RETHINKING IDIOSYNCRATIC VOLATILITY:

IS IT REALLY A PUZZLE?[1]

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SECOND DRAFT-JUNE 2008

[1] I thank Alan White, Laurence Booth, Tom McCurdy, Raymond Kan, Lukasz Pomorski, and Esther Eiling and seminar participants in University of Toronto for their helpful comments and support.

ABSTRACT

In their paper, Ang, Hodrick, Xing, and Zhang [AHXZ (2006)] show that idiosyncratic volatility (IV) is inversely related to the future return of the stock: low IV firms earn higher returns than ones with high idiosyncratic volatility. I revisit this controversial result by first replicating AHXZ's paper and then investigating the impact of the change in a firm's IV ranking on its future returns. The main contribution of this paper is to provide evidence that the change in a firm's idiosyncratic risk ranking can explain AHXZ's puzzling result. I find that firms that move from low IV quintiles to high ones earn higher positive returns. On the other hand, firms that move from high to low quintiles earn lower future returns. The impact is asymmetric; changes from low to high have larger impact than changes from high to low. However, if I only focus on firms that have highly persistent idiosyncratic volatility, which means no change in their firm specific ranking, then there is a positive relationship between the future return and idiosyncratic volatility. Lastly, I investigate the standard error and the variability of beta in each IV quintile. Both high variability and high standard error in beta estimates lead to higher future returns in the next period.

I. Introduction

There is a fast-growing and controversial body literature dealing with the impact of IV on stock returns. Standard asset pricing models, such as the Capital Asset Pricing and Fama-French (1993) models, suggest that only systematic risk factors should be related to future returns. This is because firm specific risk (idiosyncratic risk) can be eliminated by diversification, and therefore investors do not require a risk premium for bearing that risk. There are, however, some exogenous reasons under which investors hold undiversified portfolios. In these situations, firm specific risk plays a role in affecting future returns. For example, Levy (1978), Merton (1987), and Malkiel and Xu (2001) extend the CAPM by putting constraints on portfolio construction. The resulting asset pricing models capture both the systematic and unsystematic risk of the security.

The pricing of idiosyncratic risk in the cross section of security returns has been the subject of research for almost 40 years. In early work, Douglas (1969) and Lintner (1965) found that the variance of the residuals from the market model was strongly significant in explaining the cross-section of security returns. These results were subsequently neglected, as Black and Scholes (1972) and Fama-MacBeth (1973) improved the empirical methodology for testing asset pricing models. However, more recently the debate on the IV has been revived with conflicting results. On the one side, Lehmann (1990), Goyal and Santa-Clara (2003), and Malkiel and Xu (2003), Spiegel and Wang (2005), and Fu (2007) present evidence of a positive relationship between IV and future returns. On the other hand, Ang, Hodrick, Xing, and Zhang [AHXZ (2006)] find a strongly significant negative relationship between IV and security returns. In a follow-up paper, they show that this pattern is visible internationally. Finally Bali, Cakici, Yan and Zhang (2005) find that in fact there is no significant relationship between firm specific risk and the future returns.

After controlling for almost all related firm characteristics, AHXZ call their result a “puzzle”: why do low IV firms earn higher future returns than ones with high idiosyncratic volatility? This “puzzle” has attracted recent attention and there has been an increasing interest in explaining the economic reasons for AHXZ’s controversial result.

Kapadia (2006) provides evidence that skewness is responsible for the low returns to highly volatile stocks. Stocks that have exceptionally high IV are likely to have positive skewness and a preference for skewness is consistent with low expected returns, unlike a preference for variance which suggests risk-seeking behavior and high expected returns. Jiang, Xu, and Yao (2005) show that this anomaly may be induced by the information content of future earnings. They suggest that firms with poor earnings tend to provide less guidance to the investors, which results in a higher degree of heterogeneity in investors’ belief. Heterogeneous belief, in turn, translates into higher trading volume and higher stock price volatility. They also find that IV does persist. Finally, Fu (2008) suggests that AHXZ’s findings are in part explained by the return reversal of stocks with high idiosyncratic volatilities. His emphasis is on time-varying IV and its relationship to future returns.

This paper revisits the cross-sectional differences in returns based on idiosyncratic volatility. First, I replicate AHXZ’s results for the period July 1963 to December 2003. My results are similar to theirs. I find, on average that the value-weighted low IV portfolio earns approximately 1% per month more than the value-weighted high idiosyncratic portfolio. These results are even more pronounced when portfolio returns are calculated as equally-weighted. Second, I investigate the impact of a change in a firm’s IV on its future return, and I provide evidence that it is this change that produces AHXZ's results. Securities that move from lower IV quintiles to higher ones earn very high positive returns. For example, if a firm moves from Quintile 1(Low) to Quintile 5(High) and becomes highly volatile, then it earns on average 7.95% per month as a risk adjusted return. However, securities which move from higher to lower IV quintiles consistently earn lower future returns. These securities are approximately 2% of each quintile. Third, if I only focus on securities that stay in the same IV ranking in consecutive periods, then I obtain the opposite results to AHXZ: the highly persistent low IV quintile earns consistently lower returns than the quintiles with high idiosyncratic volatility. More importantly, almost 65% of all firms in each quintile do have highly persistent idiosyncratic risk.

These findings can be explained in the following way: investors requiring an ambiguity risk premium in the presence of ambiguous information and they are ambiguity averse in the Knight sense. If I exclude stocks that have low persistent idiosyncratic volatility, then I observe a positive relationship between IV and stock returns. Therefore, AHXZ's result seems to be driven by the 35% of securities that change their idiosyncratic rankings from one month to the next.

Fourth, I show that change in idiosyncratic risk ranking has an asymmetric impact on future returns. If the change is from low IV to high, then it has a higher impact (4.52% per month) than when the change is from high to low (-0.73% per month). This is analogous to the differential stock market reaction to good versus bad news: overreaction to uncertainty increases, while under-reaction to uncertainty resolution.

Finally, I provide evidence that securities with high standard errors for their beta estimates have higher future returns. Portfolios that move from low to high IV have higher betas and higher standard errors for their beta estimates after the change. This means that subsequent to a corporate event that increases uncertainty about a security, its beta estimate increases and becomes less reliable. On the other hand, if the corporate event reduces uncertainty, then the security becomes more reliable and has a lower beta. I show that highly variable beta estimates lead to higher future returns. If beta is random then the measurement of IV by an ordinary least squares (OLS) regression can be contaminated by systematic risk and it might be one reason for idiosyncratic risk to be priced.

The rest of this paper is organized as follows. In Section II, I replicate AHXZ's results by extending their sample period. In Section III, I analyze characteristics of securities that change in their IV rankings. Variation, standard error of beta estimates, trading volume, and dividend status. Then the impact of change in IV ranking with respect to future return is provided. As a robustness check, I investigate findings for different portfolio formation periods and for different measures of IV, i.e. by using the CAPM. Finally, the asymmetric impact of change in security ranking on future returns is examined. In Section IV, I provide theoretical background for the empirical results in the paper and in Section V, a conclusion.

II. IV in the Cross-Section and Future Returns

A. Estimation of IV

I collect all available data from the Center for Research in Security Prices (CRSP) for U.S. listed stocks from 1963-2003. IV is computed (as in AHXZ) as the standard deviation of the residuals from a three-factor (excess of risk free rate) model of daily returns within the month. In particular, the residuals from the following regression of daily returns for each firm, each month, give idiosyncratic volatility:

(1) $$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i$$

I define IV as $\sqrt{Var(\varepsilon_t^i)}$ in Equation 1.

Following AHXZ's method, every month I form five value-weighted quintile portfolios based on idiosyncratic volatility. These are computed using daily data over the previous month relative to the Fama-French (1993) model. Quintile 1 is the lowest and Quintile 5 is the highest IV portfolio. I run a monthly FF-3 factor model for each quintile over the entire period from 1963-2003 to estimate IV ranked portfolio alphas.

B. Replication Results

Replication of Table VI in AHXZ's paper and their original results can be seen in Panel A and Panel B of Table 1a, respectively.

[Insert Table 1a here]

AHXZ's results are based on the sample period from July 1963 to December 2000 and show that a trading rule that is long the high quintile and short the low quintile earns -1.06% per month when returns are measured as raw unadjusted returns. Replication results confirm this finding by using a sample period July 1963 to December 2003 and it shows that the same trading rules earns -1.21% per month as unadjusted simple return. These findings are both statistically and economically significant.

Table 1a also shows the results of time series regressions for each quintile from July 1963 to December 2003. The high minus low portfolio earns -1.23% per month with respect to the FF-3 Model and -1.37% per month respect to the CAPM. These results confirm AHXZ's findings which are -1.31% and -1.38% per month with respect to the FF-3 Model and the CAPM, respectively.

Firm characteristics for each quintile portfolio can also be seen in Table 1a. Firms that are in the lower quintiles are bigger, older, dividend payers and less traded, as measured by turnover.

Of all dividend paying firms in the whole sample, 30.74% are in the low quintile and 3.37% are in the high quintile.

In addition to these characteristics, I analyze each quintile's average behavior of daily estimates from Equation 1. This analysis can be seen in Table 1b.

[Insert Table 1b here]

The firms that are in the lower quintiles have consistently lower betas than ones in the higher quintiles. This means that high IV firms tend to comove more with the market, as opposed to low IV firms. Both the standard error and variability of beta are higher for high IV firms. That is, even though systematic risk is large for the securities in Quintile 5, their high standard error makes their use of questionable value for portfolio construction or arbitrage.

As seen in Table 2, unlike the high IV quintile's positive loadings on small minus big (SMB), they are negative for low IV quintiles, indicating that they are large market capitalization securities. Similarly, low quintile firms seem to be high book to market firms and are less sensitive to market movements. The sign on the risk factor loadings are in line with what I would expect given the data characteristics shown in Table 1a and Table 1b.

[Insert Table 2 here]

III. Change in IV Ranking and Future Returns

A. The Movement of Firms between Quintiles

In this subsection, I investigate the change in firms' IV rankings for two consecutive periods. To do so, every month I: 1. sort firms with respect to their previous month's IV estimated from Equation 1. 2. I sort them with respect to their contemporaneous idiosyncratic volatility. 3. I create a variable called JUMP which indicates the movement of firms from one quintile to another. Jump 0 refers to no jump. For example, at the beginning of February, if a firm is in Quintile 1 with respect to its January IV and if it is still in the same ranking with respect to its February IV, then this firm is said to be in Jump 0. In other words, firms in Jump 0 have highly persistent idiosyncratic volatilities. Similarly, Jump -4 refers to firms that were in Quintile 1(Low) with respect to their previous month's ranking and are in Quintile 5(High) according to their ranking one month later. Therefore, a firm may experience nine possible jumps, Jump X where X= -4, -3, -2, -1, 0, 1, 2, 3, 4. I discuss the characteristics of three important groups: Jump 0 and Jump -4 and Jump +4. Jump 0 represents almost 65% of each quintile; Jump -4 and Jump +4 are the extreme jumps that a firm can experience.

1. Characteristics of Firms When Jump 0

Jump 0 firms represent the largest portion of the sample. Firms that continue to be in Quintile 1 in two consecutive periods are 64.77% of all Quintile 1 firms. Similarly, 63.80% of all Quintile 5 firms stay in the same quintile in the next month. 44.06%, 39.59% and 42.41% of all Quintile 4, Quintile 3 and Quintile 2 firms, respectively, do not move. Table 3a shows the characteristics of portfolios (such as size, age, turnover, and unadjusted monthly simple returns) that have highly persistent idiosyncratic volatilities.

[Insert Table 3a here]

The mean monthly simple return across IV quintiles is similar to each other. They are approximately 1% per month. However, excess returns with respect to FF-3 Factor model are -0.46% per month for Quintile 1 and 2.6% per month for Quintile 5 (see Section B).

The turnover of low idiosyncratic risk firms is much lower than for higher quintile firms. That is, highly disagreed securities are traded heavily compared to less disagreed securities. In this context, the uncertainty level of the security is determined with respect to its idiosyncratic volatility. However, extreme disagreement, Quintile 5, translates into marginally lower trading volume than Quintile 4.

Within Jump 0, low quintile firms are bigger in size compared to the high IV firms. Figure 1 shows that within Jump 0, low quintile firms tend to pay dividends. Within the lowest quintile, 34.11% of all firms pay dividends. On the other hand, only 2% of all highest IV firms pay dividends. Moreover, low quintile firms are older and 50% of all firms in Jump 0 are traded on the NYSE.

[Insert Figure 1 here]

The estimates from Equation 1 are given in Table 3b. Beta increases as IV increases, as well as standard error of beta and variability of beta.

[Insert Table 3b here]

The pattern of average historical beta for each quintile can be seen in the Figure 2 below. Within Jump 0, firms that are in Quintile 1 have lower beta than firms in higher quintiles. For example, for Quintile 1 firms, the average beta is 0.41, whereas for Quintile 5 firms it is 0.98. This significant difference means that the highly persistent high IV firms are more sensitive to the market. In other words, firms in Quintile 5 comove with the market. In contrast, large, mature utility firms in Quintile 1 don't move with the market and have low idiosyncratic volatility.

[Insert Figure 2 here]

Figure 2 also shows the standard error and variability of beta estimates from Regression Equation 1. Historical beta estimates become more questionable as IV increases because the standard error of beta also increases. For example, beta estimates have narrower confidence intervals in the low IV quintile, whereas they are wider in the high IV quintiles. The pattern of the standard errors of beta for each quintile within the Jump 0 firms confirms the findings from

Kumar et al.: when firms have high IV in the previous month, they also have standard error beta in the next month.

Firms that are in the low IV quintiles in the past and continue to be low in the next period have the lowest variability of beta, while firms that are in the high IV quintiles in the past and continue to be in the high quintiles in the next period have higher beta variability. For instance, the monthly average beta variability of Quintile 5 is 2.3. This number can be interpreted in the following way: a least squares estimate of IV relative to the FF-3 factor model is more relevant to Quintile 5 securities' future returns simply because their firm specific risks are more contaminated by their systematic risk as shown in Equation 1.

Summary

Of the firms that have highly persistent IV in two consecutive periods (Jump 0), on average, Quintile 1 firms are bigger, less traded and tend to pay dividends. They also have low betas with very low standard errors and low variability in beta estimates. This pattern is just the reverse for Quintile 5 firms. They are smaller, more heavily traded, rarely pay dividends and are highly sensitive to the market. They also have larger standard errors level and beta variability.

2. Characteristics of Firms Which Jump from Quintile 5 to Lower Quintiles

Firms that are in the highest IV quintile with respect to their previous months ranking, for some reason, sometimes jump to the lower IV quintile in the next period. The reason for this jump may be a corporate event that decreases uncertain information surrounding the security. Figure 3 shows the percentage of firms that move from Quintile 5 to lower quintiles. Only 2% of all firms in this ranking experience extreme jumps, i.e., from the highest quintile to the lowest quintile, where Jump=4.

[Insert Figure 3 here]

Summary statistics in Table 4a and Table 4b with respect to monthly information and estimates of Regression Equation 1 show that firms that jump from Quintile 5 to 1 are the smallest of all Quintile 5 firms and almost 7% of these firms pay a dividend. On the other hand, only 2% of all firms that remain in Quintile 5 pay a dividend. Interestingly, we observe an increase in dividend paying firms as firms move from high to low IV. This could be one of the reasons why we see a resolution of the uncertainty attached to the stock in the next period. In other words, this event may reduce the uncertain information surrounding the stock and its beta and standard error are reduced. Only 9% of all firms in Jump 4 are from the NYSE.

[Insert Table 4a here]

Unadjusted monthly simple returns vary across the jump portfolios; it is 1% per month for the firms that stay in high quintile IV in two consecutive periods and 0.2% per month for firms that jump from high quintile IV to low quintile IV. Time series results in Part B confirm this observation. For example, a Jump 4 portfolio that moves from high quintile IV to low quintile IV earns -0.73% per month in excess returns.

Trading volume shows the expected pattern: as the firm becomes more uncertain in terms of its idiosyncratic risk, its proportional trading volume increases. This pattern in trading volume may be related to disagreement in the market. As a security becomes more certain, market disagreement resolves and less trading takes place.

Differences between confidence levels attached to beta estimates are significant as securities move from one quintile to another. For example, if a security stays in Quintile 5 (Jump=0), the standard error of its beta estimate is 4.15, whereas if a security in Quintile 5 makes an extreme jump to Quintile 1 (Jump=4) the standard error of its beta is 0.25. Within the highest idiosyncratic volatilty quintile, securities that experience jumps to lower quintiles have less variable betas than the ones that stay in the same idiosyncratic volatilty ranking. However, even beta variabilitiy of this particular group is not as low as the ones in Quintile 1 when there is no jump sample. For example, when Jump=0, Quintile 1 firms have on average 0.24 variability of beta, whereas securities that do jump from Quintile 5 to 1 have 1.3 on average.

[Insert Table 4b here]

Figure 4 shows that the securities that continue to have high IV relative to other securities tend to have the highest beta, standard error and variability of beta.

[Insert Figure 4 here]

Summary

Securities that jump from the highest IV ranking to the lowest (Jump= 4) are smaller in size and less traded. They also tend to pay a dividend and have lower betas with smaller standard errors and high variability.

3. Firms Jump from Quintile 1 to Higher Quintiles

Table 5a shows the characteristics of Quintile 1 firms that jump to upper quintiles, which means they become more uncertain. Only 2.3% of all firms experience an extreme jump. Such an extreme jump earns a raw excess return of 7% per month, the highest among all low quintile firms. Moreover, this particular group of firms earns the highest alpha relative to the FF-3 Factor Model: 4.25% per month.

[Insert Table 5a here]

Unadjusted monthly simple returns vary across the Jump portfolios: it is 1% per month for the firms that stay in low quintile IV in two consecutive periods and 7% per month for firms that jump from low quintile IV to high quintile IV. Time series results are given in Part B. For example, Jump -4 portfolios that move from low quintile IV to high quintile IV earn excess returns of 4.52% per month.

The trading volume per share in Jump -4 is significantly higher than for firms that jump to other high IV quintiles. This is because the uncertainty related to the securities in Jump -4 increases, which in turn is consistent with high disagreement in the market about these particular securities and consequently greater trading.

Unlike Quintile 5 securities, the number of dividend payers is high among firms that continue to have low idiosycratic volatility: 34% of Jump 0 firms. However it is only 7% of all extreme jump firms (Jump -4) that pay a dividend in the next period. Similar to Jump -4 securities, the extreme jump group within Quintile 1 contains the smallest firms as well. They are young firms as well.

[Insert Figure 5 here]

Table 5b shows the security characteristics with respect to their regression estimates from Equation 1. Within Quintile 1, average beta estimates for securities that jump to higher idiosyncratic volatilty quintiles are slighty higher than the ones that stay in the same ranking in the next period. However, the standard error of the beta estimates are much higher for Jump -4, indicating that beta estimates for these securities are not reliable. Similarly, beta estimates are highly variable for this group of securities. Beta, standard error and the variability of beta patterns can be seen in Figure 6.

[Insert Table 5b here]

[Insert Figure 6 here]

Summary

Securities that jump from the lowest IV ranking to the highest one (Jump= -4) are smaller in size, more heavily traded, and less likely to pay a dividend. They also have larger beta estimates with very high standard error (less reliable), and high beta variability of all the low quintile firms.

B. Time Series Results

1. Results When Jump= 0

In this section, I provide time series regression results for each IV quintile for Jump=0 firms. The main reason for using this particular sample of securities is that they have highly persistent IV in two consecutive months. Does this high persistence matter? Table 6 shows this impact in terms of alpha relative to the FF-3 Factor Model. Contrary to AHXZ's result, I find that the highly persistent low IV portfolio earns lower future returns, -0.46% per month, than the highly persistent high IV portfolio that is 2.60% per month. Even though the results are not statistically significant (t statistics are -1.64 and 1.28, respectively), they are economically significant and confirm that there is a positive relationship between the future return and IV if securities have highly persistent idiosyncratic volatility. According to these findings, within Jump=0 a trading rule that buys securities in the high IV quintile and sells ones in the low IV quintile earns 3% per month. This contradicts AHXZ's results that a trading rule that is long in Quintile 5 and short Quintile 1 earns -1.31% per month. There is no clear pattern for the other IV quintile portfolios in terms of their alpha estimates.

[Insert Table 6 here]

Moreover, the highly persistent low IV portfolio (Quintile 1) has low beta estimates, indicating that these securities are less sensitive to market movements and bigger in size, that is, they are value stocks. On the other hand, factor loadings of FF-3 Factor Model for the highly persistent high idiosyncratic risk portfolio (Quintile 5) indicate that these securities are small, highly sensitive to the market and growth stocks.

2. Results when Jump Occurs

In this section, the time series regression results are given for the securities that jump from one IV ranking to another in two consecutive periods. What is the impact of this jump, in a firm's IV ranking on its future returns?

I first sort firms into five portfolios with respect to their previous month's IV and then within these five portfolios, I sort them into five portfolios according to their contemporaneous IV. As a result, I have 25 portfolios. Table 7 shows that the extreme Jump -4 portfolio earns 4.52% per month which is both economically and statistically significant. On the other hand, Jump 4 portfolio earns -0.73% per month. Within each quintile, the portfolios that jump to higher IV quintiles earn generally higher returns while those that move from high IV quintiles to lower ones earn lower future returns. These findings confirm that the change in a firm's IV ranking is important for its future returns.

[Insert Table 7 here]

3. Results by Year

One might argue that the results are driven by particular time periods. To verify whether or not these results are driven by particular years, I run time series regression for each quintile. Figure 7 shows the risk adjusted excess return from a trading rule that is long in highly persistent low IV firms and is short highly persistent high idiosyncratic risk firms.

[Insert Figure 7 here]

With the exception of the early 1980s and mid 1990s, this trading rule earns a negative alpha. The year by year alpha pattern confirms that the positive relationship between IV and future returns is not driven by any particular sub-period. [2]

4. Nonlinear Impact of Jump on Future Return

In this section, I show that the change in a firm's IV ranking has an asymmetric impact on its future returns. In Table 8, for example, when the change is from the lowest to highest IV quintile, securities earn 4.52% per month. Similarly, on average, all securities that experience a jump from lowest to highest have significant positive alphas relative to the FF-3 Factor Model. However, securities that jump from high IV quintiles to low ones consistently earn negative alphas. When the jump is the extreme, Jump 4, investors earn -0.73% per month. I observe overreaction to uncertainty increases (Jump -4) while under-reaction to uncertainty resolution (Jump +4). This is analogous to the different stock market reaction to good news versus to bad news.

[Insert Table 8 here]

D. Robustness Check

In this section I check robustness of the results by first using different formation and holding period and second by measuring IV of securities using the CAPM.

1. Results for Different Formation and Holding Period: 1/1/1

I form value-weighted portfolios at time *t* by using measurement of IV computed using daily data over the *t-2* month relative to FF-3 Factor Model. That means I allow for a one month lag between the ranking of the stocks and the formation of the portfolio. The findings are

[2] The results for other jump portfolios can be provided upon request.

consistently similar to AHXZ's results. As seen in Table 9, Panel A, high IV quintile minus low IV quintile earns -1.09% per month and highly significant.

[Insert Table 9 here]

At time *t*, I sort firms with respect to their contemporaneous IV. Panel B shows time series estimates of FF-3 Factor Model for each move within each quintile. When the low IV firms at t-2 jump to the highest quintile at time *t,* they earn 5.81% per month, which is both economically and statistically very significant. On the other hand, if a firm's ranking has dropped to the lowest quintile at time *t* with respect to its IV then it earns lower future returns. For example, a portfolio that is formed by firms that are in Jump=4 earns -0.53% per month, which is a highly significant result. However, Jump=0 firms, a portfolio that is long Quintile 5 and short Quintile 1 earns 0.21% per month, which is also a statistically significant result.

2. Measuring IV Relative to Capital Asset pricing Model

I replicate AHXZ's Table VI by forming value-weighted quintile portfolios every month based on IV computed using daily data over the previous month relative to the CAPM. Table 10's results confirm the findings: a portfolio that is long high IV and short low ones earns risk unadjusted simple return of -1.77% per month, which is both economically and statistically significant. Abnormal returns relative to both the FF-3 Factor Model and the CAPM are -1.38% and -1.57% per month, respectively.

[Insert Table 10 here]

I still observe high positive alphas from a portfolio that contains firms that jump from Quintile 1 to Quintile 5: 5.28% and 5.65% relative to the FF-3 Factor Model and the CAPM, respectively. On the other hand, if a firm moves from the high quintiles to the low ones, it earns lower future returns. Contrary to the findings in Part B Section 1, a portfolio that is long high IV firms and short low IV when Jump=0 ones earn -0.25% relative to FF-3 Factor Model, but this is not statistically significant. The same trading rule can earn -0.54% per month if I measure alpha relative to the CAPM, which is statistically significant.

[Insert Table 11 here]

Figure 8 shows FF-3 factor model alphas by year from 1963 to 2003. On average, a portfolio that is long high IV quintile and short low IV quintile earns -0.33% per year which is a slightly significant result. Figure 7, which shows the alphas per year when the IV is measured relative to the FF-3 Factor Model, demonstrates a similar pattern but with different magnitudes. Positive alphas are smaller and negative alphas are bigger in Figure 8 than their counterparts in Figure 7. This might be explained by the fact that size and value effects are incorporated in IV when I measure firm specific risk relative to the CAPM.

3. Trading Rule Based on the Change in IV Ranking

Until now, I have provided evidence that the change in the IV ranking of an asset between two periods is responsible for the AHXZ's negative relationship between future returns and their IV. However, the change in ranking includes the prior month as well as the contemporaneous idiosyncratic volatility. Therefore, to profit from this regularity, an investor must be able to predict the extreme movers, that is, firms which jump from the lowest to the highest IV ranking or vice versa. This raises the question of whether or not it is possible to profit from prior extreme movers, that is, the change in the IV ranking from *t-2* to *t-1*.[3]

[3] However, once a firm experiences an extreme jump, that is if a firm moves from the highest to the lowest or the lowest to the highest idiosyncratic volatility quintile, from period t-2 to t-1, it cannot possible jump again in the same direction in the next period. The jump possibilities are either move to the lower quintiles if the stock is in the highest quintile, or move to the higher quintiles is the stock is in the lowest quintiles or stay the same.   Therefore,

To test this I first sort firms with respect to their IV computed using the FF-3 Factor Model estimated over daily data for month *t-2*. Then, I sort firms with respect to the same for month *t-1* and create a variable, Change, which indicates movement of a firm from one quintile to another. At time *t*, I form value-weighted quintile portfolios based on Change and calculate their average returns.

[Insert Table 12 here]

The portfolio that contains the extreme positive movers, that is, the stocks that move from the high to the low IV quintile, earn -0.47% per month. On the other hand, the extreme negative movers, that is, the stocks that move from the low to the high IV quintile, earn 0.01% per month. Neither of these returns is significantly different from zero indicating that trading on extreme changes in IV rankings does not represent a profitable trading strategy. Repeating the same exercise for the CAPM estimated IV rankings, produces returns of -0.53% and 0.08% per month for the two change portfolios, respectively, and results are similarly insignificantly different from zero.

IV. Possible Theoretical Explanations

A. Introduction: Risk versus Uncertainty

The distinction between risk and uncertainty dates back to Knight (1921). In his seminal work *Risk, Uncertainty, and Profit,* he says "Uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it has never been properly separated.... The essential fact is that 'risk' means in some cases a *quantity susceptible of measurement*, while at other times it is something distinctly not of this character; and there are far-reaching and crucial

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prediction of the next period's idiosyncratic volatility is important to gain a profit not the past change in idiosyncratic volatility ranking.

differences in the bearings of the phenomena depending on which of the two is really present and operating.... It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an immeasurable one that it is not in effect an uncertainty at all."

Knight proposed distinguishing situations characterized by risk (in which the possible random outcomes of a certain event have *known* associated probabilities) from those characterized by uncertainty or ambiguity (in which the randomness cannot be expressed in terms of mathematical probabilities, and the probabilities themselves are *unknown*). For example, the expected utility theory of von Nuemann and Morgenstern (vNM) (1944) is based on objectively knowable probabilities. A large body of literature suggests that individuals are always able to assign reasonable probabilities to random events. These probabilities could objectively exist in the world, as proposed by vNM (1944), and could be used to calculate expected utilities, or these probabilities could be subjective, as proposed by Savage (1954). Savage adapted expected utility theory into a theory of subjective expected utility in which, under certain assumptions, people will have personal beliefs about the possible states of nature: the subjective probabilities

With the subjective probabilities the link between the two concepts, risk and uncertainty, is established. However, in some situations, it is unrealistic to assume the existence of known or knowable probabilities or complete beliefs for probabilities over all possible outcomes. Moreover, even if individuals are served with all sufficient data about possible outcomes and associated probabilities, they may still tend to use this information in ways which are inconsistent with expected utility maximization. Individuals tend to make sometimes paradoxical, surprising, and seemingly contradictory decisions. The “Ellsberg Paradox” illustrates how ambiguous information can lead to behavior that is inconsistent with the standard expected utility paradigm, but it is also intuitive.

1. Risk Premium: Merton (1987) Argument

Merton (1987) presents an extension of the CAPM where IV risk plays a role in equilibrium. Investors in Merton's model suffer from extreme information costs and only hold securities with which they are familiar. Consequently, they hold under-diversified portfolios and demand compensation for securities' idiosyncratic risk. Levy (1978) produces similar predictions in CAPM extensions where investors hold under-diversified portfolios. The resulting asset pricing model captures both the systematic and unsystematic risk of the security, which interprets the dispersion in beliefs as risk factor. Therefore, in equilibrium, cross-sectional stock returns are positively related to their IV.

2. Ambiguity Premium Argument

Information is valuable in financial markets, since investors are faced with a large amount of news, or signals every day. The signals that investors face are presumably received from informed insiders through 1) accounting based disclosures such as earnings announcements; 2) financial policy choices such as dividend initiations or share repurchase decisions and 3) other announcements such as mergers and acquisitions. Recommendations of informed investors, such as analysts, can also be considered one of these signals.

In order to use this information investors have to decide on its reliability. However, as Epstein and Schneider (2006) say "Judging quality itself can sometimes be difficult." Quality of judging depends on the source of the information as well as the confidence of an investor's parameter estimation. Therefore risk, uncertainty, ambiguity and reliability of parameter estimates all play a crucial role in the stock picking decision and the portfolio formation decision when information is incomplete.

In Epstein and Schneider (2006), investors treat signals as ambiguous when the quality of information is difficult to judge, since there is incomplete knowledge. Beliefs are not updated as in a Bayesian fashion. Instead, investors behave as if they have multiple probabilities in mind when processing signals. Hence, they focus on an ambiguity premium induced by the ambiguous news, rather than the ambiguity in fundamentals.

As in Epstein and Schneider's model, at time 0 the investor knows that an ambiguous signal will arrive on Date1. One of the reasons put forward in the literature as to how IV is priced, is that investors don't fully diversify. However, in Epstein et al.'s paper there is an investor who holds a well-diversified portfolio. They say "As long as this investor views firm-specific news as ambiguous, she will want to be compensated for it." This investor also has "robust preferences" that is she evaluates portfolios by using the worst case scenario.

When ambiguity exists, prices depend on the prospect of low information quality. If an investor knows that an asset will become more difficult to interpret in the future; the asset is less attractive and it becomes cheaper.

Epstein and Schneider also show that investors react asymmetrically to ambiguous information: bad news affects conditional actions more than good news. Moreover, even if before an ambiguous signal arrives, agents who anticipate the arrival of low quality information will reduce current asset prices. In other words, ambiguity averse investors require compensation for holding an asset simply because low quality information about the asset is expected to arrive. In a Bayesian model, this cannot be the case.

B. Reliability and Variability of Beta and Uncertain Information Quality

1. Reliability of Beta: Estimation-Risk of Beta

Kumar, Boehme, Danielsen and Sorescu (KBDS) (2008) examine the implications of investors learning about the unknown parameters and information precision simultaneously. They find that the joint presence of estimation risk and uncertain information quality substantially affects the equilibrium asset returns. They provide evidence that firm specific events that affect investors' estimation risk will change the asset's betas. Their empirical result, based on event studies from 1988 to 2000, confirms that there is a significant reduction in post-event betas, estimated betas and standard errors when a firm initiates cash payouts through repurchases.

KBDS's theoretical work shows that the estimation risk of an asset is priced in equilibrium. With estimation risk and Bayesian learning, the risk premium of an asset will not be completely determined by its systematic risk; it is also influenced by its priced estimation risk. Thus, KBDS's model predicts that immediately following a corporate event that reduces the estimation risk of an asset, not only beta will fall, but also the standard error of the beta. KBDS also discuss events that increase estimation risk. Following these events, the estimated betas will increase, which in turn positively affects the risk premium of an asset.

2. Variability of Beta

In addition to the market imperfections which may make holding diversified portfolios difficult, the variability of beta also plays a role in the pricing of unsystematic risk. If beta itself is stochastic, then the unconditional version of conventional asset pricing models may fail to explain the cross-sectional differences in returns. This is because ordinary least squares is not appropriate to decompose total risk into systematic and unsystematic risk unless the population variance associated with the risk loadings is not significantly different from zero [Swamy (1970)], that is, the beta is constant. The average rate of return is not correlated with unsystematic risk unless the unsystematic risk is contaminated by some systematic component of risk. This is because the average rate of return is a function of market movement and the variation in the beta coefficient, and the estimated unsystematic risk is dependent on the estimated variance of the beta coefficient. This implies that it is reasonable to expect that the average rate of return is correlated with the OLS residual variance [Fabozzi and Francis (1978)].

(2) $$\frac{Var\ (e_t)}{\sum_{t=1}^{n} r_{mt}^{\ 2}} = Var\ (B_i) - \frac{Var\ (b_{it} - B_i)\sum_{t=1}^{n} r_{mt}^{\ 4}}{(\sum_{t=1}^{n} r_{mt}^{\ 2})^2}$$

Equation (2)[4] says IV can be decomposed into two parts: standard error of beta estimates from the RCM and the variability of true beta. In other words, if true beta is moving randomly, then the IV estimates from the OLS regression is upward bias. More importantly, it is this variability of beta that is priced not the IV estimates from the OLS regression. Changes in dividend policy and leverage are examples of sources of changing beta coefficient in the standard CAPM.

C. Volatility Feedback

If volatility is persistent and there is a positive relationship between the future stock returns and volatility, then current shock to volatility decreases current prices. An increase in volatility raises the expected future volatility and thus the required return on stocks. The result is an immediate negative impact on the current price. A large body of literature, including Pindyck (1984), French et al. (1987), Turner et al. (1989), Campbell and Hentschel (1992), Bekaert and

[4] Derivation can be found in Fabozzi and Francis (1978).

Wu (2000), Wu (2001), Kim et al. (2004), and Mayfield (2004) find evidence in support of a volatility feedback effect.

V. Conclusion

The importance of IV in pricing stocks has been an area ongoing research for almost 40 years. There are three different streams of evidence put forward in the literature: a negative relationship between future returns and firm specific risk, a positive relationship and, finally, no relationship. This paper attempts to reconcile these confusing empirical results by focusing on the change in idiosyncratic volatility. Even though my replication confirms the basic result of AHXZ that there is a negative relationship between IV and expected returns, I show that this is driven by changes in idiosyncratic volatility.

My empirical findings can be explained by several different theories: Merton's argument, ambiguity premium argument, volatility feedback, variability and reliability of systematic risk. All of the theories above is good to explain the positive relationship between IV and future stock returns when Jump=0 stocks are concerned. However, Eipstein and Shcneider (2006) model gives an intuitive explanation why there is a positive relationship between the IV and the stock returns of firms that jump from low to high IV quintiles. Investors who are ambiguity averse would therefore demand an ambiguity premium on such stocks given their difficulty in assessing the risk. This is because at time *t* investors know that next period there will be uncertain information about the stock.

This paper also looks at the impact of variability and reliability of beta on future rate of returns. Highly variable beta stocks' IV is incorporated into the asset price more than the assets that have low variable stocks. This is because if beta estimates are highly variable, then the OLS estimates of IV are larger than the true ones. Reliability of beta estimates also affects the future excess returns. When ambiguity rises and reliability of estimates declines, then the importance of formal quantitative metrics declines, forcing investors to use their judgment. However, judgment itself is complicated and depends on investors' risk aversion and their familiarity to the stock which in turn affects the future returns. For example, Warren Buffett states that he has made most of his money out of sectors he knows intimately, such as media and financial services, and he rarely invests outside this circle of competence.

This research shows that stocks that are persistently ambiguous, that is, have persistently high IV earn higher future returns. AHXZ's results are driven by the very high returns earned by stocks that change from low to high IV quintile. This research shows that such movements generate exceptionally large returns and predicting those stocks that change their idiosyncratic risk quintiles is the next step in interpreting the empirical results.

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Figure 1

Characteristics of Jump=0 Firms

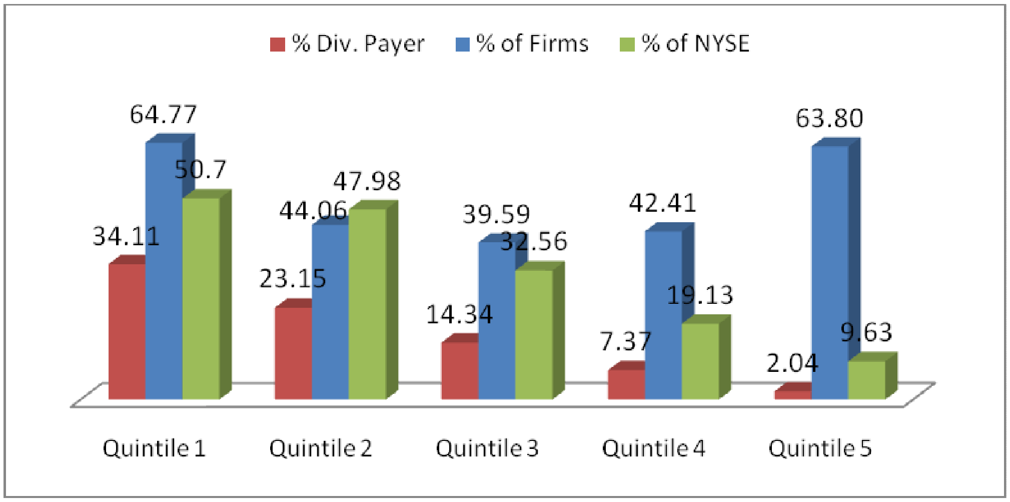

Figure 2

Beta, Standard Error and Variability of Beta of Jump=0 Firms

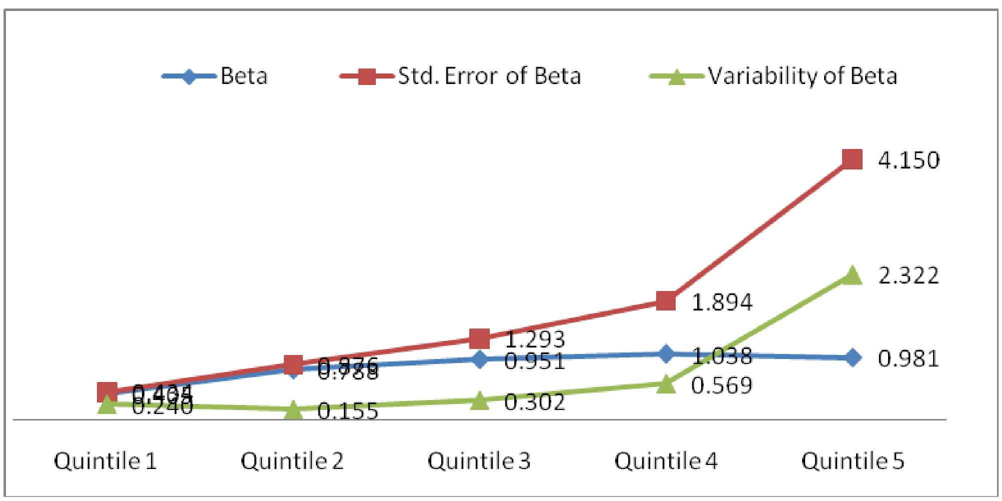

Figure 3

Characteristics of Firms that jump from Quintile 5 to Lower Quintiles

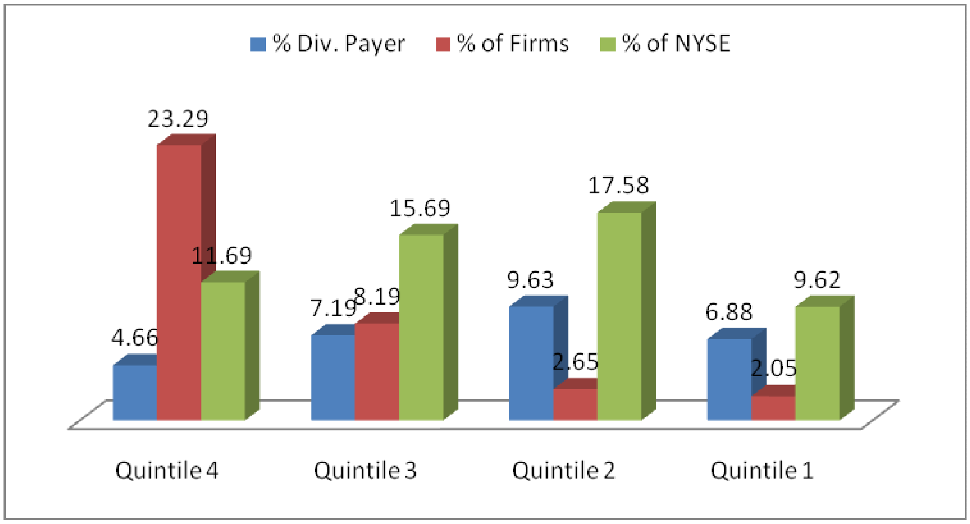

Figure 4

Beta, Standard Error and Variability of Beta of Firms

That Move from Quintile 5 to Lower Quintiles

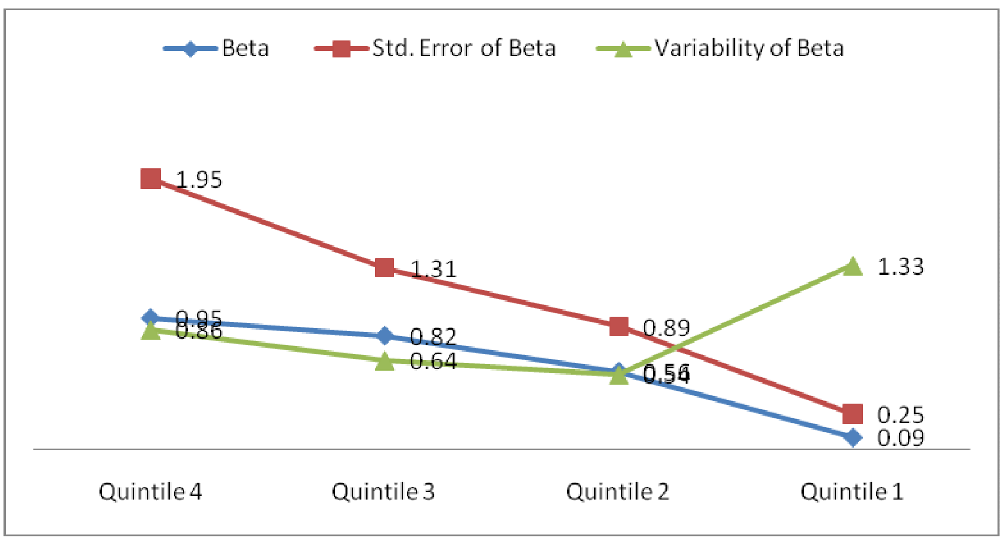

Figure 5

Characteristics of Firms that jump from Quintile 1 to Upper Quintiles

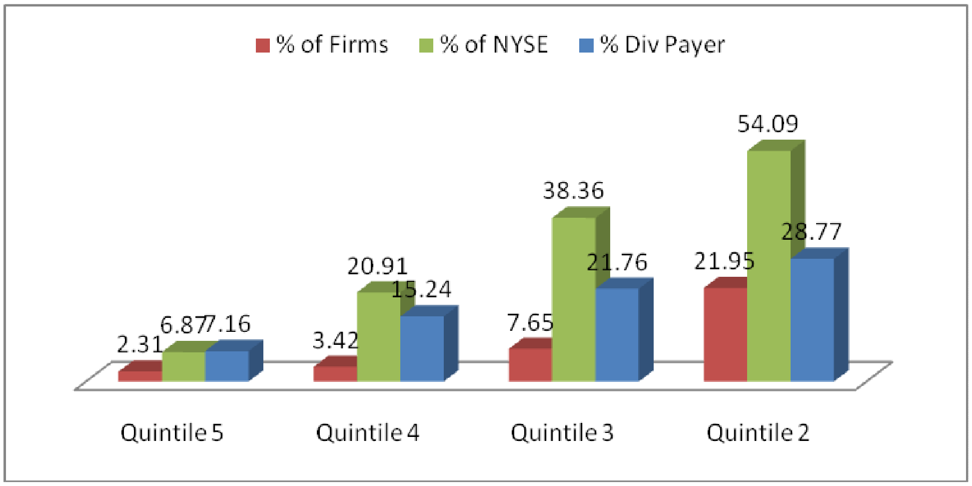

Figure 6

Beta, Standard Error and Variability of Beta of Firms

That Move from Quintile 1 to Higher Quintiles

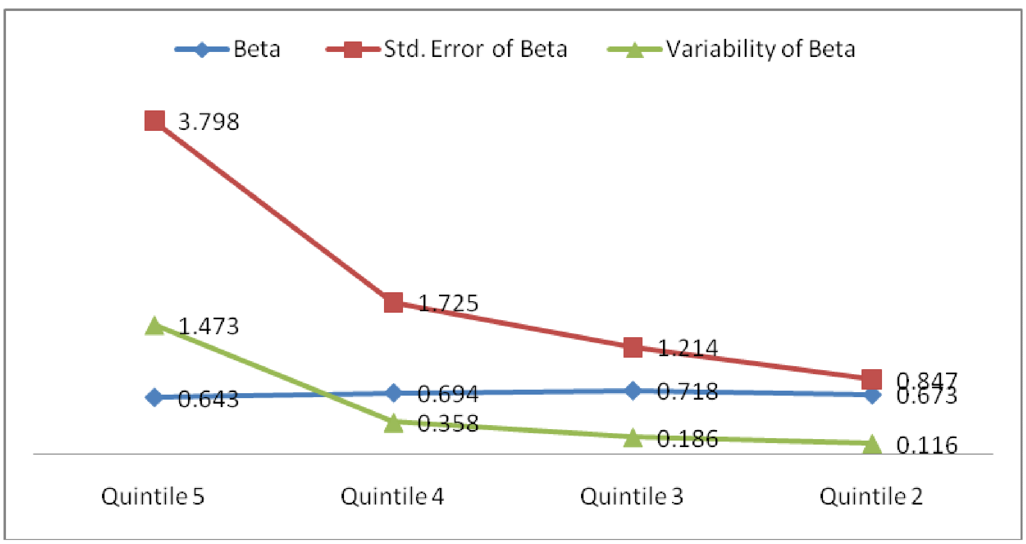

Figure 7

Alpha of a Portfolio with Respect to the FF-3 Factor Model: High –Low Quintile when Jump=0

IV is measured relative to FF-3 Factor Model

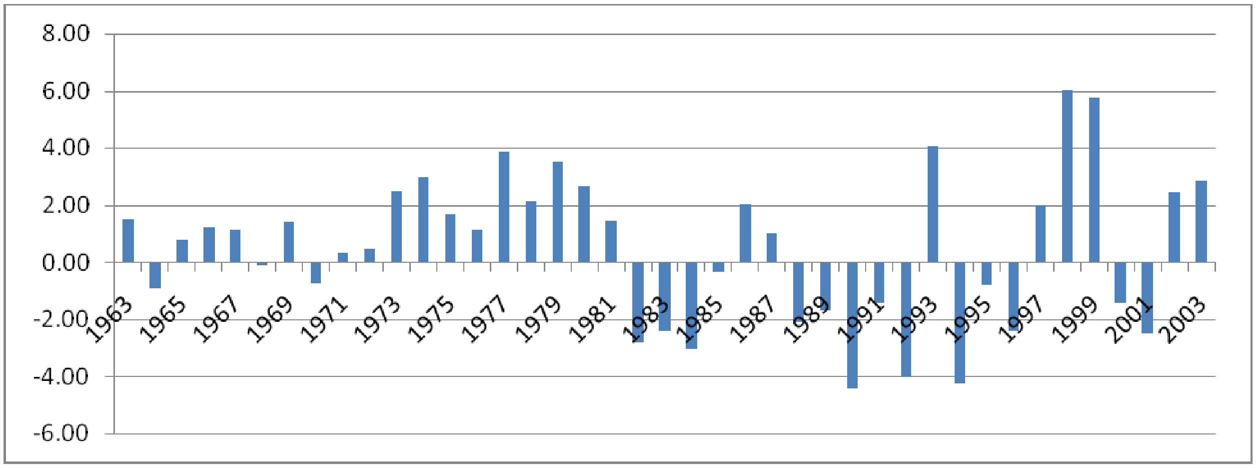

Figure 8

Alpha of a Portfolio with Respect to FF-3 Factor Model: High –Low Quintile when Jump=0

IV is measured relative to CAPM

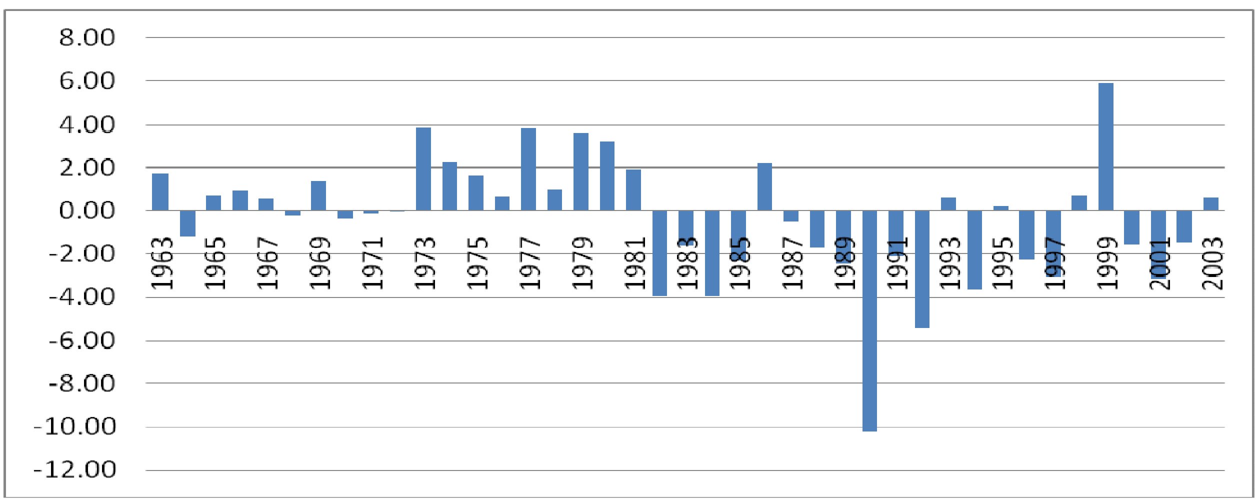

Table 1a

Replication of Panel B of Table VI in AHXZ

Value-weighted quintile portfolios are formed every month, based on IV computed using daily data over the previous month relative to FF-3 Factor Model. Mean and Std. Dev are in monthly percentage risk unadjusted simple returns. Size is the average log market capitalization of firms within the portfolio. The row “5-1” refers to the difference in monthly returns between Quintile 5 and Quintile 1. The Alpha columns show Jensen’s alpha with respect to the CAPM or to FF-3 model. Panel A. The replication sample period is July 1963 to December 2003 and AHXZ’s original result with sample period is July 1963 to December 2000. Panel B. Age is the average age of a firm in each quintile. Turnover is average trading volume in that month (in thousands) scaled by the number of shares outstanding. % of div payers is the percentage of firms that do pay dividends in each quintile. Robust Newey-West (1987) t-statistics are reported in brackets.

Panel A. Replication Results, 1963-2003						
IV Quintile	Mean	Std. Dev.	Size	%Market Share	CAPM Alpha	FF-3 Alpha
Low	1.03	3.77	4.91	46.56	0.17	0.09
					[2.80]	[2.22]
2	0.97	4.67	4.96	30.69	0.10	0.07
					[2.14]	[1.42]
3	0.92	5.78	4.34	13.76	0.00	0.03
					[-0.04]	[0.40]
4	0.55	7.03	3.68	6.54	-0.51	-0.43
					[-3.32]	[-4.06]
High	-0.19	8.66	2.71	2.44	-1.37	-1.23
					[-5.58]	[-7.29]
High-Low	-1.21					
	[-3.02]					
AHXZ's result: 1963-2000						
IV Quintile	Mean	Std. Dev.	Size	%Market Share	CAPM Alpha	FF-3 Alpha
Low	1.04	3.83	4.86	53.5	1.11	0.04
					[1.57]	[0.99]
2	1.16	4.74	4.72	27.4	0.11	0.09
					[1.98]	[1.51]
3	1.20	5.85	4.07	11.9	0.04	0.08
					[0.37]	[1.04]
4	0.87	7.13	3.42	5.2	-0.38	-0.32
					[-2.32]	[-3.15]
High	-0.02	8.16	2.52	1.9	-1.27	-1.27
					[-5.09]	[-7.68]
High-Low	-1.06					
	[-3.10]					

Panel B. Firm characteristics, 1963-2003			
IV Quintile	Age	% of Div. payers	Turnover
Low	21.31	30.74	0.53
2	21.06	22.31	0.7
3	18.33	14.81	0.91
4	16.32	8.59	1.25
High	14.52	3.37	1.09

Table 1b

Estimates of FF-3 Factor Model by Using Daily Data

$$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i$$

Value-weighted quintile portfolios are formed every month based on IV computed using daily data over the previous month relative to FF-3 Factor Model. Mean is the average of the firms' estimates in each quintile portfolio at time t. Every month, for each stock, Beta as well as its standard error is estimated from daily data by using FF-3 Factor Model. IV refers to average contemporaneous IV of the firms in each portfolio. Variability of betas is the average monthly variance of beta estimates of the stock in a year. It shows the portfolios' monthly average variability from time t-1 to t.

	Beta		Std. Error of Beta		IV		Variability of Beta	
IV Quintile	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Low	0.50	1.70	0.71	0.93	0.013	0.012	0.24	18.58
2	0.79	1.50	1.04	0.81	0.018	0.011	0.19	0.96
3	0.92	1.98	1.42	1.09	0.025	0.015	0.33	1.10
4	0.98	2.60	1.91	1.46	0.034	0.020	0.57	1.43
High	0.93	4.77	3.24	3.30	0.058	0.046	1.78	10.28

Table 2

Estimates of FF-3 Factor Model and CAPM by Using Monthly Data

$$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i$$

Value-weighted quintile portfolios are formed every month based on IV computed using daily data over the previous month relative to FF-3 Factor Model. Sample period is July 1963 to December 2003. Panel A. Time series estimates of Fama-French by Using Monthly Data. Panel B. Time series estimates of CAPM by Using Monthly Data. Robust Newey-West (1987) t-statistics are reported in brackets.

Panel A. FF-3 Factor Model, 1963-2003

IV Quintile	Market beta	SMB beta	HML beta	Alpha
Low	0.88	-0.17	0.17	0.10
	[61.01]	[-8.26]	[5.16]	[2.22]
2	1.05	-0.05	0.08	0.07
	[59.88]	[-1.37]	[2.57]	[1.42]
3	1.16	0.24	-0.07	0.03
	[58.40]	[6.31]	[-1.89]	[0.40]
4	1.20	0.71	-0.20	-0.43
	[38.60]	[15.48]	[-3.20]	[-4.06]
High	1.15	1.10	-0.35	-1.23
	[23.12]	[15.10]	[-3.39]	[-7.29]

Panel B. CAPM, 1963-2003

IV Quintile	Market beta	Alpha
Low	0.79	0.17
	[41.58]	[2.80]
2	1.01	0.10
	[65.95]	[2.14]
3	1.23	0.00
	[69.85]	[-0.04]
4	1.41	-0.51
	[34.51]	[-3.32]
High	1.49	-1.37
	[21.68]	[-5.58]

Table 3a

Portfolios when Jump=0

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. The sample period is July 1963 to December 2003. Mean and Std. Dev are in monthly percentage simple returns. Size is the average log market capitalization of firms within the portfolio. Age is the average age of a firm in each quintile. Turnover is average trading volume in that month (in thousands) scaled by the number of shares outstanding. Within the firms that do stay in the same quintile, % of div payers is the percentage of firms that do pay dividends in each quintile. % of Firms is the percentage of firms that stay in the same ranking in consecutive two months.

IV Quintile	Mean	Std. Dev.	Skewness	Size
Low	1.0	0.035	-0.579	5.097
2	1.2	0.047	-0.567	5.299
3	1.3	0.061	-0.585	4.530
4	1.4	0.080	-0.140	3.741
High	1.0	0.112	0.478	2.425

IV Quintile	Age	% of Firms	Turnover	% Div Payer	% of NYSE
Low	21.65	64.77	0.49	34.11	50.7
2	21.78	44.06	0.68	23.15	47.98
3	18.33	39.59	0.97	14.34	32.56
4	16.17	42.41	1.38	7.37	19.13
High	14.18	63.80	1.17	2.04	9.63

Table 3b

Estimates of FF-3 Factor Model by Using Daily Data when Jump=0

$$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i$$

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Within no jump, Mean is the average of the firms' estimates in each quintile portfolio at time t. Every month, for each stock, Beta as well as its standard error is estimated from daily data by using FF-3 Factor Model. IV refers to average contemporaneous IV of the firms in each portfolio. Variability of betas is the average monthly variance of beta estimates of the stock in a year. It shows the portfolios' monthly average variability from time t-1 to t.

	Beta		Std. Error of Beta		IV		Variability of Beta	
IV Quintile	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Low	0.405	1.480	0.434	0.294	0.008	0.004	0.240	22.800
2	0.788	1.194	0.876	0.435	0.016	0.004	0.155	0.766
3	0.951	1.688	1.293	0.655	0.023	0.006	0.302	0.850
4	1.038	2.375	1.894	1.003	0.034	0.009	0.569	1.388
High	0.981	5.651	4.150	3.765	0.074	0.049	2.322	12.320

Table 4a

Portfolios when Jump from Quintile 5 to Lower Quintiles

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Jump 4 refers to a firm that moves from the Quintile 5 to Quintile 1. The sample period is July 1963 to December 2003. Mean and Std. Dev are in monthly percentage simple returns. Size is the average log market capitalization of firms within the portfolio. Age is the average age of a firm in each quintile. Turnover is average trading volume in that month (in thousands) scaled by the number of shares outstanding. Within the firms that do stay in the same quintile, % of div payers is the percentage of firms that do pay dividends in each quintile. % of Firms is the percentage of firms that stay in the same ranking in consecutive two months.

Jump	Mean	Std. Dev.	Skewness	Size
0	1.0	0.112	0.48	2.43
1	-1.1	0.092	-0.23	3.17
2	-1.6	0.075	-0.36	3.30
3	-1.6	0.061	-0.62	3.14
4	0.2	0.034	-1.45	2.04

Jump	Age	% of Firms	Turnover	% Div Payer	% of NYSE
0	14.18	63.09	1.17	2.04	7.77
1	15.10	23.29	1.02	4.66	11.69
2	15.60	8.19	0.82	7.19	15.69
3	15.77	2.65	0.61	9.63	17.58
4	12.54	2.05	0.52	6.88	9.62

Table 4b

Estimates of FF-3 Factor Model by Using Daily Data

when Jump from Quintile 5 to Lower Quintiles

$$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i$$

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Jump 4 refers to a firm that moves from the Quintile 5 to Quintile 1. Mean is the average of the firms' estimates in each quintile portfolio at time t. Every month, for each stock, Beta as well as its standard error is estimated from daily data by using FF-3 Factor Model. IV refers to average contemporaneous IV of the firms in each portfolio. Variability of betas is the average monthly variance of beta estimates of the stock in a year. It shows the portfolios' monthly average variability from time t-1 to t.

	Beta		Std. Error of Beta		IV		Variability of Beta	
Jump	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
0	0.98	5.65	4.15	3.76	0.074	0.049	2.32	12.32
1	0.95	2.59	1.95	1.04	0.035	0.010	0.86	1.92
2	0.82	1.89	1.31	0.66	0.023	0.006	0.64	2.00
3	0.56	1.36	0.89	0.45	0.015	0.004	0.54	1.77
4	0.09	4.76	0.25	0.33	0.004	0.005	1.33	18.71

Table 5a

Portfolios when Jump from Quintile 1 to Upper Quintiles

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Jump 4 refers to a firm that moves from the Quintile 5 to Quintile 1. The sample period is July 1963 to December 2003. Mean and Std. Dev are in monthly percentage simple returns. Size is the average log market capitalization of firms within the portfolio. Age is the average age of a firm in each quintile. Turnover is average trading volume in that month (in thousands) scaled by the number of shares outstanding. Within the firms that do stay in the same quintile, % of div payers is the percentage of firms that do pay dividends in each quintile. % of Firms is the percentage of firms that stay in the same ranking in consecutive two months.

Jump	Mean	Std. Dev.	Skewness	Size
-4	7.0	0.192	-0.284	1.91
-3	1.0	0.103	-0.367	3.20
-2	1.0	0.067	0.065	4.30
-1	1.0	0.046	-0.677	5.21
0	1.0	0.035	-0.579	5.10

Jump	Age	% of Firms	Turnover	% Div Payer	% of NYSE
-4	13.06	2.31	0.88	7.16	6.87
-3	16.71	3.42	0.66	15.24	20.91
-2	19.80	7.65	0.57	21.76	38.36
-1	22.41	21.95	0.58	28.77	54.09
0	21.65	65.50	0.49	34.11	54.12

Table 5b

Estimates of FF-3 Factor Model by Using Daily Data

when Jump from Quintile 1 to Upper Quintiles

$$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i$$

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Jump -4 refers to a firm that moves from the Quintile 1 to Quintile 5. Mean is the average of the firms' estimates in each quintile portfolio at time t. Every month, for each stock, Beta as well as its standard error is estimated from daily data by using FF-3 Factor Model. IV refers to average contemporaneous IV of the firms in each portfolio. Variability of betas is the average monthly variance of beta estimates of the stock in a year. It shows the portfolios' monthly average variability from time t-1 to t.

Jump	Beta		Std. Error of Beta		IV		Variability of Beta	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
-4	0.643	6.043	3.798	4.001	0.063	0.046	1.473	18.470
-3	0.694	2.169	1.725	1.006	0.030	0.008	0.358	1.300
-2	0.718	1.524	1.214	0.643	0.021	0.005	0.186	0.575
-1	0.673	1.098	0.847	0.428	0.015	0.004	0.116	1.397
0	0.405	1.480	0.434	0.294	0.008	0.004	0.240	22.800

Table 6

Estimates of FF-3 Factor Model by Using Monthly Data when Jump=0

$$r_t^i - r_f = \alpha^i + \beta^i_{MKT} MKT + \beta^i_{SMB} SMB + \beta^i_{HML} HML + \varepsilon^i_t$$

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Sample period is July 1963 to December 2003. Robust Newey-West (1987) t-statistics are reported in brackets.

IV Quintile	Market beta	SMB beta	HML beta	Alpha
Low	0.29	-0.11	0.11	-0.46
	[3.65]	[-0.92]	[0.95]	[-1.64]
2	0.71	0.21	0.55	-0.76
	[4.45]	[0.70]	[2.29]	[-1.19]
3	0.86	0.12	0.41	-2.68
	[3.38]	[0.34]	[1.44]	[-3.57]
4	0.74	0.01	-0.86	-0.04
	[2.91]	[0.01]	[-1.77]	[-0.03]
High	1.67	0.13	0.16	2.60
	[3.30]	[0.13]	[0.16]	[1.28]

Table 7

Estimates of FF-3 Factor Model by Using Monthly Data when Jump Occurs

$$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i$$

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Jump -4 refers to a firm that moves from the Quintile 1 to Quintile 5 and Jump 4 refers to move from Quintile 5 to Quintile 1. Sample period is July 1963 to December 2003. Robust Newey-West (1987) t-statistics are reported in brackets.

IV Quintile	Jump	Market beta	SMB beta	HML beta	Alpha
Low	-4	1.39	1.50	0.97	4.52
		[5.93]	[4.03]	[2.21]	[4.98]
Low	-3	0.81	0.24	-1.05	-0.18
		[0.94]	[0.12]	[-0.51]	[-0.05]
Low	-2	0.85	-0.03	0.32	1.63
		[2.40]	[-0.05]	[0.50]	[1.15]
Low	-1	0.66	0.00	0.11	-0.99
		[3.21]	[-0.01]	[0.35]	[-1.32]
Low	0	0.29	-0.11	0.11	-0.46
		[3.65]	[-0.92]	[0.95]	[-1.64]
2	-3	1.07	2.69	-1.22	7.80
		[1.27]	[1.58]	[-0.89]	[1.70]
2	-2	0.99	0.91	0.03	1.34
		[1.49]	[0.80]	[0.03]	[0.64]
2	-1	1.57	-0.65	0.08	-0.60
		[4.87]	[-1.40]	[0.21]	[-0.64]
2	0	0.71	0.21	0.55	-0.76
		[4.45]	[0.70]	[2.29]	[-1.19]
2	1	0.28	-0.13	-0.15	-0.97
		[2.19]	[-0.65]	[-0.93]	[-2.16]
3	-2	1.72	-0.79	-1.11	13.35
		[1.83]	[-0.34]	[-0.62]	[2.91]
3	-1	0.38	0.98	-0.51	1.35
		[0.67]	[0.96]	[-0.84]	[0.94]
3	0	0.86	0.12	0.41	-2.68
		[3.38]	[0.34]	[1.44]	[-3.57]
3	1	0.66	-0.28	0.02	-0.45
		[3.41]	[-0.95]	[0.08]	[-0.66]

3	2	0.71	-0.65	0.10	-1.58
		[2.24]	[-1.07]	[0.22]	[-1.59]
4	-1	1.85	-0.41	0.14	0.45
		[2.73]	[-0.31]	[0.14]	[0.19]
4	0	0.74	0.01	-0.86	-0.04
		[2.91]	[0.01]	[-1.77]	[-0.03]
4	1	1.05	-0.39	0.12	-2.34
		[3.71]	[-1.44]	[0.30]	[-2.53]
4	2	0.82	0.32	-0.14	-1.61
		[2.13]	[0.47]	[-0.39]	[-1.60]
4	3	0.48	-0.19	0.64	-1.55
		[1.82]	[-0.34]	[0.49]	[-0.90]
High	0	1.67	0.13	0.16	2.60
		[3.30]	[0.13]	[0.16]	[1.28]
High	1	1.10	-0.72	-0.96	-4.23
		[4.34]	[-1.68]	[-1.34]	[-3.21]
High	2	0.28	1.08	0.53	-2.99
		[0.73]	[1.37]	[1.43]	[-1.88]
High	3	-0.31	1.27	-1.13	-3.80
		[-0.65]	[0.90]	[-1.32]	[-2.21]
High	4	0.57	0.21	0.33	-0.73
		[10.40]	[3.96]	[4.96]	[-4.40]
High-Low (When jump=0)					3.06 [3.68]

Table 8

Asymmetric Impact of Jump on Excess Returns

I first sort the firms with respect to their IV computed using daily data over the previous month relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Jump -4 refers to a firm that moves from the Quintile 1 to Quintile 5 and Jump 4 refers to move from Quintile 5 to Quintile 1. Sample period is July 1963 to December 2003. Robust Newey-West (1987) t-statistics are reported in brackets.

Jump	Market beta	SMB beta	HML beta	Alpha
-4	1.39	1.50	0.97	4.52
	[5.93]	[4.03]	[2.21]	[4.98]
-3	1.34	0.86	0.27	0.10
	[10.70]	[3.82]	[1.01]	[0.21]
-2	1.21	0.57	-0.12	0.15
	[22.29]	[6.10]	[-1.18]	[0.73]
-1	1.13	0.14	-0.01	0.24
	[59.21]	[4.82]	[-0.23]	[3.92]
0	0.93	-0.06	0.01	0.12
	[124.47]	[-4.57]	[0.65]	[4.19]
1	0.97	0.04	0.00	-0.28
	[51.45]	[1.27]	[0.05]	[-4.78]
2	0.99	0.11	0.13	-0.86
	[36.54]	[2.70]	[2.82]	[-9.25]
3	0.82	0.22	0.23	-1.31
	[21.48]	[4.00]	[3.29]	[-8.89]
4	0.57	0.21	0.33	-0.73
	[10.40]	[3.96]	[4.59]	[-4.40]

Table 9

Impact of Jump on Excess return with 1/1/1 Trading Rule:

I first sort the firms with respect to their IV computed using daily data over the t-2 relative to FF-3 Factor Model. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create MOVE that refer to the change in the rank of a firm with respect to its IV from t-2 to t. Then value-weighted portfolios are formed every month based on their move. Sample period is July 1963 to December 2003. Panel A. Time series estimates of Fama-French by Using Monthly Data for each quintile. Panel B. Time series estimates of FF-3 Factor Model for each Move within each quintile. Robust Newey-West (1987) t-statistics are reported in brackets.* refers to 1% significance.

Panel A

IV Quintile	Market beta	SMB beta	HML beta	Alpha
Low	0.89	-0.16	0.13	0.08
	[64.29]	[-7.21]	[4.24]	[1.84]
2	1.03	0.00	0.10	0.01
	[83.75]	[0.20]	[3.47]	[0.29]
3	1.10	0.31	-0.06	-0.05
	[65.37]	[11.07]	[-1.58]	[-0.77]
4	1.18	0.66	-0.30	-0.28
	[35.02]	[10.94]	[-5.68]	[-2.50]
High	1.17	1.09	-0.30	-1.01
	[23.24]	[13.54]	[-3.31]	[-5.83]
High-Low				-1.09*

Panel B

		Sorted at time t				
	IV Rank	1	2	3	4	5
Sorted at time t-1	Low	0.06%	0.18%	0.23%	-0.14%	5.81%
		[2.13]	[5.15]	[2.75]	[-0.74]	[14.78]
	2	-0.09%	0.05%	0.19%	-0.13%	1.79%
		[-2.41]	[1.60]	[4.02]	[-0.95]	[5.46]
	3	-0.44%	-0.05%	0.12%	0.35%	0.16%
		[-7.42]	[-1.23]	[2.82]	[4.81]	[0.71]
	4	-0.77%	-0.61%	-0.39%	0.07%	0.94%
		[-11.45]	[-9.74]	[-6.71]	[0.91]	[6.10]
	High	-0.53%	-1.67%	-1.94%	-1.34%	0.27%
		[-5.75]	[-15.61]	[-25.07]	[-13.93]	[2.26]
(When jump=0)	High-Low					0.21
						[7.5]

Table 10

Replication of Panel B of Table VI from AHXZ by using CAPM

Value-weighted quintile portfolios are formed every month, based on IV computed using daily data over the previous month relative to CAPM. Mean and Std. Dev are in monthly percentage risk unadjusted simple returns. Size is the average log market capitalization of firms within the portfolio. The row “5-1” refers to the difference in monthly returns between Quintile 5 and Quintile 1. The Alpha columns show Jensen’s alpha with respect to the CAPM or to FF-3 Factor Model. Robust Newey-West (1987) t-statistics are reported in brackets.

Replication of Table VI , Panel B from AHXZ, 1963-2003						
IV Quintile	Mean	Std. Dev.	Size	%Market cap	CAPM Alpha	FF-3 Alpha
Low	1.02	3.77	5.03	47.24	0.18	0.11
					[3.06]	[2.51]
2	0.94	4.68	4.95	30.95	0.09	0.05
					[1.81]	[0.96]
3	0.82	5.89	4.32	13.59	-0.01	0.02
					[-0.17]	[0.33]
4	0.40	7.27	3.65	6.05	-0.38	-0.30
					[-2.54]	[-2.93]
High	-0.75	8.77	2.68	2.21	-1.39	-1.26
					[-5.61]	[-7.07]
High-Low	-1.77				-1.57*	-1.38*
	[3.88]					

Table 11

Estimates of CAPM and FF-3 Factor Model by Using Monthly Data when Jump Occurs

I first sort the firms with respect to their IV computed using daily data over the previous month relative to CAPM. Second, I form value-weighted quintile portfolios with respect to their contemporaneous idiosyncratic volatility. Finally, I create JUMP which indicates movement of a firm from one quintile to another. Then value-weighted portfolios are formed every month based on their move. Jump 0 refers to no jump. Jump -4 refers to a firm that moves from the Quintile 1 to Quintile 5 and Jump 4 refers to move from Quintile 5 to Quintile 1. Sample period is July 1963 to December 2003. Panel A. Fama-French Model estimates. Panel B. CAPM estimates. Robust Newey-West (1987) t-statistics are reported in brackets.

Panel A: FF-3 Factor Model Estimates						
		Sorted at time t				
		1	2	3	4	5
Sorted at t-1	1	0.07	0.2	0.2	0.18	5.28
		[1.21]	[2.43]	[1.04]	[0.44]	[6.00]
	2	-0.11	0.11	0.35	-0.05	1.84
		[-1.28]	[1.57]	[3.20]	[-0.17]	[2.39]
	3	-0.59	-0.12	0.34	0.41	1.61
		[-5.16]	[-1.37]	[3.66]	[2.43]	[3.61]
	4	-1.1	-1.02	-0.58	0.06	1.14
		[-7.74]	[-7.18]	[-4.87]	[0.44]	[3.51]
	5	-0.71	-2.13	-2.39	-1.88	-0.18
		[-4.43]	[-9.65]	[-12.34]	[-9.61]	[-0.60]
(When jump=0) 5-1						-0.25
						[-0.29]
Panel A: CAPM Estimates						
		1	2	3	4	5
Sorted at t-1	1	0.15	0.29	0.29	0.43	5.65
		[2.05]	[3.26]	[1.51]	[1.05]	[6.30]
	2	-0.04	0.18	0.37	-0.02	1.88
		[-0.43]	[2.45]	[3.33]	[-0.08]	[2.48]
	3	-0.48	-0.08	0.31	0.29	1.46
		[-4.12]	[-0.96]	[2.96]	[1.40]	[2.88]
	4	-0.99	-0.96	-0.6	-0.06	0.96
		[-6.82]	[-6.84]	[-4.35]	[-0.29]	[2.26]
	5	-0.59	-2.07	-2.41	-2.02	-0.39
		[-3.67]	[-9.57]	[-11.64]	[-8.12]	[-0.96]
(When jump=0) 5-1						-0.54
						[-4.52]

Table 12

Abnormal Returns from a Trading Rule based on Change in Idiosyncratic Ranking

First, I sort firms with respect to their IV computed using daily data over the t-2 month relative to FF-3 Factor Model. Second, I sort them with respect to their previous month (t-1) idiosyncratic volatility. Finally, I create a variable called CHANGE which indicates movement of a firm from one quintile to another. At time t, I form value-weighted quintile portfolios based on change in idiosyncratic volatility. Sample period is July 1963 to December 2003. Panel A. FF-3 Factor Model estimates. Panel B. CAPM estimates. Robust Newey-West (1987) t-statistics are reported in brackets.

Panel A. FF-3 Factor Model				
Change	Market beta	SMB beta	HML beta	Alpha
Low to High	0.80	0.43	0.32	0.01
	12.70	4.62	2.94	[0.90]
High to Low	0.87	0.45	-0.07	-0.47
	10.52	3.66	-0.45	[-1.23]
			High to Low-Low to High	-0.49
				[-1.40]

Panel B. CAPM		
Change	Market beta	Alpha
Low to High	0.80	0.08
	[13.20]	[1.05]
High to Low	0.98	-0.53
	[11.08]	[-1.43]
High to Low- Low to High		-0.31 [1.47]