Corporate Hedging and the High Idiosyncratic Volatility Low Return Puzzle

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Abstract

Ang, Hoddrick, Xing and Zhang (AHXZ, 2006) document the high idiosyncratic volatility low return puzzle. Subsequent papers have offered various explanations to either support or refute the AHXZ (2006) puzzle. Fu (2009) incorporates the time-varying asymmetric nature of idiosyncratic volatility, which possibly explains an inverse risk-return relation. He finds a significantly positive contemporaneous relation between return and EGARCH idiosyncratic volatility. In our paper, we stratify Australian firms according to their consecutive hedging endeavors. We find that the main result in Fu (2009) applies only to firms that do not consecutively hedge. For firms that hedge for at least three consecutive years, idiosyncratic volatility, whether contemporaneous or lagged, is insignificant in Fama-MacBeth regressions. The results are robust to adjustments for size, book-to-market, momentum and liquidity effects. Intuitively, consecutive hedging suppresses firm-specific risks, which dilutes the role of idiosyncratic volatility in explaining cross-sectional stock returns.

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1 Introduction

Portfolio theory and CAPM are cornerstone finance concepts. In portfolio theory, firm-specific risks are fully diversifiable, hence irrelevant to expected return. In a CAPM world, all investors hold the market portfolio, such that only systematic risk matters, and firm-specific risks are irrelevant to asset pricing. There are various definitions and measures of firm–specific risk in empirical asset pricing. In our paper, we refer to firm-specific risk as idiosyncratic volatility ($\sigma_{\varepsilon i}$). We define $\sigma_{\varepsilon i}$ as the variability in stock i residual returns from Fama-French time-series regression. The idiosyncratic volatility puzzle has drawn substantial research attention in recent years. The puzzle exists at two levels.

First, a puzzle surrounds the non-trivial relation between $\sigma_{\varepsilon i}$ and stock returns (r_i). Many explanations in the literature are based on limits to diversification e.g. transaction cost in Brennan (1975); search cost in Merton (1987); over-confidence in Odean (1999); home- or geographical-biases in Grinblatt and Keloharju (2001) and Huberman (2001), and behavioral biases in Barberis and Huang (2001). Under-diversified portfolios possess non-trivial $\sigma_{\varepsilon i}$, for which investors require a return to bear. An alternative explanation is offered by Campbell et al (2001) and Goyal and Santa-Clara (2003). They argue that it is not firm-specific risk that is priced per se, but rather, $\sigma_{\varepsilon i}$ is a proxy variable for latent risks that are not captured by Fama-French factors. In sum, the various explanations posit a positive relation between $\sigma_{\varepsilon i}$ and r_i in the cross-section.

Second, Ang, Hodrick, Xing and Zhang (AHXZ 2006) documented the high idiosyncratic volatility low return puzzle. They find that stocks with high $\sigma_{\varepsilon i}$ in Month t exhibit low returns in Month $t+1$. Their result cannot be explained by CAPM or Fama-French factors, and is robust to control for momentum and liquidity effects. The AHXZ (2006) finding contradicts both risk-based and behavioral explanations of a positive relation between $\sigma_{\varepsilon i}$

and r_i. The AHXZ (2006) puzzle hints at a negative first-order cross-serial covariance between $\sigma_{\varepsilon it}$ and r_{it+1}. As such, subsequent papers e.g. Lu et al (2009); Huang et al (2010), base their explanation around return dynamics. While these papers provide empirical explanations for the AHXZ (2006) puzzle, they do not necessarily provide a conceptual insight into the puzzle.

We have two related objectives. First, we utilize the corporate hedging literature to establish a simple proposition that can explain both a significantly positive contemporaneous relation as well as an insignificant relation between r_i and $\sigma_{\varepsilon i}$. Our argument is straightforward. Firms that do not hedge possess non-trivial firm-specific risk which drives the positive contemporaneous relation between r_i and $\sigma_{\varepsilon i}$. But for firms that hedge, the contemporaneous relation between r_i and $\sigma_{\varepsilon i}$ is insignificant. Second, we empirically test our proposition using Australian data, where we hand-collected hedging activity details from financial statements.

If hedging activity reduces idiosyncratic volatility and enhances stock return, a firm's hedging policy would offer conceptual insight into the AHXZ (2006) puzzle. To the best of our knowledge, this idea has not been explored in the existing literature. Furthermore, the corporate hedging literature identifies firm attributes that explain cross-sectional variations in hedging activity. If the level of hedging activity affects the nature and strength of the cross-sectional relation between r_i and $\sigma_{\varepsilon i}$, then it is possible to identify firm attributes that cause $\sigma_{\varepsilon i}$ to be non-trivial. This would potentially offer a better understanding of the mixed empirical evidence of the relevance of $\sigma_{\varepsilon i}$ in explaining cross-sectional stock returns.

The impact of corporate hedging on firm value dates back to the MM irrelevance propositions. By curbing firm-specific risk, corporate hedging reduces the volatility in a firm's net cashflow. Smith and Stulz (1985) show that reduced net cashflow volatility adds to firm value through taxes, contracting costs and optimal investment decisions.[1] Tufano (1996) argues

[1] A firm facing an increasing marginal tax schedule pays less tax by smoothing out pre-tax earnings. Reduced net cashflow variability averts cashflow problems that often lead to financial distress. This puts a

that corporate hedging addresses managerial risk aversion. The reduced cashflow volatility enhances firm value through various channels outlined in Smith and Stulz (1985), and from reduced information asymmetry in Dadalt et al (2002).

Merton (1974) argues that equity-holders (S_t) are holding embedded call options on firm assets (V_t) against debt-holders (D_t). When the debt (X) matures at time T, $V_T = max[S_T - X; 0]$. Hedging reduces the volatility of underlying firm assets of the embedded options. This in turn reduces the premium that debt-holders charge in terms of lowering the cost of debt, which increases V_t. Furthermore, unlike a call option holder whose premium is a sunk cost, an equity-holder does not exhibit an unconditional preference for high volatility since his/her wealth is directly affected by S_t. Hedging reduces the expected agency cost associated with under-investment and adverse incentives, which arise from financial distress. The presence of an evident corporate hedging policy reduces the business (beta) risk of the firm, hence its cost of equity, which subsequently increases V_t.

$$
\begin{aligned}
r_{it} &= \alpha_i + \sum_{k=1}^{K} \beta_{ik} r_{kit} + \gamma_i \omega_{it} + r_{eit} \\
\sigma_i^2 &= \sum_{k=1}^{K} \beta_{ik}^2 \sigma_{ki}^2 + \gamma_i^2 \sigma_{\omega_i}^2 + \sigma_{ei}^2 \qquad (1)
\end{aligned}
$$

Consider the return (r_{it}) and risk (σ_i^2) equations for an unhedge Firm i in equation (1). Denote β_{ik} and r_{kit} as the sensitivity and risk premium associated with an array of orthogonal K factors. Assume that r_{it} also has a specific return exposure $\omega_{it} \sim (0, \sigma_{\omega i}^2)$ with sensitivity γ_i. Intuitively, ω_{it} arises from the nature of a firm's business operation e.g. crude oil price fluctuations for an airline company. Lastly, $r_{eit} \sim (0, \sigma_{ei}^2)$ is the residual return of Firm i. In the σ_i^2 equation, there are no covariances among orthogonal risk factors. For simplicity, we assume that ω_{it} has zero covariances with the the set of K-factors.

firm in a better position in debt negotiations and restructuring. Lastly, hedging addresses managerial risk aversion, reducing their biases towards low growth conservative projects.

We note that r_{it} is slightly different from a standard factor-structure specification e.g. Fama-French time series regression. In the latter, the residual is termed idiosyncratic return, from which AHXZ (2006) extract their monthly measure of $\sigma_{\varepsilon i}$. It is reasonable to argue that a firm is able to hedge at least some of its firm-specific risks through exchange-traded or OTC derivatives. Hence in equation (1), we express firm-specific risks into a part that can be hedged against ($\sigma^2_{\omega_i}$), and a residual risk (σ^2_{ei}). Intuitively, we can associate σ^2_{ei} with a series of unfortunate events e.g. natural calamities; industrial accidents, corporate espionage etc, which cannot be readily hedged against using derivative contracts.

$$
\begin{aligned}
r^h_{it} &= \alpha_i + \sum_{k=1}^{K} \beta_{ik} r_{kit} + (\gamma_i - \delta_i)\omega_{it} + r^h_{eit} \\
\sigma^{2h}_i &= \sum_{k=1}^{K} \beta^2_{ik} \sigma^2_{kit} + (\gamma_i - \delta_i)^2 \sigma^2_{\omega i} + \sigma^{2h}_{ei} \qquad (2)
\end{aligned}
$$

Let's assume that Firm i employs a suitable instrument to hedge against ω_{it}. Equation (2) outlines a similar pair of return-risk equations (r^h_{it}, σ^{2h}_i) for a hedged Firm i. By definition, in σ^{2h}_i, $(\gamma_i - \delta_i)^2 = \gamma^2_i + \delta^2_i - 2\gamma_i\delta_i$ must be less than γ^2_i. This implies the hedging policy must satisfy the condition $(\delta^2_i - 2\gamma_i\delta_i) < 0$ or $\delta_i < 2\gamma_i$. We can perceive δ_i as a hedge ratio that either fully ($\delta_i = \gamma_i$) or partially ($|\delta_i| < |\gamma_i|$) neutralizes the variability in ω_{it} over time[2] For example, when $\delta_i = \gamma_i$, ω_{it} drops out of equation (2). But since $E(\omega_{it}) = 0$, a full-hedge policy should not have any adverse impact on Firm i's expected return. At the same time, it reduces the overall risk level of the firm. Since the AHXZ (2006) static measure and the Fu (2009) EGARCH measure of idiosyncratic volatility both follow a standard factor-structure specification, equations (2) shows that the level of hedging activity must have an impact on idiosyncratic volatility.

We review three recent papers that examine the AHXZ (2006) puzzle. Huang et al (2010)

[2] The condition $\delta_i < 2\gamma_i$ may be violated if $\delta_i > \gamma_i$. The latter implies the firm is over-hedging against its existing exposure to ω_{it}.

attribute the significance of $\sigma_{\varepsilon it-1}$ to the omission of relevant variable problem in the Fama-MacBeth regressions. The highest $\sigma_{\varepsilon i}$ portfolio contains the largest proportion of both recent winner and loser stocks. These are also stocks with the greatest tendency to exhibit substantial return reversal the following month[3]. The return reveal effect is being absorbed by $\sigma_{\varepsilon it-1}$. By including r_{it-1}, Huang et al (2010) show that $\sigma_{\varepsilon it-1}$ is no longer significant. In stark contrast, Lu et al (2009) identify two distinct stock groups in the highest $\sigma_{\varepsilon i}$ quintile. First, small illiquid losing stocks that demonstrate strong short-run return reversal. Second, larger liquid losing stocks that display return momentum. They attribute the low subsequent return to the latter stock group. This, they argue, explains why the AHXZ (2006) finding is present only in value-weighted portfolios.

Fu (2009) provides three insights into the AHXZ (2006) puzzle. First, the positive relation that we expect should be between contemporaneous return and idiosyncratic volatility. Second, idiosyncratic volatility is time-varying. Furthermore, since it is a proxy for firm-specific risk, the estimation of $\sigma_{\varepsilon i}$ has to incorporate the leverage effect. Otherwise, the asymmetric response of $\sigma_{\varepsilon i}$ to good versus bad firm-specific news can lead to an inverse risk-return relation. Third, to ascertain if the relation between r_i and $\sigma_{\varepsilon i}$ is economically significant, Fu (2009) tests an ex-ante measure of $\sigma_{\varepsilon i}$. This is denoted as E(IVOL), which is forecasted one-month ahead from EGARCH. He finds that the positive contemporaneous relation between r_i and E(IVOL) is both statistically and economically significant. Fu (2009) attributes the AHXZ (2006) finding to return reversals in a sub-set of small stocks.

Over a 5 year period, we sort 488 of the largest companies listed on the Australian Securities Exchange (ASX) base on the number of consecutive hedging years. We consider a hedging spectrum of 5 firm groupings. At one end is Group 0, which comprises firms

[3]In value-weighted portfolios, winner stocks receive heavier weighting than loser stocks, such that return reversal by winner stocks overshadow that of loser stocks. This causes low subsequent value-weighted return.

that do not hedge at all. At the other end are Group 5 firms that hedge throughout the sample period. In between are three firm groups. Group 1-2 consists of firms that hedge for either 1 or 2 consecutive years. Group 3 contains firms that hedge for 3 consecutive years, while Group 3-5 are firms that hedge for at least 3 consecutive years. Both groups 3 and 5 are subsets of Group 3-5. We test the cross-sectional relation between r_i and $\sigma_{\varepsilon i}$ for the overall firm sample. More importantly, we examine if the results vary from one end of the hedging spectrum to the other. Following Fu (2009), we measure $\sigma_{\varepsilon i}$ from EGARCH with a Fama-French specification in the mean-equation. As a robustness check, we also measure $\sigma_{\varepsilon i}$ according to the Eckbo et al (2000) six-factor model. The latter focuses on macro-economic variables rather than firm-specific variables. Our main findings are consistent whether we use Fama-French (1993) or Eckbol et al (2000) factors[4].

We find that the difference in monthly portfolio return between Group 3-5 and Group 0 is statistically significant. Interestingly, while there is also a significant difference between Group 3 and Group 0 returns, the difference in return becomes insignificant when we compare between Group 5 and Group 0. We examine the descriptive statistics of residual returns from both Fama-French and Eckbo et al (2000) time-series regressions. The mean returns for Group 0 and Group 5 are both negative. Group 3 has the highest mean return. This suggests that hedging benefits, at least for Australian firms, are optimized over a 3-year horizon. Firms that consecutively hedge for 5 years do not appear to substantially outperform firms that do not hedge. In contrast, the standard deviation of residual return monotonically decreases from 0.0209 to 0.0167 when we move from Group 0 to Group 5. In sum, our early results show that the absence of hedging in Group 0 firms is associated with both high idiosyncratic volatility and low return.[5]

[4]The cross-sectional results based on Eckbo et al (2000) factors are excluded due to space constraint. They are available upon request.

[5]The idiosyncratic volatility in the descriptive statistics is the standard deviation of monthly stock returns. This differs from the AHXZ (2006) measure. However, it does gives an indication of how how firm-specific

We test the cross-sectional relation between contemporaneous r_i and $\sigma_{\varepsilon i}$ using Fama-MacBeth regressions on the full sample as well as across individual hedge groups. We consider four empirical specifications: Model 1 is the univariate regression of r_i against $\sigma_{\varepsilon i}$. Model 2 controls for size and book-to-market, while Model 3 further controls for momentum and liquidity effects. Model 4 is similar to Model 3 except it is based on lagged one-month $\sigma_{\varepsilon i}$. The full sample results confirm the significance of $\sigma_{\varepsilon it}$ in explaining cross-sectional returns for Australian stocks. More importantly, we show that the main result in Fu (2009) is driven by firms in Group 0 and Group 1-2 i.e. firms that do not consecutively hedge. But for firms that hedge for at least three consecutive years, $\sigma_{\varepsilon i}$ becomes insignificant in explaining cross-sectional stock returns, with or without adjustments for size, book-to-market, momentum and liquidity effects. Lagged $\sigma_{\varepsilon i}$ is insignificant in the cross-sectional regressions. However, its coefficient is negative for Group 0 firms and positive for other hedge groups.

The paper proceeds as follow. The methodology and estimation are outlined in section 2. The results are discussed in section 3. Section 4 concludes.

2 Data and Methodology

In this section, we describe our sample, empirical methodology and how we measure firm hedging activity.

2.1 Sampling and hedging details

Our sample contains 488 of the largest Australian companies listed on the ASX from January 2001 to December 2005.[6] We compute stock i monthly return r_i from Datastream's stock

risk is reduced when we move across the hedging spectrum.

[6]We start with the top 500 companies, which reduces to 488 due to unavailability of return index data for some firms.

return indices.[7] Market return r_{mt} is the log of the Datastream monthly market return index. The monthly 30-days bank-accepted-bill rate is used as the proxy risk-free rate (r_{ft}). The book-to-market ratio (B/M) is computed using book and market values of sample stocks from the FinAnalysis database on a yearly basis.

For each of the 488 firms, we hand-collect hedging information from financial reports in the Connect-4 database. Australian firms hedge mainly against three risk categories: currency, interest rate and commodity[8]. The hedging instruments used include exchange-traded as well as over-the-counter derivatives. We identify hedging activity based on the following procedure. If a company discloses an outstanding derivative position at the end of fiscal year t, it is classified as hedged in both years t and $t+1$. If a firm discloses derivative usage during fiscal year t, but has no outstanding position at the end of year t, it is classified as hedged in year t only. This is unless derivative usage is also disclosed for year $t+1$.[9] The procedure allows us to classify every firm as either hedged or unhedged on a yearly basis.

INSERT TABLE 1

Table 1 Panel A presents summary statistics of firm hedging activity, while Panel B outlines the extent consecutive hedging over the 5-year sample. The figures show that more than 50% of firms do not hedge in any given year. However, the proportion of firms that hedge has systematically increased from 28% in 2001 to 44% in 2005. Around 70% of firms

[7] The return indices are adjusted for dividends, rights issues, stock splits etc. The data is from the FAUS list in Datastream, which contains all currently listed ASX stocks. When a company is delisted, it is transferred from the FAUS list to the DEADAU list, which contains all previously delisted stocks. For firms that are delisted after 2005, we obtain the required data from the DEADAU list.

[8] Examples in each categories include i) exchange rate derivatives and currency swaps; ii) interest rate swaps, caps, collars; iii) fuel and metal derivatives.

[9] Our classification ignores potential firm endeavor to generate natural hedges from their business operations e.g. cashflow, currency or duration matching. We also ignore the use of structured products, since accounting standards do not classify them as derivative instruments. Understandably, these indirect hedging efforts are hard to identify for individual firms.

that hedge are managing either or both currency and interest rate risks, while about 25% of firms hedge against commodity risk[10]. On average, 13% of all hedging firms hedge against all three exposures. These proportions are stable during the sample period.

Panel B shows that 47.75% of firms do are in Group 0 i.e. no hedge whatsoever. The second largest is Group 5, where 18.24% of firms hedge throughout the sample period. The fact that Groups 0 and 5 encompass nearly 70% of our firm population suggests that the majority of Australian firms either do not have an explicit hedging policy, or they have an entrenched hedging policy in place. 33% of firms hedge for at least 3 consecutive years.

2.2 Returns across hedge groups

In our initial analysis, we find that a simple binary grouping will cause many firms to switch between the hedge and no-hedge group from one year to the next[11]. In Table 2 Panel A, we compare the portfolio returns between the hedge and no-hedge firm groups using two measures[12]: equally-weighted annual return (r_{pa}) and average annual holding period return (HPR_{pa}). The returns for both firm groups vary substantially over time. Furthermore, the difference in return between the two groups is also unstable from one year to the next. This suggests that it is possible for the cross-sectional relation between r_i and $\sigma_{\varepsilon i}$ to be affected not by hedging activity, but rather, simply by having different firms included in the hedge and no-hedge groups over time. More importantly, it is reasonable to assert that any hedging effect on either or both r_i and $\sigma_{\varepsilon i}$ is likely to manifest over a longer time horizon[13].

[10]Most firms have foreign currency denominated transactions and borrow funds to a certain degree. Comparatively fewer firms are directly exposed to commodity price fluctuations.

[11]For example, a firm that hedges in 2001, 2003 and 2005 will keep switching between firm groups throughout the sample period.

[12]The measures and results are discussed in details in the results section.

[13]For example, consider two otherwise comparable firms A and B. Firm A hedges in Years 1, 3 and 5, but Firm B hedges in Years 1, 2 and 3. The impact of hedging on $(r_i, \sigma_{i\varepsilon})$ is likely to differ between A and B.

INSERT TABLE 2

The preceding argument motivates our firm stratification base on the number of consecutive hedging years. Panel B shows firms that hedge for 3 consecutive years produce the highest return. Firms that hedge for between 3 to 5 consecutive years also produce higher returns than those that hedge for 2 consecutive years or less. The results are consistent across both portfolio return measures. They suggest that hedging effects seem to manifest after 3 consecutive years. This is at least partially due to our hedging classification. A firm with an open hedging position at end of fiscal year t is classified as having consecutively hedged in years t and $t+1$. However, it is possible for such a firm to open a position 3 months prior to the end of fiscal year t, only to close out 2 months into fiscal year $t+1$. Table 2 also shows that while 4 or 5 consecutive hedging years also produce higher returns, they are lower than firms that hedge for 3 consecutive years. It is possible that the marginal cost of hedging outweighs the marginal benefit after 3 years.

To formally ascertain if the return differential between hedge groups is statistically significant, we apply the Mitchell and Stafford (2000) calendar time abnormal return, or CTAR test[14]. The test is based on the time series of the return differential between two portfolios. Mitchell and Stafford (2000) show that if abnormal returns are serially correlated, the CTAR test is more appropriate than a direct comparison of cumulative abnormal return. Since incremental returns associated with hedging endeavor are likely to manifest over a longer time period, the incremental returns are likely to be serial correlation.

As an example, we calculate Group 0 and Group 3 portfolio monthly returns r_{pt}^{0} and r_{pt}^{3} respectively. Denote the difference in monthly portfolio return as $r_{pt}^{3-0} = r_{pt}^{3} - r_{pt}^{0}$. For the CTAR test, we compute the t-statistics of r_{pt}^{3-0} from its mean and standard error. If signif-

[14]This approach is introduced by Jaffe (1974) and Mandelker (1974), and has received support in Fama (1998).

icant, the CTAR test concludes that Group 3 produces statistically significant incremental return over Group 0. The test can be used on various hedge group comparisons. Specifically, we wish to examine if incremental returns along the entire hedging spectrum, or, does hedging benefits disappear after a certain number of years?

INSERT TABLE 3

In Table 3, we present CTAR test statistics for various pairwise comparisons. Earlier results indicate it is optimal to hedge for 3 consecutive years. We confirm that Group 3 firms produce significantly positive return over firms in Group 0, with r_{pt}^{3-0} having a t-stat of 2.21. Interestingly, r_{pt}^{5-0} is significant, but only at the 10% level. In contrast, r_{pt}^{5-3} is insignificant, which suggests there is limited marginal benefit from hedging beyond 3 consecutive years. The Group 1-2 and Group 3 comparison yields a significant t-stat of 2.37 for $r_{pt}^{3-(1,2)}$, while $r_{pt}^{(1,2)-0}$ is insignificant. Both results are consistent with earlier findings

Loughran and Ritter (2000) stipulate that using value-weighted returns in Fama-French time-series regressions tend to underestimate abnormal returns if the event relates to a managerial choice variable e.g. hedging. Our analysis across hedge groups consider both equally- and value-weighted portfolio returns. For the rest of this section, we outline the return measures that are analyzed in Table 2 and are used in Fama-French and Eckbo et al (2000) regressions in Tables 4 and 5 respectively. They are presented in equation (3).

$$r_i = Ln(\frac{p_{it}}{p_{it-1}}); \quad r_{pt} = \frac{\sum_{i=1}^{N} r_i}{N} \text{ or } \sum_{i=1}^{N} w_i r_i; \quad r_{pa} = \sum_{t=1}^{12} r_{pt} \tag{3}$$

The monthly return r_{it} for stock $i = 1, 2, ..., N$ is the log-of-price-relative of the Datastream return index p_{it}. Denote r_{pt} as the monthly portfolio return. We consider both equally-weighted $(\frac{\sum_{i=1}^{N} r_{it}}{N})$ and value-weighted $\sum_{i=1}^{N} w_{it} r_{it}$ monthly portfolio return, where w_{it} is the month t portfolio weight for stock i. The annual portfolio return r_{pa} is the sum of equally-weighted r_{pt}, while $\bar{r_{pa}}$ is the average annual portfolio return over the sample period.

$$\text{HPR}_{it} = \frac{r_{it}}{r_{it-1}} - 1; \qquad \text{HPR}_{pt} = \frac{\sum_{i=1}^{N} \text{HPR}_{it}}{N} \text{ or } \sum_{i=1}^{N} w_i \text{HPR}_{it}$$

$$\text{HPR}_{ia} = \prod_{t=1}^{12} (1 + \text{HPR}_{it}) - 1; \qquad \text{HPR}_{pa} = \frac{\sum_{i=1}^{N} \text{HPR}_{ia}}{N} \tag{4}$$

We examine holding period return HPR. Various measures of HPR are outlined in equation(4). HPR_{it} measures the change in r_{it} over time. Denote HPR_{pt} as the monthly portfolio return. As with r_{pt}, we compute both equally-weighted $(\frac{\sum_{i=1}^{N} \text{HPR}_{it}}{N})$ and value-weighted $(\sum_{i=1}^{N} w_{it}\text{HPR}_{it})$ HPR_{pt}. The stock i annual HPR, or HPR_{ia}, is the geometric sum of HPR_{it}. Lastly, the annual portfolio HPR, or HPR_{pa}, is the simple average of HPR_{ia} across stocks. Denote $\text{H}\bar{\text{P}}\text{R}_{pa}$ as the average annual portfolio HPR over the sample period.

2.3 Estimating idiosyncratic volatility

AHXZ (2006) measure idiosyncratic volatility in month t as the standard deviation of daily residual return ε_{it} from Fama-French time series regression in equation (5). $(r_{mt} - r_{ft})$ is the market risk premium; small-minus-big, or SMB_t, is the difference between small- and big-stock portfolio returns; high-minus-low, or HML_t, is the difference between the portfolio return of high B/M and low B/M ratio stocks; T is the total number of days in a month; b_i, s_i, h_i are the corresponding factor loadings. Although our focus is on the Fu (2009) EGARCH measure of $\sigma_{\varepsilon it}$, we want to check if the $\sigma_{\varepsilon i}$ measure used in AHXZ (2006) varies across hedge groups. For each firm, we run monthly Fama-French time-series regressions for the entire sample period to obtain the residual return series ε_{it}. We compute the descriptive statistics of ε_{it} and average them across firms in each hedge group.

$$r_i - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + s_i(SMB_t) + h_i(HML_t) + \varepsilon_{it}$$

$$\sigma_{\varepsilon i} = \sqrt{\frac{\sum_{t=1}^{T}(\varepsilon_{it} - \bar{\varepsilon}_i)^2}{T}} \tag{5}$$

Each year, we sort firms into 3 size portfolios. Each of the first/small (S) and third/big (B) size-sorted portfolios is further sorted into three B/M-ranked portfolios: Low (L), Medium (M) and High (H). Accordingly, we have six size-B/M sorted portfolios: $\{SL, SM, SH; BL, BM, BH\}$.[15] We compute value-weighted monthly returns for the six portfolios over the sample period. SMB_t is the difference between the average monthly return of the small portfolios (SL, SM and SH) and big portfolios (BL, BM and BH). HML_t is the difference between the average monthly return of the high B/M portfolios (SH and BH) and low B/M portfolios (SL and BL).

Many studies follow AHXZ (2006) and measure $\sigma_{\varepsilon i}$ relative to Fama-French factors. However, it remains debatable as to how applicable they are to Australian stock returns. As a robustness check, we consider an alternative measure of $\sigma_{\varepsilon i}$ relative to the Eckbo et al (2000) six factor model in equation (6). Eckbo et al (2000) identify a set of macro-level variables to explain cross-sectional stock returns: ΔRPC_t is the change in real per capita consumption of nondurable goods(%); $(\text{Baa-Aaa})_t$ is the credit default spread between Moody's Baa and Aaa corporate bonds; UI_t is unanticipated inflation; $(20yr - 1yr)_t$ is the long-term spread between the 20-year and 1-year Treasury bonds; $(90d - 30d)_t$ is the short-term spread between the

[15]For example, the S/L portfolio contains small stocks in the low-B/M group; the B/H portfolio contains big stocks in the high B/M group.

90-day and 30-day Treasury bills.

$$r_i = \alpha_i + \beta_{1i}(r_{mt}) + \beta_{2i}(\Delta RPC)_t + \beta_{3i}(Baa - Aaa)_t$$

$$+\beta_{4i}(UI)_t + \beta_{5i}(20yr - 1yr)_t + \beta_{6i}(90d - 30d)_t + \varepsilon_{it} \quad (6)$$

There are some limitations with using Australian data to construct the Eckbo et al (2000) factors. Australian government bonds are issued up to 10 years. Our inflation figures are reported on a quarterly rather than monthly basis. Lastly, Baa and Aaa corporate bond yields are not readily available from Datastream for all Australian firms. This is mainly because most Australian firms do not issue corporate bonds.[16] We use ΔCCL_t, the change in Consumer Confidence Level[17] as a proxy for $\Delta RPC)_t$. Instead of $(20yr - 1yr)_t$, we use $(10yr-2yr)_t$ for the long-term spread. We proxy UI_t with monthly unemployment rate UR_t. Lastly, we proxy $(Aaa - Bbb)_t$ with the credit spread between corporate and government bonds of similar term structures $(Corp - Govt)_t$.

Fu (2009) provides three important insights into the AHXZ (2006) puzzle. First, he rightly points out that the positive risk-return relation should be contemporaneous. Second, he incorporates the time-varying asymmetric response of $\sigma_{\varepsilon i}$ to good versus bad firm-specific news i.e. leverage effect[18] during idiosyncratic volatility estimation. The inverse $(r_i, \sigma_{i\varepsilon})$ relation could be partially driven by the leverage effect. Third, his cross-sectional tests are based on an out-of-sample expected idiosyncratic volatility measure, which Fu (2009) denotes as E(IVOL). Doing so allows him to address both statistical and economical significance of $\sigma_{\varepsilon i}$ from forming long-short portfolios ranked based on $\sigma_{\varepsilon i}$. Fu (2009) address all three issues with Nelson's (1991) EGARCH model.

[16]The corporate bond market in Australia is not as established as in the US.
[17]This is downloaded from Reserve Bank of Australia website
[18]When share price falls (rises) due to bad (good) news, the firm's leverage ratio is mechanically increased (reduced), thus raising (lowering) its firm-specific risk.

$$r_{it} - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + s_i(SMB_t) + h_i(HML_t) + \varepsilon_{it}$$
$$\varepsilon_{it} \sim N(0, \sigma_{it}^2)$$
$$Ln(\sigma_{it}^2) = a_i + b_i\sigma_{it-1}^2 + c_i\{\gamma(\frac{\varepsilon_{it-1}}{\sigma_{it-1}}) + \alpha[|\frac{\varepsilon_{it-1}}{\sigma_{it-1}}| - \frac{2}{\Pi}^{1/2}]\} \quad (7)$$

We generate monthly idiosyncratic volatility $\sigma_{\varepsilon it}$ from an EGARCH (1,1) specification in equation(7)[19]. Following Fu (2009), we include Fama-French factors in the mean equation. The residual return ε_{it} is assumed normally distributed with zero mean and conditional variance σ_{it}^2. The latter's functional form is outlined in the variance equation $Ln(\sigma_{it}^2)$. The α coefficient is associated with the magnitude term. Regardless of direction, a shock that enters the mean equation via ε_{it} has a positive effect on $Ln(\sigma_{it}^2)$, such that $E(\alpha) > 0$. The coefficient γ corresponds to the directional term. If conditional volatility is indeed asymmetric, then $E(\gamma) < 0$. For robustness, we also estimate the EGARCH with Eckbo et al (2000) factors in the mean equation.

2.4 Cross-sectional analysis of return and idiosyncratic volatility

Our main objective is to see if consecutive hedging affects the cross-sectional relation between return and idiosyncratic volatility. We perform two sets of Fama-MacBeth regressions: i) pooled firm sample and ii) hedge group samples. Each month t=1,2,...,T, we run the cross-sectional regression for firms i=1,2,...,N in equation(8).

$$r_{it} = \beta_{0t} + \sum_{k=1}^{K} \beta_{kt} X_{kit} + \epsilon_{it} \quad (8)$$

Denote r_{it} as the stock i realized return in month t. Let X_{kit} represent a set of intended variables to explain cross-sectional stock return, such that ϵ_{it} represents the devi-

[19]Fu (2009) estimates EGARCH (p,q) specifications for permutations of $1 \leq p \leq 3$ and $1 \leq q \leq 3$.

ation of r_{it} from its expected value. The focus variable is $\sigma_{\varepsilon it}$. The control variables are size Ln(ME), book-to-market ratio Ln(BE/ME), Jegadeesh and Titman (1993) six-month momentum RET(-2,-7) and Chordia et al (2001) liquidity TURN and CV(TURN). Other than Fama-French factors, momentum and liquidity effects are probably the other two robust variables that can explain explain cross-sectional stock returns. We compute RET(-2,-7) as the compounded gross return from Month t-7 to Month t-2. Jegadeesh (1990) argue that including Month t-1 return will generate spurious results associated with thin-trading and bid-ask bounce. This can be an issue for smaller stocks, even for monthly returns. Chordia et al (2001) find that liquidity in terms of both magnitude and fluctuation in turnover volume help explain cross-sectional stock returns. TURN is the average monthly turnover volume over the past 36 months and CV(TURN) is the coefficient of variation in TURN.

We consider four empirical specifications of equation(8) to test the cross-sectional relation between r_i and $\sigma_{\varepsilon i}$. Model 1 is simply a univariate regression of r_i on $\sigma_{\varepsilon i}$. Model 2 controls for Fama-French Ln(ME) and Ln(BE/ME). Model 3 further controls for momentum RET(-2,-7) and liquidity TURN and CV(TURN). Lastly, Model 4 is similar to Model 3, except we replace $\sigma_{\varepsilon it}$ with $\sigma_{\varepsilon it-1}$ It is important to note that our $\sigma_{\varepsilon it-1}$ is from EGARCH and not the AHXZ (2006) standard deviation measure.

$$\hat{\beta}_k = \frac{1}{T}\sum_{t=1}^{T=60}\hat{\beta}_{kt}$$

$$Var(\hat{\beta}_k) = \frac{\sum_{t=1}^{T=60}(\hat{\beta}_{kt} - \hat{\beta}_k)^2}{T(T-1)} \tag{9}$$

The estimation of Equation(8) yields a time series of b_{kt} for each of the K variables. To ascertain if a variable explains cross-sectional returns over time, we test if the corresponding average slope coefficient is significantly different from zero. A coefficient's t-statistics is calculated base on equation(9) as the average slope $\hat{\beta}_k$ divided by its standard error $\sqrt{\frac{Var(\hat{\beta}_k)}{T}}$.

3 Discussion of Results

If consecutive hedging enhances firm value, we expect firms with limited or no hedging activity to produce negative α relative to Fama-French factors. Conversely, firms that consistently hedge should not produce any significant α relative to priced factors, even when idiosyncratic volatility is not included in the estimation. Since consecutive hedging suppresses firm-specific risk, idiosyncratic volatility should not affect the time series of returns.

Base on the above, we expect firms with limited hedging activity to produce significantly negative abnormal returns from time-series regression. We also expect idiosyncratic volatility to explain cross-sectional returns for such firms. We present time-series estimates from the EGARCH mean-equation as well as Fama-MacBeth cross-sectional results. As our formal analysis does not consider the AHXZ (2006) measure of $\sigma_{\varepsilon i}$, we start by examining the standard deviation of residual returns from multi-factor least-square regressions.

3.1 Descriptive statistics of hedge group residual returns

We present results for both Fama-French and Eckbo et al (2000) factors in Table 3 Panel B. We report the results based on equally-weighted hedge group returns. These are consistent with results based on the averaging of individual firm returns within each hedge group[20]. Panel B shows a gradual decline in the monthly standard deviation of Fama-French residual returns from 0.02092 to 0.016645 as we move from Group 0 to Group 5. A pairwise comparison of Group 0 and Group 5 based on Eckbo et al (2000) residual returns confirm a non-trivial difference in the standard deviation of the two extreme groups. The annualized idiosyncratic volatility is 11.95% for Group 0 and 6.655% for Group 5 firms.

[20] They are readily available upon request.

3.2 Time-series estimates from the EGARCH mean-equation

We examine the sign and magnitude of α_p from the EGARCH mean-equation to ascertain whether firms that undertake little or no hedge produce significantly negative abnormal returns relative to firms that hedge on a consistent basis. Here, the returns are abnormal in a sense that they are not being explained by priced factors. We separately consider Fama-French and Eckbo et al (2000) factor specifications for three different return measures. The first and second are EGARCH portfolio level estimations base on equally- and value-weighted returns of the various hedge groups. The weights are calculated every month[21]. Third, we estimate EGARCH for each of the 488 firms in our sample. We then compute the average coefficient estimates and t-stats within each hedge group.

INSERT TABLE 4

We report Fama-French mean-equation estimates in Table 4 across three panels. In Panel A, only Groups 0 and 1-2 produce significantly negative α_p. Both market and size are significant, while HML is significant only in Groups 0 and 5. Base on value-weighted returns, only the market risk premium is significant. Furthermore, the adjusted R^2 in Panel B for most of the hedge groups are substantially lower than their corresponding peers in Panels A and C. For example, the adjusted R^2 for Group 0 is 0.87 and 0.89 in Panels A and C respectively, but it is only 0.53 in Panel B. The results for Panel C, which are based on within hedge group averages of firm-level estimates, are consistent with Panel A. Only Group 0 and Group 1-2 have significantly negative α. Furthermore, Group 0 has a smaller α than Group 1-2. This suggests that hedging, even over a short horizon, adds some value to the firm. Interestingly, HML is significant across all hedge groups in Panel C.

[21] Each month, we multiply share price by number of shares outstanding to work out the market capitalization of each firm. The weight of each firm in a given hedge group is simply its market capitalization divided by the total market capitalization of the hedge group.

Smith and Stulz (1985) argue that corporate hedging improves a firm's investing and financing posture, which subsequently lowers its beta risk. However, it is a latent benefit that is gradually realized over time. Panels A and C show that Group 3 has the lowest β among the hedge groups. This is consistent with our earlier results suggesting three consecutive hedging years as optimal for Australian firms.

INSERT TABLE 5

In Table 5, we re-estimate EARCH with Eckbo et al (2000) factors in the mean-equation. The adjusted R^2 column suggests that, at least for Australian stocks, the macro-level factors possess less explanatory power than Fama-French factors. Interestingly, while the results for α and β are not strictly similar to those in Table 4, their implications are quite consistent. If hedging adds to firm value, we expect firms that (do not) actively hedge to produce significantly positive (negative) α. Table 5 Panel A shows that Groups 3-5 and Group 5 firms produce significantly positive α. This is consistent with Table 4 Panel A, which finds significantly negative α for Group 0 and Group 1-2 firms.

Table 5 Panels A and C also show that Group 5 has the lowest β. This differs from Table 4, which shows Group 3 having the lowest β. However, both tables are consistent in suggesting that consecutive hedging reduces beta risk, with β gradually declining as we move away from Groups 0 and 1-2. When we compare across the three panels in Table 5, it is interesting to note that the Eckbo et al (2000) factors offer substantially better explanatory power in Panels A and B relative to Panel C. This would suggest that the macro-level variables are better at explaining portfolio returns than they are at explaining stock returns.

3.3 Cross-sectional estimates from Fama-MacBeth regression

We report $\hat{\beta}_k$ with t-stat in Table 6. Panel A is based on the pooled firm sample, while Panel B reports within hedge group estimates. The results in Panel A confirm the main finding in Fu (2009) of a positive contemporaneous relation between r_i and $\sigma_{\varepsilon it}$ for Australian stocks. The magnitude of the average slope $\hat{\beta}_{\sigma_{\varepsilon it}}$ for $k = \sigma_{\varepsilon it}$ is stable at around 0.057 across Models 1 to 3. It is significantly positive in Model 1, with a t-stat of 1.92. While the t-stat drops slightly when we control for various risk factors, $\sigma_{\varepsilon it}$ remains significant at the 10% level.

Unlike AHXZ (2006) and Fu (2009), we do not find a significant $\sigma_{\varepsilon it-1}$. Furthermore, it is 0.0078 i.e. positive. The positive coefficient could be due to the fact that our $\sigma_{\varepsilon it-1}$ is measured from EGARCH, which incorporated the leverage effect. Furthermore, a popular explanation for the AHXZ (2006) puzzle is small stock return reversal. The smaller stocks in our sample are not small per se, since we consider the top 488 Australian firms.

We discuss three related findings in Panel B. First, we find that the significance of $\sigma_{\varepsilon it}$ in Panel A is mainly driven by Group 0 and Group 1-2 firms. Between the two hedge groups, $\hat{\beta}_{\sigma_{\varepsilon it}}$ is significantly positive at around 0.2. For example, in Model 3, $\hat{\beta}_{\sigma_{\varepsilon it}}$=0.2535 for Group 0 and 0.1643 for Group 1-2. The magnitude of the coefficients are also robust to risk adjustments. For example, in Model 1, $\hat{\beta}_{\sigma_{\varepsilon it}}$ for Group 1-2 is 0.1729. It drops slightly to 0.1709 and 0.1643 in Models 2 and 3 respectively.

INSERT TABLE 6

Second, we show that $\sigma_{\varepsilon it}$ becomes insignificant in explaining cross-sectional stock returns of firms that hedge for at least 3 consecutive years. In other words, the main finding in Fu (2009) does not hold across hedge groups. Firms that continuously hedge their business operations are able to suppress their firm-specific risks. Consequently, this dilutes any systematic relation between r_i and $\sigma_{\varepsilon it}$, whether positive or negative. In our Fama-MacBeth regressions, the $\hat{\beta}_{\sigma_{\varepsilon it}}$ from Group 3 onwards are all insignificant. The insignificance in $\hat{\beta}_{\sigma_{\varepsilon it}}$ is also robust across Models 1-3. The results thus far are consistent with the analysis of hedge group excess return in Table 4. EGARCH estimations based on equally-weighted hedge group return in Panel A and individual stock return in Panel C both show insignificant α for firms that hedge for at least 3 consecutive years. Fama-MacBeth results in Table 6 confirm the insignificance of $\sigma_{\varepsilon it}$ from Group 3 onwards.

Third, $\sigma_{\varepsilon it-1}$ remains insignificant across hedge groups in Model 4. However, $\hat{\beta}_{\sigma_{\varepsilon it-1}}$ is negative for Group 0. It is the only negative coefficient in Table 6, and shows that any traces of the high $\sigma_{\varepsilon i}$ low r_i puzzle is associated with firms that perform limited hedging. In sum, Table 6 shows that, if there are any evidences to suggest i) $\sigma_{\varepsilon i}$ matters and ii) the cross-sectional relation between $(r_i, \sigma_{i\varepsilon})$ is negative, they are found in Group 0 and Group 1-2 i.e. firms that do not consistently hedge.

3.3.1 Some caveats and future research direction

We discuss three caveats. First, our measure of $\sigma_{\varepsilon it}$ is estimated within-sample. In Fu (2009), the Month t idiosyncratic volatility $E(IVOL_t)$ is projected out-of-sample. This allows Fu (2009) to test the economic significance of the positive cross-sectional relation between contemporaneous $\sigma_{\varepsilon i}$ and stock returns in a simple trading rule[22]. The inclusion of hedging activity constrains our sample period to 60 monthly observations. If we impose a minimum 30 month estimation window, we can only generate 30 out-of-sample observations for $E(IVOL_t)$ to be used in the cross-sectional regressions. Our main research question in this paper is whether the $r_i, \sigma_{\varepsilon it}$ relation is affected by the extent of firm hedging activity. Hence,

[22]Rank stocks based on E(IVOL) and form a long-short portfolio by buying and shorting stocks with the highest and lowest $E(IVOL_t)$ at Month $t - 1$.

we focus on in-sample estimation, which allows us to generate a longer time series of $\hat{\beta}_{\sigma_{\varepsilon it}}$ to enhance the power of Fama-MacBeth cross-sectional tests in Table 6. Currently, we are expanding our sample to 10 years. This allows us to address the question of economic significance in a follow-up paper.

Second, we did not formally consider the AHXZ (2006) measure of $\sigma_{\varepsilon i}$. Fu (2009) has to formally consider the AHXZ (2006) measure as a benchmark against his EGARCH measure of $\sigma_{\varepsilon i}$. Since Fu (2009) has convincingly shown that the AHXZ (2006) measure is not suitable, we focus on showing that hedging activity influences the $(r_i, \sigma_{i\varepsilon})$ relation, using an appropriate conditional idiosyncratic volatility measure.

Third, the current draft does not include the Huang et al (2010) return reversal effect in the cross-sectional tests. It would be interesting to see if return reversal effects matter across the hedging spectrum. We will include this an updated draft.

4 Concluding Remarks

In recent years, many papers have attempted to address the AHXZ (2006) high idiosyncratic volatility low return puzzle. Recent studies by Huang et al (2010), Fu (2009) and Lu et al (2009) attribute it to return dynamics and the time-varying nature of idiosyncratic volatility.

In this paper, we put forth a simple proposition that high idiosyncratic volatility low return are ex-ante driven by the absence of corporate hedging. The corporate hedging literature provides theoretical and empirical evidence that continued hedging endeavor suppresses idiosyncratic volatility and enhances stock return. Furthermore, conditional on hedging activity, we can understand the mixed empirical findings in the literature on whether idiosyncratic volatility matters. We find a significantly positive relation between contemporaneous return and idiosyncratic volatility, consistent with Fu (2009). But more importantly, we trace the non-trivial cross-sectional relation to a subset of firms that do not hedge. Firms that continuously hedge their business operations are able to suppress their idiosyncratic volatilities, making them irrelevant in explaining cross-sectional stock returns.

Our results imply a reversion to the traditional finance paradigm that idiosyncratic volatility does not matter when firms continuously hedge, even if idiosyncratic volatility is a contemporaneous conditional measure. The relevance of idiosyncratic volatility is primarily driven by limits to diversification arguments. Limits to diversification at the investor level do not matter when firm-specific risks are neutralized at the firm-level.

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Table 1: Descriptive statistics of hedging activity

Panel A: Summary of hedge information

Total sample: 488 firms	Year	**2005**	**2004**	**2003**	**2002**	**2001**	**5-year average**
No hedge	No. of firms	273	276	316	339	353	311
	% of total	55.94%	56.56%	64.75%	69.47%	72.34%	63.81%
Hedge	No. of firms	215	213	172	149	135	177
	% of total	44.06%	43.65%	35.25%	30.53%	27.66%	36.23%
All derivative categories	No. of firms	29	29	23	18	18	23
	% of hedge	13.49%	13.62%	13.37%	12.08%	13.33%	13.18%
Currency	No. of firms	167	167	115	113	108	134
	% of hedge	77.67%	78.40%	66.86%	75.84%	80.00%	75.76%
Interest rates	No. of firms	136	140	113	103	91	117
	% of hedge	63.26%	65.73%	65.70%	69.13%	67.41%	66.24%
Commodity	No. of firms	58	55	45	32	32	44
	% of hedge	26.98%	25.82%	26.16%	21.48%	23.70%	24.83%

Panel B: Summary information on consecutive hedging

Total sample: 488 firms	**Never hedge**	**1 year**	**2 years**	**3 years**	**4 years**	**5 years**
Number of firms	233	26	68	43	29	89
% of total	47.75%	5.33%	13.93%	8.81%	5.94%	18.24%

	Less than 3 years' of consecutive hedging	**3 or more years' of consecutive hedging**
Number of firms	327	161
% of total	67%	33%

Table 2: Return comparison across hedge groups

Panel A: Monthly and holding period return comparisons

Year	2005		2004		2003		2002		2001	
	Hedge	No hedge	Hedge	No hedge	Hedge	No hedge	Hedge	No hedge	Hedge	No hedge
r_{pa}	6.62%	2.44%	24.87%	18.60%	26.82%	37.30%	-3.27%	-3.84%	3.62%	-11.59%
HPR_{pa}	12.77%	13.56%	34.39%	33.37%	39.02%	70.92%	5.51%	13.75%	13.78%	11.78%

Panel A provides inconclusive results for comparing stock returns for hedged group and unhedged group. Regrading to LNR, the returns of hedged group is higher than the return of unhedged group during 5-year period from 2001 to 2005 except 2003. However, for HPR, hedged group has the higher return only in 2001 and 2004, but in 2002, 2003 and 2005, it is has lower than unhedged group.

Panel B: Portfolio returns across consecutive hedge groups

	Never hedged	1 year	2 years	3 years	4 years	5 years
r_{pa}	5.68%	10.10%	5.49%	18.05%	13.91%	13.98%
HPR_{pa}	42.78%	23.14%	30.76%	49.30%	44.85%	35.76%

	Less than 3 years' of consecutive hedging	3 or more years' of consecutive hedging
r_{pa}	5.99%	15.05%
HPR_{pa}	38.67%	41.01%

Panel B presents that, on average, firms that consecutively hedged for longer period have higher returns both in LNR and HPR. Firms that consecutively hedged equal to or more than 3 years within the sample period have average annual LNR and HPR returns of about 14% and 41.0% respectively, while firms that consecutively hedged less than 3 year within the sample period have both lower average annual LNR and HPR returns of about 6% and 38.7% respectively.

Table 3: Comparison of return and idiosyncratic volatility across hedge groups

Panel A: CTAR tests for pairwise comparisons between hedge groups

	$r_{pt}^{3} - r_{pt}^{0}$	$r_{pt}^{5} - r_{pt}^{0}$	$r_{pt}^{5} - r_{pt}^{3}$	$r_{pt}^{3} - r_{pt}^{1,2}$	$r_{pt}^{1,2} - r_{pt}^{0}$	$r_{pt}^{3,5} - r_{pt}^{0}$
Mean difference in monthly return	1.00%	0.63%	-0.35%	1.01%	-0.35%	0.72%
	(2.21)[a]**	(1.72)*	(-0.53)	(2.37)**	(-0.58)	(2.03)**

[a] t-statistics in parentheses; **: Significant at 5% level; *: Significant at 10% level

Panel A shows that the use of derivatives for at least three consecutive year period generates abnormal return. The difference in return between Group 3 and either Group 0 or Group 1-2 is statistically significant. The incremental return from hedging five years instead of three is insignificant. The incremental return from either one or two years instead of no hedging is also insignificant.

Panel B: Descriptive statistics of residual returns from time series least square regressions

	Fama-French regression				*Eckbo et al (2000) regression*	
	r_{pt}^{0}	r_{pt}^{1-2}	r_{pt}^{3-5}	r_{pa}^{5}	r_{pt}^{0}	r_{pa}^{5}
Mean	-5.1E-19	1.07E-18	3.76E-19	2.5E-18	-8.1E-19	-1.9E-18
Standard Error	0.002701	0.002419	0.002285	0.002149	0.004453	0.002456
Standard Deviation	0.020921	0.01874	0.017703	0.016645	0.034492	0.019021
Skewness	3.910464	2.476639	1.009161	0.551526	1.227331	-0.27389
Kurtosis	-0.4885	-0.68334	0.31716	0.344687	-0.367709	-0.1917
Confidence Level (95.0%)	0.005405	0.004841	0.004573	0.0043	0.00891	0.004914

Table 4: EGARCH estimates from Fama-French mean-equation

	α_p	$r_{mt} - r_{ft}$	SMB_t	HML_t	$Adj\,R^2$
	Panel A: Equally-weighted portfolio return				
Group 0	-0.0086	0.9109	0.6113	0.1989	0.87
	(-3.74)[a]**	(10.39)**	(12.73)**	(2.11)*	
Group 1-2	-0.0064	0.9209	0.4515	0.0769	0.74
	(-2.16)*	(7.98)**	(6.61)**	(0.5)	
Group 3	-0.00002	0.8897	0.2675	0.1480	0.51
	(-0.003)	(6.41)**	(3.37)**	(0.8)	
Group 3-5	0.0001	0.9453	0.2409	0.2003	0.765
	(-0.05)	(11.51)**	(4.51)**	(1.95)	
Group 5	-0.0007	0.9009	0.2206	0.1803	0.756
	(-0.30)	(11.22)**	(4.18)**	(2.07)*	
	Panel B: Value-weighted portfolio return				
Group 0	0.0007	0.4222	0.0909	0.0272	0.53
	(0.17)	(3.21)**	(0.63)	(0.59)	
Group 1-2	0.0028	1.0844	0.1120	0.1523	0.57
	(0.57)	(7.37)**	(1.73)	(0.99)	
Group 3	0.0013	1.2811	0.1162	0.1436	0.59
	(0.27)	(8.62)**	(1.62)	(0.87)	
Group 3-5	0.0006	0.8589	0.0890	0.0527	0.708
	(0.21)	(8.24)**	(1.97)*	(0.57)	
Group 5	-0.0003	0.5973	0.0710	-0.0035	0.43
	(-0.11)	(5.67)**	(1.35)	(-0.03)	
	Panel C: Individual stock return				
Group 0	-0.0170	0.8019	0.2263	0.5950	0.89
	(-6.82)**	(9.14)**	(2.55)*	(12.27)**	
Group 1-2	-0.0117	0.8401	0.2074	0.4278	0.80
	(-3.34)**	(8.92)**	(1.74)	(7.72)**	
Group 3	0.0055	0.7433	0.0502	0.2385	0.65
	(0.720)	(8.10)**	(0.25)	(3.47)**	
Group 3-5	-0.0004	0.8762	0.1726	0.2376	0.78
	(-0.17)	(14.94)**	(2.56)*	(8.13)**	
Group 5	-0.0031	0.8519	0.2337	0.2322	0.77
	(-1.66)	(10.99)**	(3.63)**	(5.94)**	

[a] t-statistics in parentheses; **: Significant at 1% level; *: Significant at 5% level

Table 5: EGARCH estimates from Eckbo et al (2000) mean-equation

	α_p	$r_{mt} - r_{ft}$	ΔCCL_t	UR_t	$T\text{-}Bill\,Spr_t$	$(10yr - 2yr)_t$	$(Corp - Govt)_t$	$Adj\,R^2$
Panel A: Equally-weighted portfolio return								
Group 0	0.0083	1.0594	0.0259	-0.2717	0.0619	-0.0403	-0.0084	0.443
	(1.81)	(6.58)**	(0.21)	(-1.15)	(1.37)	(-1.19)	(-0.04)	
Group 1-2	0.0057	1.0465	0.0400	-0.1445	0.0612	-0.0169	-0.0818	0.504
	(1.25)	(6.84)**	(0.39)	(-0.85)	(1.27)	(-0.51)	(-0.45)	
Group 3	0.0080	0.9286	-0.0458	-0.1420	0.0107	-0.0416	0.1080	0.44
	(1.74)	(7.05)**	(-0.88)	(-0.99)	(0.17)	(-1.24)	(0.66)	
Group 3-5	0.0080	0.9347	0.0227	-0.1113	0.0372	-0.0241	0.0215	0.682
	(2.86)*	(9.57)**	(0.51)	(-1.02)	(1.36)	(-1.23)	(0.19)	
Group 5	0.0065	0.8811	0.0354	-0.1190	0.0485	-0.0135	0.0079	0.691
	(2.46)*	(9.35)**	(0.69)	(-0.98)	(2.20)*	(-0.77)	(0.07)	
Panel B: Value-weighted portfolio return								
Group 0	0.0030	0.3824	0.0334	0.1938	0.0209	-0.0014	-0.1548	0.217
	(0.77)	(2.76)**	(0.56)	(0.89)	(0.61)	(-0.06)	(-1.51)	
Group 1-2	0.0077	1.0814	-0.0542	0.0927	0.0690	0.0270	-0.2598	0.60
	(2.10)*	(8.16)**	(-0.63)	(0.50)	(2.18)*	(1.54)	(-1.81)	
Group 3	0.0059	1.2628	0.0502	0.0322	0.0392	0.0162	-0.0890	0.585
	(1.30)	(8.50)**	(0.60)	(0.13)	(0.93)	(0.79)	(-0.58)	
Group 3-5	0.0029	0.8804	0.0168	-0.1616	0.0183	0.0176	0.0658	0.713
	(1.25)	(10.29)**	(0.32)	(-1.55)	(0.96)	(1.01)	(0.68)	
Group 5	0.0006	0.6339	-0.0076	-0.2419	0.0120	0.0213	0.1563	0.488
	(0.18)	(4.99)**	(-0.13)	(-1.70)	(0.50)	(0.80)	(1.44)	
Panel C: Individual stock return								
Group 0	0.0085	1.0707	0.0240	-0.2692	0.0654	-0.0477	-0.0001	0.169
	(4.22)**	(12.45)**	(0.66)	(-3.00)**	(3.34)**	(-3.19)**	(0.00)	
Group 1-2	0.0058	1.0852	0.0395	-0.1404	0.0724	-0.0193	-0.0960	0.176
	(2.25)*	(9.69)**	(0.97)	(-1.04)	(2.13)*	(-1.43)	(-0.93)	
Group 3	0.0120	0.9311	-0.0466	-0.1409	0.0097	-0.0418	0.1085	0.198
	(4.18)**	(10.49)**	(-0.76)	(-1.40)	(0.230)	(-2.58)**	(0.90)	
Group 3-5	0.0082	0.9447	0.0273	-0.1053	0.0363	-0.0233	0.0236	0.209
	(6.46)**	(17.06)**	(1.16)	(-2.06)*	(2.44)*	(-2.94)**	(0.43)	
Group 5	0.0065	0.8811	0.0354	-0.1190	0.0485	-0.0135	0.0079	0.204
	(4.32)**	(11.35)**	(1.33)	(-1.87)	(3.40)**	(-1.42)	(0.12)	

[a] t-statistics in parentheses; **: Significant at 1% level; *: Significant at 5% level

Table 6: Fama-MacBeth regression of stock returns on idiosyncratic volatility and firm characteristics

Panel A: Pooled sample

Model	$\sigma_{\varepsilon it}$	Ln(ME)	Ln(BE/ME)	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	$\sigma_{\varepsilon it-1}$	Adj R^2
1	0.0576 (1.92)[a*]							0.0141
2	0.0568 (1.78)	0.0001 (0.34)	0.0013 (2.77)**					0.0239
3	0.0569 (1.77)	0.0000 (0.17)	0.0010 (2.44)**	0.0183 (3.00)**	0.0041 (0.25)	0.0026 (1.06)		0.0467
4		0.0002 (1.07)	0.0008 (1.88)	0.0143 (2.20)*	0.0065 (0.42)	0.0029 (1.28)	0.0078 (0.64)	0.0374

Panel B: Hedge sample

Model		$\sigma_{\varepsilon it}$	Ln(ME)	Ln(BE/ME)	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	$\sigma_{\varepsilon it-1}$	Adj R^2
1	**Group 0**	0.2204 (4.12)**							0.054
	Group 1-2	0.1729 (2.22)*							0.063
	Group 3	0.0894 (0.96)							0.07
	Group 3-5	0.0915 (1.43)							0.04
	Group 5	0.0898 (1.50)							0.053
2	**Group 0**	0.2525 (4.50)**	0.1032 (2.92)**	0.0036 (4.90)**					0.077
	Group 1-2	0.1709 (2.11)*	0.2245 (1.78)	-0.0013 (-1.47)					0.092
	Group 3	0.1139 (1.22)	0.1075 (1.10)	-0.0003 (-0.19)					0.115
	Group 3-5	0.1024 (1.55)	0.0014 (1.77)	-0.0010 (-3.24)**					0.053
	Group 5	0.1062 (1.70)	0.1575 (2.02)*	-0.0008 (-2.34)**					0.072

Model		$\sigma_{\varepsilon it}$	Ln(ME)	Ln(BE/ME)	Ret(-2,-7)	Ln(TURN)	Ln(CVTURN)	$\sigma_{\varepsilon it-1}$	Adj R^2
3	**Group 0**	0.2535 (4.25)**	0.2780 (1.34)	0.0028 (3.71)**	0.0131 (1.85)	0.0434 (0.88)	0.0006 (0.19)		0.129
	Group 1-2	0.1643 (2.06)*	0.1999 (1.46)	-0.0016 (-1.56)	0.0190 (2.18)*	-0.0282 (-0.86)	-0.0007 (-0.17)		0.155
	Group 3	0.1197 (1.26)	-0.0199 (-0.15)	-0.0022 (-0.75)	0.0241 (1.38)	0.0172 (0.32)	0.0051 (0.46)		0.293
	Group 3-5	0.0989 (1.54)	0.1119 (1.36)	-0.0010 (-3.11)**	0.0275 (3.21)**	-0.0050 (-0.23)	0.0023 (0.64)		0.096
	Group 5	0.1156 (1.80)	0.1044 (1.02)	-0.0008 (-1.86)	0.0236 (2.70)**	0.0169 (0.44)	0.0020 (0.47)		0.137
4	**Group 0**		-0.0036 (-1.54)	0.0034 (3.93)**	0.0080 (1.02)	0.0883 (1.58)	0.0002 (0.06)	-0.0227 (-0.92)	0.0917
	Group 1-2		0.0023 (1.53)	0.0009 (0.55)	0.0191 (1.80)	-0.0342 (-1.00)	0.0028 (0.69)	0.0355 (1.63)	0.112
	Group 3		-0.0016 (-1.07)	0.0000 (0.00)	0.0297 (1.98)*	-0.0071 (-0.12)	0.0078 (0.70)	0.0281 (1.36)	0.251
	Group 3-5		0.0006 (0.76)	-0.0012 (-3.51)**	0.0236 (2.63)**	0.0013 (0.06)	0.0022 (0.66)	0.0303 (1.83)	0.073
	Group 5		0.0003 (0.28)	-0.0011 (-3.48)**	0.0180 (1.92)	0.0258 (0.66)	0.0027 (0.64)	0.0148 (0.39)	0.111

[a] t-statistics in parentheses; **: Significant at 1% level; *: Significant at 5% level

The table presents time-series averages of slope coefficients from Fama-MacBeth (1973) cross-sectional regressions. The t-statistic is calculated using the average slope coefficient divided by its time-series standard error. The sample period is January 2001 to December 2005. The dependent variable is the monthly stock return. $\sigma_{\varepsilon it}$ is the month t idiosyncratic volatility from EGARCH while $\sigma_{\varepsilon it-1}$ is the one-month lagged idiosyncratic volatility. ME and BE/ME are the size and book-to-market factors constructed according to Fama and French (1993). RET(-2,-7) is the compound gross return from Month -7 to Month -2. TURN is the average turnover volume over the past 36 months and CVTURN is the coefficient of variation in TURN. In the last column, we report the adjusted R2 that is averaged across the cross-sectional regressions.