idiosyncratic volatility and expected stock returns is mixed. Ang et al. (2006,

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2009) find that realized monthly idiosyncratic volatility estimated from daily returns is negatively related to stock returns in the subsequent month, while Spiegel and Wang (2006) and Fu (2009) document a significant positive relation when using an EGARCH model to estimate conditional idiosyncratic volatility from monthly returns. In this article, we show that omission of the previous month's stock returns results in a negatively biased coefficient on idiosyncratic risk, especially if one uses realized idiosyncratic volatility in the previous month as a proxy for idiosyncratic risk. This bias is largely attributed to the negative serial correlation in monthly returns and the positive contemporaneous relation between realized idiosyncratic volatility and stock returns.

Using different estimates of the unobservable idiosyncratic risk from both daily and monthly returns, we conduct cross-sectional regressions to examine the relation between idiosyncratic risk and expected stock returns. Our empirical results indicate that there is a large negative bias when the conditional idiosyncratic volatility is estimated from daily returns. When previous monthly stock returns are included to account for return reversals, idiosyncratic risk is no longer negatively related to expected returns. On the contrary, the positive relation remains robust between monthly return-based idiosyncratic volatility and future stock returns after we control for stock return reversals.

Ang et al. (2006) document that portfolios with high (low) realized idiosyncratic volatility deliver low (high) VW average returns in the subsequent month. Bali and Cakici (2008), however, find no significant relation between idiosyncratic volatility and EW portfolio returns. We demonstrate that both relations are the consequence of short-term return reversals. In particular, we observe that there is a high concentration of winner and loser stocks in the portfolio with the highest idiosyncratic volatility, and both experience strong return reversals. However, the winner stocks have relatively larger firm size and hence greater weight than the loser stocks in the portfolio formation month, which drives down the VW portfolio returns in the next month and causes the negative relation to appear. In contrast, there is no significant difference in the EW returns in the five portfolios sorted by idiosyncratic volatility because winner stocks and loser stocks receive equal weight, and return reversals of winner and loser stocks offset each other.

Overall, our results suggest that short-term return reversals are a primary reason for the negative relation between realized idiosyncratic volatility and stock returns in the subsequent month. With a more accurate estimate from the monthly data, we confirm that the idiosyncratic risk is positively related to expected returns. This relation is robust after stock returns in the previous month are included to account for return reversals. Our study thus contributes to a better understanding of the role of idiosyncratic risk in asset pricing and demonstrates the importance of properly controlling for short-term return reversals in empirical asset pricing tests.

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