Beta Reversal and Expected Returns*

Yexiao Xu
Jindal School of Management
The University of Texas at Dallas

Yihua Zhao
A.B. Freeman School of Business
Tulane University

This Revision: January 2015

Abstract

In this paper we show that it is the beta reversal among a small group of stocks that prevents the CAPM beta from predicting individual stocks' expected returns as documented by Fama and French (1992). These stocks tend to have both large beta and high idiosyncratic volatility. Consequently, even when the CAPM holds period-by-period, the confounding effect of beta reversal diminishes the significance of the CAPM beta in the cross-sectional tests. The cross-sectional explanatory power of beta is restored after we take into account the beta reversal effect in each of the three ways. More important, the market risk premium estimated from cross-sectional regression analysis is almost identical to the historical average of market excess returns. All results are robust with respect to different measures of beta and idiosyncratic volatility as well as different subsamples. We also find that beta reversal is likely to be a result of several factors including the wealth effect, earnings announcement effect, and real option realization.

Key Words: Adjusted Beta, Beta Reversal, Expected Return, Idiosyncratic Volatility, and Market Beta

*We are indebted to John Y. Campbell, Long Chen, Jie Gan, Haitao Li, Michael Rebello, Zhongzhi Song, Wilson Tong, Kam-Ming Wan, Steven X. Wei, Wayne Yu, Harold Zhang, and Feng Zhao for their insightful comments. We have also benefited from helpful comments from seminar participants at the 2014 FMA conference, 2012 CICF conference, Cheung Kong Graduate School of Business, Hong Kong Polytechnic University, Seoul National University, and the University of Texas at Dallas. This paper previously circulated under the title "Beta Is Still Useful!" The corresponding author's address is: Yexiao Xu, 800 West Campbell Road, SM31, The University of Texas at Dallas, Richardson, TX 75080; Telephone (972)883-6703; FAX (972)883-6522; Email: yexiaoxu@utdallas.edu.

Beta Reversal and Expected Returns

Abstract

In this paper we show that it is the beta reversal among a small group of stocks that prevents the CAPM beta from predicting individual stocks' expected returns as documented by Fama and French (1992). These stocks tend to have both large beta and high idiosyncratic volatility. Consequently, even when the CAPM holds period-by-period, the confounding effect of beta reversal diminishes the significance of the CAPM beta in the cross-sectional tests. The cross-sectional explanatory power of beta is restored after we take into account the beta reversal effect in each of the three ways. More important, the market risk premium estimated from cross-sectional regression analysis is almost identical to the historical average of market excess returns. All results are robust with respect to different measures of beta and idiosyncratic volatility as well as different subsamples. We also find that beta reversal is likely to be a result of several factors including the wealth effect, earnings announcement effect, and real option realization.

Key Words: Adjusted Beta, Beta Reversal, Expected Return, Idiosyncratic Volatility, and Market Beta

1 Introduction

Perhaps the most tested model in asset pricing is the Sharpe (1964), Lintner (1965), and Black's (1972) capital asset pricing model (CAPM). However, the empirical evidence supporting the model is far from conclusive. For example, Fama and French (1992) has shown that the systematic risk measure beta from the CAPM is incapable of explaining cross-sectional differences of individual stocks' expected returns. Such evidence seems at odds because the CAPM beta is still widely used both in practice and in most empirical studies. In this study, we take another look at the evidence and provide a new perspective by arguing that beta reversal among a small group of stocks is the culprit for the failure of the CAPM beta, especially in cross-sectional studies. With a simple control for such a beta reversal effect, we are able to restore the positive relation between the conventional measures of beta and expected returns of individual stocks.

In a typical empirical study in asset pricing, all individual stocks are equally treated from a statistical perspective. Accordingly, we begin our investigation from examining whether the failure of the market beta in cross-sectional studies is pervasive or limited to certain stocks. There are two pieces of evidence from existing studies that motivate us to take this unconventional approach and may hold a clue in understanding the seemingly inconsistency between the cross-sectional evidence documented in Fama and French (1992) and the time-series evidence in Fama and French (1993). The first piece of evidence is from Fama and French (1992) who show that stocks with large beta estimates have relatively low expected returns, which result in a flat relation between beta and future returns. This result can be interpreted as suggesting that. The second piece of evidence is provided by Ang, Hodric, Xing, and Zhang (2006) who document that stocks with large idiosyncratic volatilities tend to have low future returns. These two pieces of evidence imply that stocks with both high idiosyncratic and systematic risks may have obscured the true beta-return relation in a short-run. We, therefore, conjecture that beta fails mostly among stocks with certain characteristics, and investigate why these stocks behave abnormally. By doing so we are able to propose simple but practical approaches to restore the explanatory power of the market beta, instead of building a more complicated model than the CAPM model or introducing alternative factors.[1]

A simple way to demonstrate the "limited" failure of the market beta is to show a positive beta-return relation after excluding a small group of stocks with certain characteristics. As an exercise, we exclude 10% of the stocks with the largest beta and idiosyncratic volatility simultaneously from our original sample (accounting for 5% of the market capitalization). When the remaining stocks are sorted into 25 portfolios according to their size and book-to-market measures, portfolio returns are positively related to their beta estimates. One possible cause for this finding is that measures of the market beta of some stocks tend to reverse despite the CAPM holds period by period.[2] The adverse effect of beta reversal could be strong enough to mask any cross-sectional evidence supporting a positive risk-return relation implied by the CAPM particularly when beta estimates are noisy at the same time.

Although beta reversal may be a short-term phenomenon, its effect is very different from the error-in-variables (EIV) bias (see Fama and MacBeth, 1973) that is well-understood in the literature. In fact, to reduce the risk premium estimate from cross-sectional regression analysis by 80%, estimation errors must be four times as large as the cross-sectional variation in beta. This is highly unlikely as echoed in Fama and French (1992) when using portfolio beta. Nevertheless, we show that estimation errors can interact with the limited beta reversal to create a much large effect that prevents us from finding a positive beta-return relation.

Our simple exercise also reveals that such a beta reversal effect can be controlled since it occurs largely among stocks with both large market beta and high idiosyncratic volatility. Without excluding any stocks from the whole sample, we can take into account the beta reversal effect in three different ways in a conventional cross-sectional regression model (see Fama and French, 1992). In particular, the coefficient estimate of the beta variable from the Fama-MacBeth regression analysis is very significant and close to the sample market risk premium as predicted by the CAPM. Moreover, all previously documented firm-level

[1]We refer to the CAPM in a loose sense by focusing on the explanatory power of the market beta.

[2]In cross-sectional studies, we usually try to tie beta to future returns. In a normal case, when the current beta is high, future beta will continue to be high, which in turn results in high future returns according to the CAPM. However, if future beta of these stocks tends to reverse, their realized returns will be low on average even when the CAPM holds each period. Of course, the failure of the market beta could also be a result of the covariance between the time-varying risk and time-varying beta. We assume away this possibility since such a covariance risk is too small as shown by Lewellen and Nagel (2006).

variables such as size, book-to-market ratio, Amihud illiquidity measure, momentum, and return reversal do not subsume the market beta's predictive power for expected returns as long as the beta reversal effect is controlled for. These results are very robust to a range of alternative specifications and variable definition.

Given the significant effect of beta reversal, it is important to understand why beta of certain stocks with both high idiosyncratic and systematic risks tends to reverse in the future. Different from mean-reversion in beta, which might be driven by changes in the economy-wide risks that develop over a longer horizon and happen to all stocks, beta reversal is likely to occur over a short-horizon and is limited to stocks with certain characteristics. We accordingly investigate three possible channels: the wealth effect, the earnings announcement effect, and the growth option realization. First, on the wealth effect, if some investors prefer stocks with large idiosyncratic volatility (see Han and Kumar, 2013, and Falkenstein, 1996), increases in the holdings of these stocks will drive up their weights in the market portfolio. These stocks will then covary more with the market portfolio by construction as pointed out by Cochrane, Longstaff, and Santa Clara (2008). We do find that changes in individual stocks' idiosyncratic volatilities are positively related to changes in their market capitalizations, which in turn are related to changes in their beta estimates. More important, these changes tend to reverse in the future. Second, beta reversal might be related to earnings announcement events as suggested by Patton and Verardo (2012). A typical stock's beta tends to increase before earnings announcement because of shared uncertainty with other stocks and subsequently revert when uncertainty resolves. We also find that controlling for earnings announcement does significantly affect the beta reversal effect. Finally, when a firm realizes its growth options, its beta tends to drop because asset in place are less riskier than growth option (see Cooper and Priestley, 2011, Da, Guo, Jagannathan, 2012, and Grullon, Lyandres, and Zhdanov, 2012). We do find that small firms, growth firms, and young firms tend to experience beta reversal more frequently than other types of firms, which is consistent with the real growth option mechanism if these firms are more likely to realize their growth options.

We contribute to the asset pricing literature in three important ways. First, different from existing studies, we actually show that the fundamental relation between the market beta and the expected return holds well, except for a small group of stocks. Second, we document that beta of high risk stocks tends to reverse, which obscures the whole risk-return relation in a conventional test. Consistent with the mechanism proposed above, we further show that beta reversal is predictable via the interaction between realized idiosyncratic volatility and beta. Consequently, we propose three simple approaches to restore the cross-sectional beta-return relation for all stock–the direct control approach, the predicted beta approach, and the adjusted beta approach. Finally, the mechanism of beta reversal reconciles the contradictory evidence between the large time-series explanatory power of the market factor and the market beta's inability to differentiate future returns across individual stocks. When the CAPM holds period by period, the contemporaneous correlation between market factor and individual stocks' returns are large, while a large current beta may drop and result in a lower future return on average. Although beta reversal is not pervasive and might occur among different stocks over time, such a limited reversal interacted with noises in the beta estimates is able to severely distort the conventional cross-sectional tests.

Our study is related to several recent papers on adjusting the CAPM beta. For example, when beta varies over time, its estimate based on historical returns may not contain sufficient forward-looking information, which could affect its ability to predict future returns. Buss and Vilkov (2012) propose using the option-implied beta to capture forward-looking information. Over a shorter sample period from 1996 to 2009, they find a positive beta-return relation. In the context of our framework, we show that the success of their approach can be contributed largely to sample selection. Due to the availability of option data, their sample does not include stocks that are likely to reverse. In fact, our reversal-adjusted beta takes away most of the explanatory power of the option-implied beta. Another possibility for observing low returns on stocks with high beta is suggested by Frazzini and Pedersen (2013). They argue that margin constrained investors tend to bid up high-beta stocks' prices which consequently have low returns. To test the idea, they construct a so called "Betting-Against-Beta" (BAB) factor by longing on low beta stocks and shorting on high beta stocks and examine the explanatory power of the factor. Despite some similarity between their BAB factor and our beta-reversal factor, the two factors are quite different from both theoretical and empirical perspectives.

At the very least, beta reversal concentrates on a much smaller sample of stocks than the stocks affected by the BAB factor. The correlation between their BAB factor and our beta reversal factor is only 43%. Moreover, we show that the BAB factor is unable to adjust the conventional beta estimates to restore their cross-sectional explanatory power.

The literature on idiosyncratic risk is also relevant to our study. Although Ang, Hodrick, Xing, and Zhang's (2006) finding on idiosyncratic volatility motivates our study, a simple control for idiosyncratic risk does not restore the explanatory power of beta. Moreover, whether the negative relation between idiosyncratic volatility and future return is due to return reversal (Huang, Liu, Rhee, and Zhang, 2010), learning model parameters (Pastor and Veronesi, 2009), or the gambling effect (Bali, Cakici, Whitelaw, 2011) bears no consequence on the market beta itself. In contrast, we take a step further by examining how idiosyncratic volatility affects the role of beta, and in turn alters future returns.[3] Another related study by Ang and Chen (2007) utilizes an econometrics approach to explicitly model the dynamics of the market risk premium, market volatility, and asset beta. They find that the time-varying beta estimates explain the return differences between value and growth stocks. In contrast, we rely on a much simpler approach and are able to restore the beta-return relation once the beta reversal effect is controlled for. Finally, researchers find that idiosyncratic volatility is related to a firm's growth options (see Bernardo, Chowdhry, and Goyal, 2007, Cao, Simin, and Zhao, 2008, Da, Guo, and Jagannathan, 2011, and Johnson, 2004), which is one of the channels for beta reversal explored in our study.

The rest of the paper proceeds as follows. In the next section, we first motivate the idea of beta reversal and its effect on asset prices. We also propose three possible channels that could cause such a reversal, and outline strategies to detect and control for beta reversal. In Section 3, we describe our data source and discuss the construction of variables used in our study. For consistency, we compare the summary statistics of our variables with those used in

[3]When using alternative measures of idiosyncratic risk, such as the conditional measure (Fu, 2009) or the portfolio measure of idiosyncratic risk (Malkiel and Xu, 2003), others find that idiosyncratic volatility is positively related to future returns, which suggests a pricing effect for idiosyncratic risk. Cao and Xu (2009) further point out that the priced idiosyncratic risk is a relatively small component in the total idiosyncratic risk due to the diversification effect. In contrast, mispricing is therefore a first order effect in short-run. We accordingly focus primarily on the realized idiosyncratic volatility measure.

the literature. Our empirical results presented in Section 4 started from portfolio analysis and followed by cross-sectional regression results. We contrast our study with other related work and support the possible mechanisms of beta reversal with some further evidence in Section 5. A robustness analysis is carried out in Section 6. Section 7 concludes.

2 Theoretical Motivation

Since the idea of beta reversal is new, we first motivate the idea and its impact on asset prices from a theoretical perspective. We then offer three possible channels through which beta reversal can occur. To control for beta reversal in testing the beta-return relation, we propose three empirical strategies.

2.1 Motivating Beta Reversal

Fama and French's (1992, 1993) results are both surprising and controversial. For example, some researchers believe that both the size and the book-to-market variables are either not robust or subject to certain biases.[4] Regardless of the importance of these arguments, the beta variable continues to be insignificant in explaining cross-sectional return differences. Other researchers have attempted to patch the CAPM with different model structures. One example is the idea of time-varying risk and risk premium of Merton (1976) due to changes in investment opportunities. In such a framework, investors demand additional compensation for the covariance risk between time-varying risk and market risk premia even when a conditional CAPM model holds perfectly (see Jagannathan and Wang, 1996). However, from an empirical perspective, Lewellen and Nagel (2006) show that such a covariance risk is too small to account for the large deviation from the CAPM.

While the idea of time-varying risk could still be quite useful over a longer horizon, beta might change for reasons other than time-varying risk in short-run, especially for some stocks. In such a case, the CAPM relation may continue to hold period-by-period in a first order, yet

[4] An incomplete list includes Ang and Chen (2007), Barber and Lyon (1997), Daniel and Titman (1997), Daniel, Titman and Wei (2001), Dijk (2011), Horowitz, Loughran and Savin (2000), Kim (1997), Knez and Ready (1997), Kothari, Loughran (1997), Shanken, Sloan (1995), Shumway (1997), and so on.

we are unable to detect such a relation in an empirical test. This could happen when future realized returns are used as proxies for conditional expected returns of individual stocks in cross-sectional tests as proposed by Fama and MacBeth (1976).[5] Over such a short horizon, a stock with large current beta might actually have a low future return if its beta reverses, which means weak evidence on the beta-return relation from a cross-sectional regression perspective. This idea is motivated by Fama and French (1992) who find that stocks with large beta tend to have low future returns, and Ang, Hedrick, Xing, and Zhang (2006) who find that stocks with high idiosyncratic risks also tend to have low future returns. To verify these observations and to see if beta reversal is pervasive, we sort all stocks first into five groups according to their beta estimates, and then into five sub-quintiles based on their realized idiosyncratic volatility measures (IV_d) defined in Section 3.2. Results are reported in Table 1.

Insert Table 1 Approximately here

At a first glance, we observe some systematic patterns between portfolio returns and idiosyncratic volatilities. For example, portfolio returns seem to increase with their idiosyncratic volatilities when beta estimates are relatively low, consistent with Merton (1987) and Malkiel and Xu's (2002) arguments. For extremely large beta portfolios, the pattern is reversed as shown in the last column of Table 1, consistent with Ang et. al.'s (2006) finding of a negative relation between idiosyncratic volatility and future returns. In fact, the return difference between the high and the low idiosyncratic volatility portfolios is -0.70% and is statistically significant. For median beta portfolios, the relation between return and idiosyncratic volatility is hump-shaped. This is consistent with Bail et. al.'s (2007) finding of a non-monotonic relation between idiosyncratic volatilities and portfolio returns.

On the beta dimension, the beta-return relation holds relatively well except for portfolios with both large idiosyncratic volatility and large beta. For example, when idiosyncratic volatility is relatively low, portfolio returns increase with their beta monotonically. In fact, the difference between the high and the low beta portfolio returns in the lowest idiosyncratic

[5] Although estimates of a cross-sectional regression equation using the future realized return as a dependent variable is inefficient, it is unbiased as long as the future idiosyncratic return is uncorrelated with the current beta measure.

volatility group is 0.43% per month and is statistically significant. When idiosyncratic volatility increases, however, this monotonic relation begins to reverse. That is, the relation between return and beta appears to be hump-shaped for portfolios with median levels of idiosyncratic volatility. Combining with the patterns on the return-idiosyncratic-volatility relation, we observe a reversed relation at the lower-right corner of Table 1.

These well-behaved patterns suggest that it is unlikely that the CAPM has failed completely, rather the market beta may reverse for stocks with both large beta and high idiosyncratic risk. Even when the CAPM relation holds period-by-period, this small group of stocks may experience beta reversal, which drive down their future returns. Therefore, we are unable to empirically identify a cross-sectional positive risk-return relation. In contrast, individual stocks' returns can still comove contemporaneously with market returns when the CAPM holds period-by-period. In other words, beta reversal also explains why the market factor is still the single most powerful factor in explaining time-series asset returns even when the market beta is incapable of differentiating future returns among individual stocks.

2.2 The Effect of Beta Reversal

The evidence from Table 1 also suggests that beta reversal is limited to a small group of stocks. Therefore, it is important to understand why such a limited beta reversal can lead to a failure of empirical tests. From a theoretical perspective, this could happen as long as beta is sufficiently noisy in addition. As pointed out by Fama and MacBeth (1976), individual stocks' beta estimates are subject to large estimation errors (about 1/3),[6] where both the current and future beta estimates could be off by 1/3 on average. Beta could also vary over time due to time-varying risk. In fact, Lewellen and Nagel (2006) find large variations in beta over time (about 0.38).[7] We thus refer both the estimation error and time-varying beta as "beta instability" in our discussion.

[6] When using monthly returns to estimate beta, the estimation error can be approximated by: $s(\hat{\beta}_i) = s(\epsilon_i)/[\sqrt{60}s(r_m)] = 14.43/(\sqrt{60}5.77) = 0.32$, where ϵ_i and r_m are the idiosyncratic and market returns, respectively.

[7] They estimate that "beta has a standard deviation of roughly 0.30 for a 'small minus big' portfolio, 0.25 for a 'value minus growth' portfolio, and 0.60 for a 'winner minus loser' portfolio," which corresponds to an average of 0.38. When considering both estimation errors and the time-varying nature of beta, the total variation in beta could be as large as 50% ($= \sqrt{0.33^2 + 0.38^2}$) if the two variations are independent.

Despite substantial "noises" in beta estimates, instability alone cannot account for the failure in cross-sectional tests. In fact, Fama and French (1992) recognize the issue of estimation error, but their approach of applying portfolio beta estimates as proxies for individual stocks' beta estimates does not salvage the beta-return relation. In contrast, we can show how a partial beta reversal in the presence of beta instability masks the true beta-return relation in empirical tests. To illustrate the mechanism, we start from the following conditional CAPM,

$$R_{i,t} = \beta_{i,t} R_{m,t}, \tag{1}$$

where $R_{.,t}(= E_t[\tilde{r}_{.,t+1}])$, $\tilde{r}_{.,t}$, and $\beta_{i,t}$ are the conditional expected return, excess return, and, conditional systematic risk measure, respectively, while i and m denote individual stock i and the market, respectively. Since our focus is not on the time-varying expected return, we can simply assume that $Cov(\beta_{i,t}, R_{m,t}) = 0$. Therefore, from a time-series perspective, equation (1) can be rewritten as,

$$\tilde{r}_{i,t} = \beta_{i,t} \tilde{r}_{m,t} + \epsilon_{i,t}, \tag{2}$$

where $\epsilon_{i,t}$ is the idiosyncratic return.

Equation (1) can also be used in a cross-sectional tests. Due to the difficulty in estimating an individual stock i's conditional expected return, Fama and MacBeth (1973) recognize the following relation,

$$\tilde{r}_{i,t+1} = R_{i,t} + \eta_{i,t+1}, \tag{3}$$

which suggests the use of the future realized return ($\tilde{r}_{i,t+1}$) as a proxy for the expected return ($R_{i,t}$) as long as $\eta_{i,t+1}$being independent across stocks and being uncorrelated with $\beta_{i,t}$. In other words, we can regress $\tilde{r}_{i,t+1}$ on $\beta_{i,t}$ in cross-sectional regression analysis. Again if we do not consider the persistent time-varying risk, variations in beta can be captured by the following simple structure,

$$\beta_{i,t} = \beta_i + u_{i,t}, \tag{4}$$

where β_i is the long-term mean of $\beta_{i,t}$; $u_{i,t}$ represents the short-term beta variation (such as beta reversal) and is assumed to be $i.i.d.$ across stocks with variance σ^2. Since in practice we use an estimate of $\beta_{i,t}$ in cross-sectional regression analysis, $u_{i,t}$ should also reflect beta "instability". To study properties of cross-sectional regression estimates, we further assume that β_i is a realization from a random variable $\beta \sim i.i.d(\bar{\beta}, \sigma_\beta^2)$. Under the true time-series return structure of equation (2) and utilizing the rule of decomposition of covariance ($Cov(x,y) = E_z[Cov(x,y|z)] + Cov_z[E(x|z), E(y|z)]$), we can show that the asymptotic cross-sectional regression estimate γ from regressing $\tilde{r}_{i,t+1}$ on $\beta_{i,t}$ can be expressed as follows,

$$\gamma = \frac{Cov(\tilde{r}_{i,t+1}, \beta_{i,t})}{Var(\beta_{i,t})} = \left(1 - \frac{\sigma^2}{\sigma_\beta^2 + \sigma^2} + \frac{Cov(u_{i,t+1}, \beta_{i,t})}{Var(\beta_{i,t})}\right) \bar{R}_m. \tag{5}$$

When $u_{i,t+1}$ and $\beta_{i,t}$ are independent, the estimate $\gamma[= (1 - \frac{\sigma^2}{\sigma_\beta^2+\sigma^2})\bar{R}_m]$ is biased downward, reflecting the beta instability (or error-in-variables) problem. For example, when assuming $\sigma_\beta = 1/3$ and the monthly $\bar{R}_{m,t} = 0.67\%$ over the Fama and French's (1992) sample period, we should have seen a risk premium estimate of 0.206% even if beta instability is as large as $\sigma = 50\%$. In order for the γ estimate to be close to that observed in Fama and French's study (0.14%), beta instability must be as large as $\sigma = 65\%$ on average, which is unlikely.

When beta also reverses at the same time, we do not need to have such large beta instability to explain the failure of cross-sectional tests. One simple way to capture beta reversal is to assume the following structure for $u_{i,t+1}$,

$$u_{i,t+1} = \begin{cases} -\alpha v_{i,t} + \sqrt{1-\alpha^2} v_{i,t+1} & \textit{with probability} \quad p \\ v_{i,t+1} & \textit{with probability } (1-p) \end{cases}, \tag{6}$$

where $v_{i,t+1}$ is $i.i.d.$ with zero mean and variance σ^2. This is equivalent to require p percent of stocks to reverse at any given point of time. Under this structure, we can show that,

$$\gamma = \left(1 - \frac{\sigma^2}{\sigma_\beta^2 + \sigma^2} - \alpha p[1 - p(1 - \sqrt{1-\alpha^2})] \frac{\sigma^2}{\sigma_\beta^2 + \sigma^2}\right) \bar{R}_{m,t}. \tag{7}$$

Assuming $\sigma_\beta = 33.33\%$ and $\alpha = 66.67\%$ as an example, we have the following two cases that will all result in $\gamma = 0.14\%$ found in Fama and French (1992):

- Case I: $\sigma = 35\%$ and $p = 100\%$, and
- Case II: $\sigma = 45\%$ and $p = 33.33\%$.

Comparing the above two cases, the first case requires all stocks to reverse (with a low level of beta instability), while only a small group of stocks needs to reverse in the second case (with a high degree of beta instability). This simple exercise demonstrates that beta reversal among a small group of stocks can reduce the γ estimate in a significant way. In our empirical sections, we intend to show that the second case is likely to prevail.

There are two additional features from this analysis worth noting. First, it is important to recognize that such a reversal may occur once a while and is temporal for a particular stock, but at any given point of time there exists beta reversal among some stocks. Second, if α in equation (6) is related to some exogenous variables, such as idiosyncratic volatility, beta reversal may be predictable by the product of beta and idiosyncratic volatility. This means that we are able to remove the catalyst of beta reversal and to restore the predictive power of beta even if beta is still instable. Therefore, controlling for beta reversal is the key to find a positive beta-return relation in cross-sectional tests.

2.3 Detecting Beta Reversal

To substantiate our analysis in Section 2.2 we need to show that beta indeed reverse. In general, beta varies significantly from period to period in a complicated way, making it difficult to isolate the reversal effect. One way to identify beta reversal is to study the conditional distribution of beta over time. As a simple exercise, we can compute a transition probability matrix. In practice, beta estimates are also persistent due to the time-varying risk suggested by Merton, which means that individual stocks' betas also revert to their mean in long-run. Such a feature is not captured by the model discussed in Section 2.2 above. It is therefore inappropriate to directly compute the transition probabilities. Given the short-run nature of beta reversal, a simple solution is to focus on the transition probabilities conditioning on the level of last period beta but net of the persistence effect.

Patterns in transition probabilities can then be analyzed against certain benchmarks. Such a benchmark can be established from a theoretical transition probability matrix under a simple distribution assumption. In order to capture both the long-run persistence and short-run reversal in a similar spirit of equation (6), we assume a simple $ARMA$ model for beta as,

$$\beta = (1-\rho)\mu + \rho\beta_{-1} + \eta - \phi\eta_{-1}. \tag{8}$$

Since beta estimates seem to follow a normal distribution and the corresponding conditional distribution can be easily computed, we assume that η and η_{-1} follow a joint normal distribution with zero means. Assuming $Var(\beta) = \sigma^2$, we have a conditional distribution as,

$$f(\tilde{\beta}|\beta_{-1}) = N\left[(1-\rho)\mu - \phi\kappa(\beta_{-1} - \mu), \kappa(1+\phi^2)\sigma^2\right], \tag{9}$$

where $\kappa = \frac{1-\rho^2}{1-2\rho\phi+\phi^2}$ and $\tilde{\beta} = \beta - \rho\beta_{-1}$ is the relative beta net of the persistence effect. Applying Equation (9), we can compute the transition probability for stocks in one of the three equally divided groups during the next period. For example, the probability for a stock to remain in the small group without the persistence effect is:

$$P(\tilde{\beta} \leq b_{1,small}|\beta_{-1} = \bar{\beta}_{small}) = \Phi\left(\frac{b_{1,small} - [(1-\rho)\mu - \phi\kappa(\bar{\beta}_{small} - \mu)]}{\sqrt{\kappa(1+\phi^2)}\sigma}\right). \tag{10}$$

For each group, $\bar{\beta}_{.}$ in the base period can be computed in the following way. When $\mu = 1$ and $\sigma = 0.5$, we can divided betas into three equal probability groups with breaking points of $b_{0,small} = 0.78$ and $b_{0,large} = 1.22$. With these break points, the group means of beta in the small, median, and large groups are $\bar{\beta}_{small} = 0.45$, $\bar{\beta}_{median} = 1.00$, and $\bar{\beta}_{large} = 1.55$, respectively.[8]

To incorporate different levels of beta reversal, we choose three different values of ϕ, but set $\rho = 0.4$ according to our empirical estimate. In Case I, there is no beta reversal with $\phi = 0$; in Case II, beta reverses at a moderate level with $\phi = 0.4$; and in Case III, beta reverses substantially over time with $\phi = 1.0$. We then compute the breakpoints for the relative beta in the next period using the same approach but under the unconditional distribution of $f(\tilde{\beta}) = N[(1-\rho)\mu, \kappa(1+\phi^2)\sigma^2]$. The corresponding group break points are: $b_{1,small} = 0.385$ and $b_{1,large} = 0.815$ in Case I; $b_{1,small} = 0.37$ and $b_{1,large} = 0.83$ in Case II; and $b_{1,small} = 0.34$ and $b_{1,large} = 0.86$ in Case III. With these parameter values, the theoretical transition probability matrices can be computed as,

$$\begin{array}{l} \\ small \\ median \\ large \end{array} \begin{array}{c} Case\ I:\ \phi = 0 \\ \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} \end{array} \quad v.s. \quad \begin{array}{c} Case\ II:\ \phi = 0.4 \\ \begin{bmatrix} 0.20 & 0.31 & 0.49 \\ 0.33 & 0.34 & 0.33 \\ 0.49 & 0.31 & 0.20 \end{bmatrix} \end{array} \quad v.s. \quad \begin{array}{c} Case\ III:\ \phi = 1.0 \\ \begin{bmatrix} 0.14 & 0.28 & 0.58 \\ 0.33 & 0.34 & 0.33 \\ 0.58 & 0.28 & 0.14 \end{bmatrix} \end{array}.$$

[8] For a random variable x with a normal distribution, $N(\mu, \sigma)$, the conditional mean is: $E(x|x \geq c) = \mu + \sigma\phi(\frac{c-\mu}{\sigma})/[1 - \Phi(\frac{c-\mu}{\sigma})]$, where $\phi(.)$ and $\Phi(.)$ are the *pdf* and *CDF* of a standard normal, respectively.

The transition probabilities is evenly distributed when the relative beta is independent over time as expected. In contrast, the transition probabilities should be concentrate on the opposite diagonal when beta reverses. This is exactly the pattern found in above transition matrices. Moreover, a moderate reversal effect results in significant changes in the transition probabilities compared to the base case of no reversal. These patterns from the three cases will be compared to the actual transition probability matrix computed in our empirical section.

2.4 Why Does Beta Reverse?

Although we are focusing on documenting beta reversal and its effect on asset pricing tests, we now make a first attempt to explore potential channels for beta reversal. Due to its short-term nature, beta reversal is more likely to be "caused" by market frictions and short-term investor behavior. In addition, beta reversal might be related to risk shift. We propose three channels–the wealth effect, earnings announcement effect, and growth option realization.

First, beta reversal might be related to investors' speculative trading activities. When investors are actively chasing certain stocks, the rising prices will increase these stocks' market capitalizations. Consequently, their weights in the market portfolio will increase since the market portfolio is a value-weighted portfolio. As argued by Cochrane, Longstaff, and Santa Clara (2008), these stocks will covary more with the market portfolio due to larger shares in the market portfolio. The covariance-based beta measure for these stocks will therefore temporally deviate from their fundamental values. At the same time, these stocks will have low future realized returns because of temporal increases in the current prices despite increases in their beta. Moreover, if speculators prefer stocks with high risks (see Han and Kumar, 2013, and Falkenstein, 1996), stocks with both large systematic and large idiosyncratic risks tend to reverse more, other things being equal. An indirect approach to investigate this possibility is to study links among changes in idiosyncratic volatilities, market capitalizations, and beta estimates of individual stocks.

The second reason for beta to reverse is motivated by Patton and Verardo (2012). They find that more than 20% of stocks' betas rise before earnings announcement and reverse following the announcement. This is because an earnings announcement by a firm not only reveals information regarding that particular firm but also contains information about the overall market. Investors of non-announcing firms will thus try to learn the profitability of their firms by paying attention to the announcing firm. Such a learning activity across all firms will increase the return covariance of the announcing firm with the overall market, leading to an increase in its beta. When uncertainty is resolved following earnings announcement, beta reverses to its normal level. Patton and Verardo (2012) also find that beta reversal is strong when earnings announcement surprises are large. As documented by Jiang, Xu, and Yao (2007), firms with large idiosyncratic risks tend to have large earning surprises. This means that beta reversal is more likely to occur among stocks with large idiosyncratic volatility. We assess this particular channel of beta reversal by investigating whether the reversal effect weakens when observations pertaining to earnings announcement months are removed.

Finally, beta reversal might also be a result of risk shift. For example, a firm's risk changes with the amount of real options that it possesses (see Da, Guo, Jagannathan, 2012 and Grullon, Lyandres, and Zhdanov, 2012). In general, young firms, small firms, and growth firms not only tend to have large beta, but also are likely to possess more growth options.[9] It is believed that growth options are riskier than assets-in-place. When these firms realize their real options, their beta measures will drop accordingly, other things being equal. Although this is a dynamic implication and depends on the realization of growth options, we can indirectly investigate whether changes in firms' beta estimates are positively related to their characteristics such as, size, book-to-market ratio, and firm age under the assumption that firms are more likely to realize their growth options when they possess more.

The effect of beta reversal on asset prices are very different from that of time-varying risks. The latter is largely driven by macroeconomic conditions and affects the fundamental risks of all firms. Therefore, one can view our effort as complementing the existing studies using time-varying factors in cross-sectional tests. This also means that it is important to control for persistence of beta when investigating beta reversal as discussed in Section 2.3.

[9]As shown by Malkiel and Xu (2003), a fast growing firm usually has large beta and high idiosyncratic volatility at the same time.

2.5 Controlling Beta Reversal

If beta reverses, it is critical to control for its effect in the conventional asset pricing tests in order to obtain unbiased estimates. Since beta reversal is likely to occur among stocks with both large idiosyncratic and systematic risks (see Section 2.4), a simple control for idiosyncratic volatility will not restore the predictive power of beta. In fact, Ang, Hodrick, Xing, and Zhang (2006) show that beta is still insignificant after including idiosyncratic volatility in their regression. We therefore offer three feasible approaches to account for beta reversal in our empirical study.

Because of beta reversal, a simple cross-sectional regression of $\tilde{r}_{i,t+1}$ on $\beta_{i,t}$ will introduce a bias as discussed in Section 2.2. To eliminate the bias, Equations (5) suggests that we should regress $(\tilde{r}_{i,t+1} - u_{i,t+1}\bar{R}_m)$ on $\beta_{i,t}$ instead, which is equivalent to rewriting the cross-sectional regression equation as,

$$\tilde{r}_{i,t+1} = \gamma\beta_{i,t} + \gamma u_{i,t+1} + \xi_{i,t+1}. \tag{11}$$

According to equation (6), if $u_{i,t+1} = g(\beta_{i,t}, z_{i,t}) + \nu_{i,t+1}$, where $z_{i,t}$ represents other exogenous variables, we are able to get an unbiased estimator $\gamma = \bar{R}_m$ when using $g(.)$ as an additional regressor. To capture the first order effect, we further assume that $z_{i,t}$ is the idiosyncratic volatility $IV_{i,t}$, and $g(\beta_{i,t}, z_{i,t}) = \kappa\beta_{i,t} \times IV_{i,t}$ according to our discussion in Section 2.4. Under this specification, we can directly run a multivariate regression that includes an additional interaction term between the past beta and past idiosyncratic volatility as a control. This direct approach is efficient, but may not be robust to the functional form of $g(.)$.

The idea behind our direct approach is to control the potential correlation between residuals (represented by the last two terms in equation (11)) and the beta variable by explicitly specifing the second term in equation (11). An alternative approach is to combine the first two terms in equation (11). That is, we can define $\hat{\beta}_{i,t+1} = \beta_{i,t} + g(\beta_{i,t}, z_{i,t})$, and use $\hat{\beta}_{i,t+1}$ in the cross-sectional regression. Normally, it is difficult to directly compute $\hat{\beta}_{i,t+1}$ without knowing the exact function of $g(.)$. Fortunately, in the context of beta reversal, we can use $\beta_{i,t+1}$ as an estimate for $\hat{\beta}_{i,t+1}$. If beta reversal can be predicted by firm characteristics such as the interaction between the past idiosyncratic volatility and past beta, we can use a two-step procedure. In the first step, we estimate the prediction equation by regressing $\beta_{i,t+1}$ on elements in $\hat{\beta}_{i,t+1}$ using the whole sample. These coefficient estimates will be used to compute the predicted beta estimate $\hat{\hat{\beta}}_{i,t+1}$ each month. In the second step, we use these predicted beta estimates in the cross-sectional regression analysis.[10] This procedure is more robust than the direct approach although it is less efficient.

Finally, if beta reversal imposes a systematic risk to ordinary investors, they are willing to pay for a price to hedge such a risk. For example, investors might care about the adverse effect created by speculative trading, or the increased comovement leading toward earnings announcement, or drop in systematic risk. Similar to Fama and French (1993), we can construct a hedging factor reflecting such a risk. When estimating an individual stock's beta, we can then include both the market factor and the beta reversal factor in the regression. The corresponding market beta estimate from such a two-factor model is called beta reversal adjusted beta. If a stock is sensitive to beta reversal, its return will comove more with the reversal factor than the market factor, which reduces its comovement with the market factor. This will make the market beta estimate smaller than that only using the market factor. Such an adjusted beta will be applied in the cross-sectional regression to account for beta reversal. The beta reversal factor is constructed following Fama and French (1993) by sorting all stocks into five idiosyncratic volatility and five beta groups, resulting 25 portfolios. We then subtract the portfolio of stocks with both the smallest idiosyncratic volatility and the smallest beta from the portfolio containing stocks with both the largest idiosyncratic volatility and the largest beta to form the beta reversal factor.

3 Data Sample and Variables

In order for our study to be replicable, we first describe our sample of data. We then provide detailed information on variable construction. Summary statistics is also discussed to ensure the comparability of our analysis with existing studies.

[10] One caveat regarding this procedure is the potential forward-looking bias. This is less of a concern if our purpose is to find the true structure $g(.)$ instead of constructing a trading strategy. Theoretically we should have used the true parameters in the prediction equation to estimate the predicted beta, but this is impossible. We therefore resort to the second best by utilizing as much information as possible in order to accurately estimate the prediction equation.

3.1 Data Sample

Our sample covers all available stocks traded on the NYSE, AMEX, and NASDAQ exchanges over the sample period from July 1963 to December 2010. This choice of sample period also reflects the availability of daily data. Stock returns are obtained from the Center of Research in Security Price ($CRSP$) and factor returns are collected from Kennneth French's website. As a common practice, our sample is restricted to ordinary common stocks with a share code of either 10 or 11. Financial firms, ADRs, shares of beneficial interest, companies incorporated outside the U.S., American Trust components, close-ended funds, preferred stocks, and real estate investment trusts (REITs) are excluded from our sample. Accounting information is acquired from the $COMPUSTAT$ database. To ensure having all information on each stock, we use the merged $CRSP$ and $COMPUSTAT$ database.

At any month, we only include firms that have data for all variables in cross-sectional regression analysis. As a result, we have more than 5000 firms each month on average. In order to reduce the effect of possible outliers or influential observations on the coefficient estimates, we also winsorize all independent variables each month at the 0.5% and 99.5% levels. We ensure the robustness of our results by splitting the whole universe of stocks into the $NYSE/AMEX$ subsample and $NASDAQ$ subsample, and dividing the whole sample period into two equal subsample periods from 1963 to 1986 and from 1987 to 2010.

3.2 Variables

We follow Fama and French's (1992) approach to construct our key variables. For example, we estimate the pre-ranking rolling market beta ($Beta_r$) from a market model based on the past 24 to 60 monthly returns (as available) in order to accommodate the feature of time-varying beta. Since individual stocks' beta estimates are very noisy (that is "unstable"), Fama and French (1992) also use the so-called post-ranking portfolio beta estimate ($Beta_p$) as a proxy for individual stocks' beta estimates in the portfolio to alleviate the possible error-in-variables problem. For robustness check, we construct the same 100 size and pre-ranking beta sorted portfolios and estimate their beta. We then reassign these portfolio betas to individual stocks within each portfolio to obtain the post-ranking beta of individual stocks. These post-ranking beta estimates also vary over time.[11] According to Ang, Liu and Schwarz (2010), however, portfolio beta conceals important information contained in individual stocks' beta, particularly in short-run. Our main results are therefore based on the rolling beta estimates ($Beta_r$) of individual stocks.

The above two approaches of estimating beta may not be powerful enough to capture all features of beta reversal since they are long-window estimates despite frequent updates. Lewellen and Nagel (2006) propose an alternative approach by using the short-window regression to estimate beta. They argue that such a beta estimate is an unbiased estimate of the conditional beta. Following their procedure, we also estimate beta based on the daily returns over either the past one month ($Beta_{d,1}$) or three months ($Beta_{d,3}$) in our robustness study.[12]

To reflect the new findings of this study, we propose a new beta estimate adjusted for beta reversal as discussed in Section 2.5. This measure is similar to $Beta_r$, but is estimated from the following model for each individual stock,

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{adj,i}(r_{m,t} - r_{f,t}) + b_i r_{rev,t} + \epsilon_{i,t}, \tag{12}$$

where r_{rev} is the beta-reversal factor. We accordingly denote the estimate β_{adj} from equation (12) as $Beta_{adj}$ in our empirical section. The adjusted beta is designed to alleviate the beta reversal effect.

The second key variable used in our study is the idiosyncratic risk measure. Following Campbell, et al (2001), and Ang et. al. (2006), we use the realized idiosyncratic volatility calculated based on the daily residual returns in the last month with respect to the following model:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + s_i r_{SMB,t} + h_i r_{HML,t} + u_i r_{UMD,t} + \epsilon_{i,t}. \tag{13}$$

where $r_{smb,t}$, $r_{hml,t}$, and $r_{umd,t}$ are Fama-French's size, book-to-market, and Carhart's momentum factor, respectively. We then sum residual squares to compute the idiosyncratic volatility

[11] If beta reversal is either reflected in the pre-ranking beta or correlated with size, the post-ranking beta will continue to carry such characteristics since whether a stock belongs to a high or low beta groups is determined by its pre-ranking beta and size.

[12] These measures are not used to present our main results because the idiosyncratic volatility measure used in the same regression analysis is estimated also using daily returns from the past month.

in that month (IV_d).[13] Any estimates of idiosyncratic risk depend on a particular asset pricing model. For robustness, we also use a total volatility measure (TV_d) computed from daily excess return ($r_{i,t} - r_{f,t}$) as a proxy since more than 80% of the total volatility is idiosyncratic.

The realized idiosyncratic volatility measure is not only more accurate but also more powerful in predicting beta reversal. As argued by Merton, an estimate of volatility is more accurate when high frequency returns are used. In addition, our use of idiosyncratic volatility is primarily for predicting and controlling the beta reversal effect rather than assessing its pricing effect. If we use the conditional idiosyncratic volatility measure of Fu (2009), we not only limit our sample size due to the convergence issue in estimating the conditional idiosyncratic volatility, but also are subject to a forward-looking bias in the volatility estimate as suggested by Guo, Kassa, and Ferguson (2014). However, as an alternative, we also use a rolling idiosyncratic volatility measure (IV_r) estimated by applying the above model to monthly returns on a 60-month rolling basis (see Malkiel and Xu, 2003).

As popularized in the current literature, we construct several control variables related to firm characteristics that help to explain the cross-sectional expected returns. Following Fama and French (1992), we obtain the market capitalization (ME) and the book-to-market ratio (B/M) for each firm. We also include the one-month lag return of $Ret(-1)$ in order to capture the return reversal effect, the lag two-month to seven-month compounded return of $Ret(-2, -7)$ to control for the momentum effect, and the Amihud (2002) illiquidity measure ($Illiq$) to control for the liquidity effect. The Amihud illiquidity is defined as the average ratio of the daily absolute return to the dollar trading volume in the last month. In addition, we obtain the option-implied beta estimate from Professor Buss and the betting-on-beta (BAB) factor from Professor Peterson's website.

3.3 Summary Statistics

The summary statistics for variables used in our study are reported in Table 2. Over the sample period from 1963 to 2010, the average monthly return (Ret) is 1.2%. Although this

[13] On average, there are 21 daily returns each month. In order to reduce the impact of extreme returns and for robustness, we also estimate the idiosyncratic volatility using daily returns in the last three months. These results are stronger in general.

is somewhat higher than the historical norm, it is not the average market return but instead the firm-month average.[14] The median return of 0.0% indicates a skewed return distribution. The average portfolio beta ($Beta_p$) of 1.36 is comparable to that reported in Fama and French (1992). In contrast, the average rolling beta ($Beta_r$) of 1.16 is reasonable with a median of 1.09. Since the rolling beta is measured on individual stocks, it has more than twice the variation (0.74) as the portfolio beta. This comparison suggests that to a large extent the volatility in individual stocks' beta estimates reflects beta instability over time. It is also interesting to see that the average beta of 0.737 computed from daily returns ($Beta_{d,-1}$) is much lower than the beta estimates for monthly returns, consistent with those reported in Ang, Hodrick, Xing and Zhang (2006). This is largely a result of low comovement in daily returns due to large idiosyncratic volatilities. This fact also contributes to the high variations in beta estimates across all stocks with a standard deviation as high as 1.37. In order to reduce possible noise, we also use $Beta_{d,-3}$ in our robust analysis.

Insert Table 2 Approximately here

Despite the difference in calculating idiosyncratic volatilities using daily returns (IV_d) versus using the past 24 to 60 monthly returns (IV_r), the averages of these estimates are very similar (12.7% versus 12.6% per month). However, the IV_d measure fluctuates 40% more than the IV_r measure, meaning that the realized idiosyncratic volatility measure might be more suited to capture features of beta reversal than the rolling idiosyncratic volatility measure. Consistent with the literature, idiosyncratic volatility does account for a major part of the total volatility of 15.1% on average.

The statistics for control variables including the size, book-to-market, momentum, return reversal, and illiquidity are comparable to those reported in the literature. For example, the average firm size is \$100 million with 25% of the firms having an average market value being less than \$20 million, and 25% of the firms having an average market value being greater than \$440 million. The mean and median of the log book-to-market ratios are -0.47 and

[14] One can consider the standard deviation for the firm-month observations of 15.9% as the total return volatility, consistent with the finding of Campbell et al (2001) that idiosyncratic volatility accounts for a majority part of the total volatility.

−0.38, respectively, indicating a negative skewed distribution in the variable. The mean and standard deviation of the compounded returns from past month 2 to month 7 are 7.8% and 43.1%, respectively, consistent with those of the average monthly return. Also consistent with other studies, the Amihud (2002) illiquidity measure tends to skew to the right.

4 Empirical Results

Before discussing evidence supporting the pricing role of the market beta, we first establish the fact of beta reversal. We then illustrate how the beta-return relation can be restored in the absence of beta reversal based on portfolio analysis with a two-way sorting approach. Our main results are obtained from cross-sectional regression analysis controlling for the beta reversal effect in three ways, including the introduction of an interaction term, the application of the predicted beta, and the use of the adjusted beta.

4.1 Beta Reversal

In order to show that beta reversal is the culprit in the failure of most cross-sectional tests of the market beta, we must first show that beta does reverse. In practice, beta reversal may not be apparent due to its persistent nature, possibly reflecting a time-varying risk. Moreover, beta estimates contain errors by definition. As discussed in Section 2.3, we will examine transition probabilities of beta by controlling for both persistence and errors.

From a theoretical perspective, beta reversal is likely to occur among stocks with large idiosyncratic risks as discussed in Section 2.4. We therefore compare the transition probabilities of beta for different groups of stocks. In order to alleviate the persistence in the beta estimates from using overlapping samples, we focus on $Beta_{d,-1}$ measure estimated from daily returns within a month. In particular, we first sort all stocks into three groups each month according to their $Beta_{d,-1}$ in order to determine the breakpoints of beta. Because of limited beta reversal, we resort all stocks into five groups according to their idiosyncratic volatility IV_d in the same month. Stocks in the lowest (highest) idiosyncratic volatility group are sorted again into three groups according to the beta breakpoints. Stocks in each beta-group are traced to one of the three groups (the small, median, and large beta groups) next period according to their next period persistence-adjusted beta.[15] We report transition probability matrices of beta in Table 3. Numbers reported in brackets represent the distribution of stocks within the group.

Insert Table 3 Approximately here

For stocks with low idiosyncratic volatilities, there is no particular pattern in the transition probability matrix as shown in Panel A of Table 3, except that most stocks tend to have median levels of beta in the next period. This is because the number of stocks in each group at t are uneven with most stocks in the median group as shown from the numbers in the brackets. In contrast, the transition probability matrix for stocks with high idiosyncratic volatilities exhibits an apparent pattern as shown in Panel B of Table 3. The opposite-diagonal elements are much larger than the corresponding diagonal elements. For example, stocks with small (large) beta estimates at time t will have more than 53% chance to fall into the large (small) beta group at time $t+1$. Except for stocks with median beta estimates, this pattern is similar to that of the theoretical transition probability matrix discussed in Section 2.3 when beta reverses.[16] Beta reversal is therefore evident among stocks with large idiosyncratic volatilities.

Establishing the fact of beta reversal is only the first step in understanding the failure of beta in asset pricing tests. In order to restore the explanatory power of beta in cross-sectional tests, we need to be able to "predict" beta reversal. This cannot be done simply using the past beta since beta is persistent in the long-run while beta reversal is a short-term phenomenon. As shown in Table 3 reversal occurs mostly among stocks with large idiosyncratic volatilities, and from our discussion in Section 2.4, we expect that beta reversal can be predicted by the interaction between beta and idiosyncratic volatility.[17] The results are reported in Table 4.

[15] As a result, stocks in each group are unevenly distributed. The persistence-adjusted beta is calculated according to $Beta_{t+1,(d,-1)} - 0.24Beta_{t,(d,-1)}$, where the adjustment coefficient is obtained from Table 4.

[16] This is consistent since most stocks in this group seem to have either small or large beta estimates to begin with as indicated by the number reported in bracket.

[17] For robustness, we have also explored other predictors, such as size, book-to-market, liquidity, and firm age, and their interaction with past beta. Among them only size and idiosyncratic volatility have independent explanatory power. Due to high correlation between the two variables and the use of idiosyncratic volatility is economically motivated, we decided to focus on idiosyncratic volatility only. Results are available upon request.

Insert Table 4 Approximately Here

The first regression equation in Panel A of Table 4 is simply an autoregressive model applied to beta in a cross-sectional setting. Since the autoregressive coefficient estimate of 0.24 is very significant, it is consistent with the idea of time-varying risk found in many other studies. Although beta persistence is largely associated with a long-term effect, beta also interacts with idiosyncratic volatility to predict beta reversal. As shown in the second equation, the negative coefficient estimate of the interaction term (-0.596) is not only statistically significant at a 1% level, but also indicates beta reversal. Persistence in beta also amplifies the variability of beta estimates, no matter it is due to shocks or estimation errors (see the summary statistics in Table 2). Beta instability also interacts with beta reversal to destroy the explanatory power of beta as discussed in Section 2.2.

The persistence estimate in Panel A of Table 4 may seem too be low. One possibility contributor is the estimation error when using insufficient data. Our second exercise uses daily returns from the last quarter (three months) to estimate beta $Beta_{d,-3}$. As shown in Panel B of Table 4, when the same future beta estimate is regressed on such a new beta measure $Beta_{d,-3}$, the corresponding autoregressive coefficient estimate indeed increases to 0.45. The coefficient estimate for the interaction term between the past beta and idiosyncratic volatility accordingly does not change much (from -0.596 to -0.562) shown in the last equation. Therefore, predicting beta reversal is not very sensitive to the kind of beta estimates. This result is also consistent with Galai and Masulis's (1976) prediction that beta drops with an increase in the total volatility, which largely consists of idiosyncratic volatility.

These results demonstrate that beta not only reverses in the short-run, but is also predictable. We show in the next section how such beta reversal affects the cross-sectional return-beta relation, and how we can restore the explanatory power of beta.

4.2 Portfolio Analysis

After showing that beta reverses in short-run in the last section, we continue to investigate how beta reversal among a small group of stocks can lead to a failure in cross-sectional tests of beta, and more important, whether the explantory power of beta can be restored. As an intuitive way to answer these questions and examine the potential complicated relation between risk and return, we start from the two-way sorting approach. A more comprehensive study on these issues will be based on cross-sectional regression analysis in the next subsection.

Starting from replicating the Fama and French's results, we first illustrate the failure of market beta in Panel A of Table 5. In order to be consistent with regression analysis in the next subsection, we focus on the rolling beta measure ($Beta_r$). In particular, we sort all stocks into five groups based on $Beta_r$ at the beginning of each month and simultaneously into five groups according to their book-to-market ratios (B/M).[18] Consistent with Fama and French (1992), portfolio returns increase with the book-to-market ratios when all stocks are used in sorting. The return differences between portfolios with the highest and lowest book-to-market ratios vary from 0.75% to 1.07%, and are significant for any beta groups. In contrast, at any level of B/M, portfolio returns do not increase monotonically with their betas.

Insert Table 5 Approximately here

To show that beta reversal among a small group of stocks (see Table 1) is responsible for above observed patterns, the simplest exercise is to investigate whether or not the beta-return relation can be restored after deleting the stocks that are likely subject to beta reversal. Based on our discussion in Section 2.1, we choose to delete the four stock portfolios in the lower left corner of Table 1, which account for approximately 5% of the total market capitalization. In order to place our results into the perspective of Fama and French (1992), we then simultaneously sort the remaining stocks into 25 portfolios according to beta and book-to-market. In contrast to Panel A of Table 5, there is a clear monotonic relation between portfolio returns and beta (except for two portfolios) as shown in Panel B. More important, for portfolios with similar book-to-market ratios, the return difference between the largest and smallest beta portfolios is positive and significant except for portfolios with very large book-to-market ratios. This simple exercise reveals two facts. First, beta is still useful in explaining cross-sectional

[18] The general pattern discussed in this section holds when sorting stocks according to firm size and beta instead. Since size and idiosyncratic volatility are highly correlated, we only report one table to save space.

return differences of majority stocks. Second, when only a small group of stocks experiencing beta reversal, its impact is still pervasive if beta is also instable at the same time. Thus, beta reversal is a driving force for the dramatic difference between Panels A and B in Table 5.

An alternative way to show the pervasive impact of beta reversal on the overall risk-return relation is to plot the ex-post beta-return relation using the popular Fama and French 25 size-B/M sorted portfolios. For each portfolio, we fit a simple market model over the whole sample period to obtain the beta estimate. We then plot the average return for each portfolio against its beta estimate in Panel A of Figure 1. Clearly there is no relation between average portfolio returns and portfolio betas. In fact, three portfolios with the largest returns do not have the largest betas. We then reconstruct these 25 portfolios in the same way as in Fama and French (1993) but for the reduced sample used in Panel B of Table 5. After re-estimate portfolio betas, we plot a similar graph in Panel B. There is a clear positive relation between average returns of new portfolios and their beta estimates. Although the range of beta estimates remains the same from 0.8 to 1.4, the three portfolios with the large returns in Panel A are now having the largest betas. On average, portfolio returns are located around the theoretical line. Therefore, beta reversal is an important factor in helping us understand why market beta lacks explanatory power for expected returns.

Insert Figure 1 Approximately here

4.3 Evidence from Fama-MacBeth Regression Analysis

Our portfolio analysis in the previous section provides intuitive evidence on the adverse effect of beta reversal and the existence of a positive risk-return relation when the beta reversal effect is removed. However, the double-sorting approach is limited to the dimensions of sorting variables. A rigorous asset pricing test must be performed on a full sample. An alternative approach to "remove" the effect of beta reversal is to control for such an effect in a regression framework. From the analysis of Section 4.1, this is possible since we are able to "predict" beta reversal. We thus apply the standard Fama-MacBeth regression approach on individual stocks to better isolate the pricing effect of beta in the presence of beta reversal, while considering effects from other known factors including the size, book-to-market, momentum, liquidity, and return reversal factors.

As discussed in Section 2.5, we can control for the beta reversal effect in three ways. The direct approach adds an interaction term between the past beta and the past idiosyncratic volatility in our regression models. In order to be consistent with the literature, we use the past rolling beta estimate $Beta_r$ and the past idiosyncratic volatility measure IV_d in cross-sectional regression equations. Results are reported in Table 6 along with the Newey-West (1987) robust $t-$statistics.

Insert Table 6 Approximately Here

Estimates shown under Model 2 and Model 3 in Table 6 confirm the Fama and French's (1992) finding that the market beta has no explanatory power for expected returns, while book-to-market does offer explanatory power. Different from Fama and French (1992), the size variable is insignificant, which is consistent with many recent studies that find a weak explanatory power of the size variable in recent sample period. Interestingly, when including the realized idiosyncratic volatility in Model 4, the size variable becomes very significant again. This could be a result of high correlation between idiosyncratic volatility and size (see Malkiel and Xu, 1997), which helps reduce the noise in the size variable if size is a proxy for some risk factors. Consistent with Ang, et. al. (2006), the realized idiosyncratic volatility is negatively related to future returns. However, the beta measure remains to be insignificant.

After controlling for beta reversal using an interaction term between beta and idiosyncratic volatility in Model 1 of Table 6, the beta variable now becomes very significant with a positive coefficient estimate of 0.5% per month, consistent with the CAPM theory. Although the estimate is a little higher than the average excess market return of 0.44%,[19] it is an impressive improvement compared to that of the Fama and French (1992). At the same time, the interaction term between beta and the realized idiosyncratic volatility has a negative sign and is statistically significant as hypothesized. The significance of the beta variable remains even after controlling for Fama and French's (1992) size and book-to-market factors as shown

[19]Statistically, we cannot reject the hypothesis that they are the same.

in Model 5. This result once again demonstrates the importance of beta reversal in affecting asset returns.

Controlling for beta reversal seems to subsume the negative relation between the realized idiosyncratic volatility and future returns found in Ang, et. al. (2006). The negative relation is thus limited to stocks with large beta estimates, possibly due to investors' short-term behavior of chasing stocks with high idiosyncratic risk. In fact, the idiosyncratic volatility variable is even positive although insignificant in Model 1.[20] We further control for return reversal and momentum in Model 6, and the additional liquidity effect in Model 7. The coefficient estimate of beta even drops to 0.4%, matching with the actual market excess return over the same sample period. The interaction term continues to be significant while idiosyncratic volatility is insignificant. The beta reversal effect is therefore unlikely to be a proxy for other known factors that might drive stock returns.

The strong evidence presented in this section has three additional implications. First, the beta reversal effect can also reconcile the seemingly contradictory evidence between the large explanatory power of the market factor and no predictive power of beta for cross-sectional returns. When the CAPM holds period by period, stock returns will highly covary with market return by construction. Yet, high current betas do not necessarily imply large future returns from a cross-sectional perspective if these betas reverse. Second, the beta reversal effect is likely to be independent of the time-varying risk effect of Jagannathan and Wang (1996) since it occurs over an inter-median term. If beta reversal is a short-run phenomenon, our evidence is also consistent with Kothari, Shanken, Sloan's (1995) finding that the CAPM relation holds in low frequency data. Third, the beta reversal effect can be controlled such that the market beta is capable of predicting the expected return for *all* stocks.

4.4 Controlling Beta Reversal with the Predicted or Adjusted Betas

Direct control of the beta reversal effect is efficient but may not be robust as discussed in Section 2.5. An alternative approach is to use a predicted beta $\widehat{Beta}$ that reflects beta reversal

[20]This indicates that idiosyncratic risk might have a pricing effect, but the realized idiosyncratic volatility measure is too noisy to capture the priced component of idiosyncratic risk as argued by Cao and Xu (2009).

in cross-sectional regression analysis. In particular, it is estimated using both the lagged beta and the interaction term between the lagged beta and the lagged idiosyncratic volatility as in Table 4. With such a predicted beta measure, we not only are able to eliminate the potential bias in the coefficient estimate, but also can directly estimate the market risk premium using the coefficient estimate. Our results are reported in Table 7.

Insert Table 7 Approximately here

Different from Table 6, the primary beta estimate used in Table 7 is based on daily returns in the past month in order to avoid excessive sample overlapping and remain consistent with the results in Table 4. As shown in Panel A of Table 7, the predicted beta variable by itself is now significant at the 5% level. The coefficient estimate of 0.40% is close to the sample mean of the market excess return as predicted by theory. This result becomes even stronger when used with the size and book-to-market variables. For example, the coefficient estimate for the predicted beta is now 0.7% per month in Model 2, and is significant at the 1% level. One possible reason for the large estimate is that the true market risk premium might be higher than the sample average when other risks are properly controlled for. This explanation seems to be plausible since the coefficient estimate becomes even larger when idiosyncratic volatility is explicitly included in Model 3. These results are robust even when controlling for return reversal and momentum in Model 4, and liquidity in Model 5.[21]

Evidence from the predicted beta continues to support the existence of beta reversal. Although the predicted beta approach is robust, it may not be efficient. This is the main reason for us to focus on the direct control approach in Table 6 and in most of our empirical study. Moreover, misspecification in the direct approach tends to bias us against finding significant results. Alternatively, if investors care about the beta reversal effect due to temporary increases in beta from either speculative trading or the uncertainty around earnings announcements (or others as discussed in Section 2.4), they will try to hedge such a risk. Using a beta-reversal hedging factor, we can obtain a reversal-adjusted market beta $Beta_{adj}$ as discussed in Section 3.2. Our results are reported in Panel B of Table 7.

[21] We have also attempted to compute the predicted beta using alternative beta estimate. The results are very similar.

Due to the construction of the reversal factor, the sample period is a little shorter (starting from 1965 instead of 1963). For comparison, we first show the Fama and French specification in Model 1 using the original rolling beta measure $Beta_r$. The coefficient estimates are very close to those reported in Model 3 of Table 6, and the beta variable continue to be insignificant. When the adjusted beta ($Beta_{adj}$) is used instead, it becomes very significant at a 1% level shown in Model 2 of Table 7. Although the magnitude of the coefficient estimate is half of the actual risk premium over the same period, it is a significant improvement over the Fama and French's results. The smaller estimate may be a result of using a noisy hedging factor in estimating the adjusted beta. Including the idiosyncratic volatility measure IV_d in Model 3 has no effect on beta but made the size variable significant. When all variables are included in Model 5, the adjusted beta becomes even more significant. To a large extent, the increased significance in the adjusted beta is not coming from the IV_d variable. This is apparent when the IV_d variable is removed while all other controlling variables are included in Model 4. The significance of the adjusted beta also suggests we should use a two-factor model (see Equation 12) in time-series analysis in order to correctly estimate the beta.

4.5 Predicting the Expected Return

The strong cross-sectional evidence from effective control of beta reversal does not necessarily indicate a large overall explanatory power of beta for expected returns. We further assess the effectiveness of controlling for beta reversal by computing the predicted returns of each stock according to Model 1 of Table 6.[22] Individual stocks' expected returns are then aggregated into 100 portfolios' expected returns in order to achieve better visualization. The construction of these portfolios is based on sorting all stocks according to their rolling betas and realized idiosyncratic volatilities.[23] We plot the time-series average of each portfolio's expected returns against the average return of each portfolio in Panel B of Figure 2. For comparison, we also compute the expected returns of individual stocks using the rolling beta and realized idiosyncratic volatility only as a base model. The corresponding portfolios' expected returns and average portfolio returns are plotted in Panel A of Figure 2.

[22] Results are virtually the same when the complete Model 7 is used instead.

[23] This sorting schedule ensures the maximum spread in the expected returns.

Insert Figure 2 Approximately Here

In theory, each portfolio should lie on the 45-degree line in the graph. When the expected return is computed from the base model using beta and idiosyncratic volatility variables only, the relation between the expected returns and the average returns is flat as shown in Panel A of Figure 2. In contrast, portfolios are now scattered around the 45-degree line in Panel B of the same figure when beta reversal is controlled in computing the expected return. The dramatic difference between the two graphs not only shows the importance of the traditional market beta, but also demonstrates the economic significance of the beta reversal effect.

5 Why Beta Reversal Is An Independent Factor?

Our empirical results not only provide evidence on beta reversal, but also show both the statistical and economic significance of this factor in cross-sectional asset pricing tests. However, to convincingly claim that beta reversal is the main cause for the failure of beta in cross-sectional tests "beyond reasonable doubt," we need to both show that beta reversal is not a proxy for other factors and demonstrate the significance of economic links behind beta reversal. In this section, we first investigate the relation between our beta reversal factor and the betting-against-beta (BAB) factor of Frazzini and Pedersen's (2014) and the possible reflection of the option-implied beta (Buss and Vilkov, 2012). We then study the three possible channels behind beta reversal discussed in Section 2.4.

5.1 Is Beta Reversal Independent of Other Factors?

There is a large empirical literature on investigating the pricing power of the market beta. As a result, many alternative approaches and measures of systematic risk have been proposed. We intend to make a case for the uniqueness of our beta reversal factor.

5.1.1 Betting Against Beta

One explanation for the flat relation between beta and return is the leverage constraint argument proposed by Frazzini and Pedersen (2014). In the CAPM world, less risk averse investors will use leverage to achieve high expected returns. However, if some investors are margin constrained, they will alternatively take a relatively larger position on risky stocks than that prescribed by the market portfolio. The overweight on risky stocks will consequently result in low returns for these stocks. To show the importance of such a leverage effect, they construct a BAB factor by longing leveraged low-beta assets and shorting high-beta assets.

Although beta reversal is closely related to idiosyncratic risk, which is very different from imperfect diversification, it is still possible that the BAB factor shares common empirical effects with our beta-reversal factor (BR). Due to their focus on portfolio analysis across different country and different classes of assets, we compare the explanatory power of the BAB factor against that of our BR factor over our sample period. For the Fama and French 25 size and book-to-market sorted portfolio returns, we run time-series regression on the BAB and/or BR factors. The regression coefficients of the two factors are reported in Table 8.

Insert Table 8 Approximately here

The BR factor and BAB factor are used in regression equations in the left and right parts of Panel A of Table 8, respectively. Clearly, most of the portfolios are significantly loaded on the respective factors when each factor is used separately. Both factors are therefore important and may share some commonality. To study the unique contribution of each factor, we include both factors in the same regression. Results from Panel B of suggest that the two factors seem to be orthogonal to each other. Both factors have similar numbers of portfolios significantly loaded on. More important, most of the portfolios only loaded on one of the factors.

Time-series evidence does not necessarily translate into cross-sectional support. Since our study focuses on cross-sectional evidence, we can further investigate the relative importance of our BR factor versus the BAB factor on individual stocks. One approach is to construct an equivalent BAB-adjusted beta and compare its cross-sectional explanatory power to that of the the BR-adjusted beta. In particular, the BAB-adjusted beta is also constructed by running a two-factor model using both the market factor and the BAB factor as a control factor, and record the coefficient estimate on the market factor as the BAB-adjusted beta, $Beta_{BAB}$. Results from cross-sectional regression analysis using the BAB-adjusted beta are reported in Table 9. Comparing to those using the BR-adjusted beta in Panel B of Table 7, the BAB-adjusted beta is insignificant and does not behave differently from the rolling beta. Therefore, despite its time-series explanatory power, the BAB factor lacks cross-sectional explanatory power. In this sense, our BA factor is more fundamental than the BAB factor.

Insert Table 9 Approximately here

5.1.1 Option-Implied Beta

Another possible source for lacking the explanatory power of the conventional beta measure is the efficiency of the measure. Incorporating additional information from the option data may improve the efficiency of beta estimates since option prices reflect the most recent market information. Following this idea, Buss and Vilkov (2012) estimate the option-implied beta for stocks in the $S\&P$ 500 portfolio and find a positive risk-return relation with a slope estimate close to the market excess return. Although they suggest that the success of the option-implied beta is its ability to capture the time-varying risk, it is also possible that option traders recognize the feature of beta reversal in the short-run and discount such a risk accordingly in the option prices. In this case, the option-implied beta should subsume the explanatory power of our BR-adjusted beta. We study the beta reversal effect under the same framework as Buss and Vilkov (2012).[24] In order to be comparable to their study, we apply our BR-adjusted beta to the same sample and using the same regression models. Following Buss and Vilkov (2012), we sorting all 500 stocks into 50 portfolios according to their option-implied beta $Beta_{opt}$ each month and compute their next month value-weighted portfolio returns and current month value-weighted portfolio beta estimates. Results are reported in Table 10.

Insert Table 10 Approximately here

We first replicate Buss and Vilkov's (2012) main result in Panel A of Table 10. When regressing average portfolio returns on average option-implied betas in Model 1, the coefficient estimate is 0.43%, which is very significant but somewhat higher than the market risk premium

[24] We are grateful to Professor Grigory Vilkov for providing us with the option-implied beta estimates.

of 0.35% over the sample period from 1996 to 2009. As a comparison, we reconstruct the portfolios according to our BR-adjusted beta $Beta_{adj}$. A similar cross-sectional regression reported in Model 2 of the same panel shows a even better result. The coefficient estimate of 0.36% is not only more significant but is also identical to the market excess return.

It is also possible that the particular sample used here does not suffer from the beta reversal effect, which makes the option-implied beta to perform well. In order to test this possibility, we also sort stocks into portfolios according to their rolling beta ($Beta_r$). As shown in Equation 3, the coefficient estimate from a similar cross-sectional regression equation is as large as 0.28% and is very significant, suggesting that the sample is less affected by beta reversal. To further confirm this possibility, we compare the distribution of the Buss and Vilkov's (2012) sample to that of the sample that constructs the 25 beta-idiosyncratic-volatility sorted portfolios used in Panel B of Table 5. As shown in Panel C of Table 10,[25] the Buss and Vilkov's (2012) sample is not draw evenly across all stocks in each portfolio. In fact, most of their sample contains stocks with very small beta and low idiosyncratic volatilities, which do not suffer much of the beta reversal effect.

For the stocks that are subject to beta reversal in the Buss and Vilkov (2012) sample, we cannot conclude whether the option-implied beta contains more relevant information than the BR-adjusted beta from a univariate regression. Given the limitation of the data, we attempt to reach a conclusion based on multivariate regression analysis. This exercise cannot be carried out on a portfolio level as in Buss and Vilkov (2012) since most of the variations across different measures will be averaged out causing a severe multicollinearity problem. In order to be close to the spirit of original study, we perform pooled regression analysis on individual stock level but and use double clustered standard errors on both the firm level and the time dimension in Panel C of Table 10. When used alone, each of the beta measures is statistically significant at the 1% level similar to those reported in Panel A. When the BR-adjusted beta is used with the rolling beta, only the BR-adjusted beta is significant as expected. Similarly, when the BR-adjusted beta is used with the option-implied beta, the letter becomes insignificant as shown in Model 4. This is a direct evidence indicating that the option-implied beta mainly

[25] The number in each cell represents the percentage of stocks in the corresponding full sample beta-idiosyncratic-volatility sorted portfolio goes to the Buss and Vilkov's (2012) sample.

reflects some of the beta-reversal effect in the sample.

5.2 The Wealth Effect and Beta Reversal

Evidence presented so far suggests that beta reversal is not only critical in contributing to the failure of the market beta in the cross-sectional tests, but also independent of other factors. To further demonstrate that the effect of beta reversal is unlikely to be a result of data snooping, we now provide some evidence supporting economic links discussed in Section 2.4. The first channel for beta reversal is the wealth effect proposed by Cochrane, Longstaff, and Santa Clara (2008). We test this link indirectly by examining how changes in the market capitalization (firm size), idiosyncratic volatility, and beta of an individual stock are related to each other as predicted by the theory. Results are reported in Table 11.

Insert Table 11 Approximately here

As shown in Model 1 of Table 11, changes in market capitalizations of firms are positively related to corresponding changes in their idiosyncratic volatilities. This contemporaneous relation is very strong and significant. Moreover, a small portion of the increase in a firm's size is reversed in the next period as shown in Model 2. If such an increase in firm size results in a temporary increase in beta as hypothesized, we have a case for beta reversal. In order to be consistent with the discussion in Section 4.1, we use the daily beta estimate of $Beta_d$. As shown in Model 3, a temporal increase in a firm size is strongly related to a temporal increase in the firm's beta estimate. Roughly a 2.7 times increase in a firm size is associated with a 0.526 increase in its beta. As firms with high idiosyncratic risks tend to have large beta (see Model 4), changes in beta might also be a result of an increase in idiosyncratic risk directly. The size variable in Model 5 is still very significant although reduced to 0.407 after controlling for idiosyncratic volatility.

In order to establish beta reversal, it is also important to know if such a temporary increase in beta disappears in the future. We therefore study how a temporal increase in firm size affects the firm's future beta. Model 6 of Table 11 shows that changes in beta are negatively related to increases in firm size in the past. We can also see from Model 7 that both the temporary increase in beta and the post reversal exist simultaneously. Although the lagged idiosyncratic volatility change becomes insignificant, all other variables continue to be very significant with consistent signs. Therefore, the wealth effect is likely to drive beta reversal.

There are two caveats. First, despite stocks with a high level of idiosyncratic risk tend to experience large changes in their idiosyncratic volatilities, and are more likely to be traded by speculators, it is unlikely that the same set of stocks is of interest every period. This means that beta reversal is likely to occur in different stocks from time to time. Second, the relative change in the market capitalization of a stock in the market portfolio tends to be small, which is unlikely to cause a large change in beta and the subsequent reversal. However, the wealth effect might have had a positive feedback effect or interact with other factors discussed next.

5.3 Earnings Announcement and Beta Reversal

As discussed in Section 2.4, the second channel for beta reversal is uncertainty surrounding an earnings announcement as proposed by Patton and Verardo (2012). Therefore, an indirect but simple test of the earning announcement effect on beta reversal is to compare the beta reversal effect in a sample without earnings announcement events to that in a sample with the earnings announcement events. To implement, we define a dummy variable to be one for firm without experiencing earnings announcements in the month, and zero otherwise. We then include the dummy variable in regression analysis to separate the pricing effects with and without earnings announcements in Table 12.

Insert Table 12 Approximately here

Since quarterly financial reports began in 1971, our sample in this section begins in the same year. We accordingly first redo some of the regression analysis in Table 6 here. The beta reversal effect continues to be strong with a risk premium estimate close to the sample mean when comparing the main result from Model 1 of Table 12 to that of the same equation in Table 6. Such a risk premium estimate is not affected when either controlling for the Fama and French factors in Model 2 or controlling for all other factors in Model 3. However, the reversal effect does seem to be smaller. The coefficient estimate for the interaction term drops from -0.029 in Model 1 to -0.019 in Model 3.

As hypothesized, the reversal effect should be stronger during earnings announcement months. When including the dummy variable and its interaction with the reversal variable in Model 5, this is exactly the case with a reversal estimate of -0.036. In contrast, the three-way interaction term representing the incremental reversal effect during the non-announcement month is positive. It is also true that the estimated market risk premium should not be different during the announcement or non-announcement periods. The last equation of Table 12 shows that the premium difference is not significant from zero. Therefore, the earnings announcement effect is likely to be a driving force for beta reversal.

5.4 Real Options and Beta Reversal

Another possible explanation for beta reversal is related to real growth options. As discussed in Section 2.4, we can test its implication by linking changes in firms' beta estimates to their characteristics such as, size, book-to-market ratio, and firm age under the assumption that firms are more likely to realize their growth options when they possess more. Results are reported in Table 13.

Insert Table 13 Approximately here

As expected, growth firms with large beta estimates are more likely to experience beta drops than value firms as shown in the second equation. This is true even when controlling for other firm characteristics (see Model 5). Similarly, young firms are more likely to experience beta reversal than mature firms as shown in the third equation. Although small firms are also likely to realize real options, the effect is insignificant no matter whether the size variable is used alone (see Model 1) or with other control variables (see Model 4). One possible reason for the insignificant estimate is that small firms might have limited real options to begin with. We also include the lagged beta change in the cross-sectional regression analysis since beta estimates are persistent.[26] When all variables, including size, book-to-market, and age, are used in the same model (see Model 7), the same pattern continues with the right signs.[27] Therefore, exercising real options is also a contributing factor.

6 Robustness Study

Too often we see that results from some studies are challenged when applying different measures or different samples. Despite our strong results and the use of popular control variables in our analysis, we continue to investigate the robustness of our results. In fact, one effective way to alleviate the data snooping or data mining concern is to use different measures of beta and idiosyncratic volatility, and to apply different samples and over different sample periods.

6.1 Other Popular Estimates of Beta

The rolling beta estimate used in our main study may not be an efficient estimate of the true beta. It is possible that our significant results are driven by some unknown correlation between the noise in the beta estimate and pricing errors. We therefore examine two alternative estimates of beta. Since either the data frequency or the estimation method used to construct these measures are different, the possible correlation is unlikely to be repeated. The first measure is the post-ranking portfolio beta, $Beta_p$, which is commonly used in cross-sectional regression analysis to reduce the error-in-variables bias. Although this measure is still time-varying, some of the short-term variations not related to sorting variables might be lost. Moreover, it may conceal important information contained in an individual stock's beta as pointed out by Ang, Schwarz, and Liu (2010). We therefore apply a second estimate of beta based on daily individual stocks' returns. In particular, we use the past three months of daily returns to estimate $Beta_{d,-3}$ in order to reduce possible market microstructure effect and to avoid high cross-sectional correlation between beta and idiosyncratic volatility, which is estimated using one month of data. The cross-sectional regression results are reported in

[26]Without such a control, estimates might be biased due to correlations between residuals and firm characteristics.

[27]When a firm is likely to accumulate growth options, for example firms with liquid asset, its beta will increase instead, which is why we also control for illiquidity in our cross-sectional regression analysis.

Panel A of Table 14 for portfolio beta $Beta_p$ and in Panel B for the $Beta_{d,-3}$ measure.

Insert Table 14 Approximately Here

The overall results are very similar to those reported in Table 6. The estimate on $Beta_p$ remains insignificant when used alone although the estimate has increased somewhat compared to that in the Fama and French (1992) (see Model 2 of Table 14). While idiosyncratic volatility is indeed significant and negative consistent with Ang, et. al. (2006), beta remains insignificant shown in Equation 3. In contrast, when only controlling for the beta reversal effect in Model 1, the portfolio beta becomes significant again with the coefficient estimate of 0.9%.[28] With control of the size and book-to-market factors, this estimate drops significantly to 0.5%, consistent with the average market risk premium of 0.44%. Further controlling for return reversal, momentum, and liquidity does not affect the significance of the market beta.

When using the second alternative beta measure, $Beta_{d,-3}$, in Panel B of Table 14, the beta reversal effect is again very significant with the coefficient estimate for the beta variable close to the market excess return when all control variables are included in the regression analysis (see Model 5). Despite the pluses and minuses of each measure of beta, our main results continue to hold significantly. This suggests that the performance of beta in cross-sectional regression analysis relies not only on the accuracy of the beta estimate but, more important, on how it captures the beta reversal feature as well.

6.2 Alternative Estimates of Idiosyncratic Volatility

Idiosyncratic risk plays an important role in our study both theoretically and empirically. However, it is unobservable and must be estimated with respect to an asset pricing model. In addition to the popular realized idiosyncratic volatility measure, $Beta_d$, used to obtain our main results, several other measures of idiosyncratic volatility have been proposed in the literature. For example, Bali et. al. (2009) use the rolling realized idiosyncratic volatility measure. We have tried the same measure, and find that the overall results are surprisingly

[28] These large estimates could be a result of omitting other factors in the regression.

similar to those reported in Table 6. To save space we do not report these results.[29]

As advocated by Campbell, et. al. (2001), a model-free approach to estimate idiosyncratic risk may be more efficient. However, their approach is difficult to implement in our case since we focus on individual stocks. One possible alternative is to use the *total* volatility as a proxy for idiosyncratic risk since idiosyncratic risk counts more than 90% of the variations in individual stocks' daily return movement. All things being equal, using total volatility as a proxy for idiosyncratic risk will bias us against finding supportive evidence for the pricing of the market risk since the total volatility contains the market risk. To implement, we replace the IV_d variable in Table 6 with total volatility TV_d estimated using individual stocks' daily returns within a month. Results are reported in Table 15.

Insert Table 15 Approximately here

When comparing each equation in Table 15 to the corresponding equations in Table 6, we see that both the coefficient estimates for the market beta and the controlling variables are surprisingly similar, except for the total volatility variable itself. Since total volatility contains market risk which has a positive risk premium, the negative effect on total volatility becomes smaller. Similarly, the estimates on the interaction term reflecting beta reversal also become smaller in magnitude, reflecting a noisy proxy for idiosyncratic risk. Our general conclusion is therefore very robust and not affected by a particular measure of idiosyncratic risk.

6.3 Stock Exchanges and Subsample Periods

Since beta reversal is likely to occur among stocks with certain characteristics, its effect might be different for stocks traded on different exchanges. Stocks traded on the NYSE exchange tend to be large and mature firms, while AMEX/NASDAQ firms are usually small and/or young firms that might be subject to greater speculation. We therefore examine the significance of the beta variable for the two markets. Results are reported in Panels A an B of Table 16for

[29] Another measure used in the literature is the Fu's (2009) conditional idiosyncratic volatility (the EGARCH estimate). We do not adopt such a measure because of the potential forward-looking bias and its focus on the pricing effect for idiosyncratic volatility itself. As discussed in Section 3.2, beta reversal is more likely to be related to the mispricing effect of idiosyncratic volatility instead.

the $NYSE$ and $AMEX/NASDAQ$ stocks, respectively. For comparability, we use the same measure of beta and idiosyncratic volatility as in Table 6.

Insert Table 16 Approximately here

When the beta variable is used alone, it is insignificant for stocks traded in both exchange markets. Including the size, book-to-market, and idiosyncratic volatility in Model 3 of Table 16 does not change the significance of beta. Although the book-to-market variable is significant for both groups of stocks, the size variable is only marginally significant for the $NASDAQ$ stocks. When controlling for the interaction term in Model 1, the beta variable becomes significant for both groups of stocks. However, the coefficient estimate is smaller for the $NASDAQ$ stocks than for the $NYSE/AMEX$ stocks. Finally, with all control variables, the coefficient estimates for the market beta are 0.4% and 0.3 for $NYSE/AMEX$ and $NASDAQ$, respectively. The results are therefore stronger for large and mature firms than for young firms. One possible reason for the difference is that beta instability is much larger for NASDAQ stocks than NYSE/AMEX stocks in addition to beta reversal.

The behavior of idiosyncratic volatility has changed significantly in the past decade as documented in Campbell, and et. al. (2001). At the same time, the explanatory power of the market factor becomes less significant in explaining the time-series return variation. In order to see if beta reversal is still important in recent years and how the pricing effect of the market beta changes over time, we further examine two equal subsample periods from 1963 to 1986 and from 1987 to 2010. Panels C and D of Table 16 summarize the main results.

The explanatory power of the market beta continues to be strong in both subsample periods after controlling for beta reversal (see Models 1 and 4). The coefficient estimates for the beta variable are 0.5% and 0.4% for the first and second subsample periods, respectively, consistent with the evidence on decreasing risk premia in recent years. Relatively speaking, controlling for beta reversal is more important in the first subsample period than in the second subsample period. It is also interesting to see that the size variable is insignificant in the second subsample period, consistent with other studies. Our results are therefore also robust with respect to different subsamples and sample periods.

The phenomenon of beta reversal and its impact on asset pricing are thus pervasive, independent of the way we estimate beta and idiosyncratic risk, and insensitive to different subsamples. Once such a short-term beta reversal effect is controlled, the conventional beta measure still matters significantly in differentiating cross-sectional returns of individual stocks.

7 Conclusion

In the absence of Roll's critique, the failure of finding empirical support for the pricing role of the market beta lead many researchers to conclude that the CAPM does not hold. Consequently, many complicated remedies have been proposed with limited success. Given its simplicity and the wide application in practice, we believe that the CAPM model might hold in the first order. Different from existing approaches, we find that the explanatory power of market betas is strong for most stocks except for a small group of stocks whose betas reverse over time. This group of stocks tends to have both high systematic and idiosyncratic risks. As a result, current market betas may not be associated with future returns even when the CAPM holds period by period in a dynamic setting. This is especially problematic when the beta estimate carries large noise. We offer simple solutions by either directly controlling for beta reversal, or using predicted betas, or adopting adjusted betas in a cross-sectional setting to restore the explanatory power of market betas.

We demonstrate that the market beta is not only significant in predicting future returns under a very robust setting after controlling for beta reversal, but the coefficient estimate from cross-sectional regression analysis is very close to the actual market risk premium over the same sample period as predicted by the CAPM theory. The mechanism behind beta reversal is very different from others, such as time-varying beta, the betting-against-beta factor of Frazzini and Pedersen (2013), and forward-looking factor of Buss and Vilkov (2012). From an empirical perspective, our beta reversal effect dominates all these factors.

In addition, we show both directly and indirectly that beta does reverse significantly from period to period, and the magnitude of the reversal can be predicted by an interaction term between beta and idiosyncratic volatility. To understand the economics behind beta reversal, we propose several channels that can drive such a reversal, including the wealth effect of Cochrane, Longstaff, and Santa Clara (2008), the earnings announcement uncertainty of Patton and Verardo (2012), and the real growth option effect (Cooper and Priestley, 2011). These plausible "causes" are also supported by our empirical evidence. Therefore, our results are unlikely affected by the potential data snooping bias.

Our finding of beta reversal is also useful to reconcile the contradictory evidence from current literature between the large time-series explanatory power of the market factor and weak cross-sectional explanatory power of the market beta. From a cross-sectional perspective, future returns will be low for a stock with a high current beta estimate even when the CAPM holds period-by-period. With proper control for beta reversal, the market beta continues to be the most important risk measure in pricing risky assets. We hope that future research will offer additional insights and identify other channels for beta reversal, as well as provide a better way to construct the beta reversal factor. Based on our evidence, we believe that the fundamental beta-return relation holds, at least in the first order, but the relation is likely to be distorted by a small group of stocks with a high degree of beta reversal from time to time.

References

[1] Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

[2] Ang, Andrew, and Joe Chen, 2007, CAPM Over the Long Run:1926-2001, *Journal of Empirical Finance* 14, 1-40.

[3] Ang, Andrew, Robert Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 51, 259-299.

[4] Ang, Andrew, Jun Liu , and Schwarz Krista, 2010, Using Stocks or Portfolios in Tests of Factor Models, working paper, Columbia University.

[5] Bali, Turan G. and Nusret Cakici, 2008, Idiosyncratic Volatility and the Cross-Section of Expected Returns, *Journal of Financial and Quantitative Analysis* 43, 29-58.

[6] Bali, Turan, Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns, *Journal of Financial Economics* 99, 427-446.

[7] Barber, Brad and John Lyon, 1997, Firm size, book-to-market ratio, and security returns: a holdout sample of financial firms, *Journal of Finance* 52, 875-883.

[8] Barber, Brad, Terrance Odean, and Ning Zhu, 2009, Do retail trades move markets? *Review of Financial Studies* 22, 152-186.

[9] Berk, Jonathan, Green, Richard, and Naik, Vasant, 1999, Optimal Investment, Growth Options, and Security Returns, *Journal of Finance* 54, 1553-1607.

[10] Bernardo, Antonio, Chowdhry Bhagwan, and Goyal Amit, 2007, Growth Options, Beta, and the Cost of Capital, *Financial Management* 36, 1-13.

[11] Black, Fischer, 1972, Capital Market Equilibrium with Restricted Borrowing, *Journal of Business* 45, 444-454.

[12] Black, Fischer, and Myron Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy* 81, 637-654.

[13] Buss, Adrian, and Grigory Vilkov, 2012, Measuring Equity Risk with Option-Implied Correlations, *Review of Financial Studies* 25, 3113-3140.

[14] Cao, Xuying, and Yexiao Xu, 2009, Long-Term Idiosyncratic Volatilities and Cross-Sectional Returns, working paper, The University of Texas at Dallas.

[15] ochrane, John H., Francis A. Longstaff and Pedro Santa-Clara, 2008, Two Trees, *Review of Financial Studies* 21, 347-385.

[16] Cooper, Ilan, and Richard Priestley, 2011, Real investment and risk dynamics, *Journal of Financial Economics* 101, 182-205.

[17] Da Zhi, ReJin Guo, and Ravi Jagannathan , 2012, CAPM for Estimating the Cost of Equity Capital: Interpreting the Empirical Evidence, *Journal of Financial Economics* 103, 204-220.

[18] Daniel, K. and S. Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* 52, 1-33.

[19] Daniel, K., S. Titman, and K. Wei, 2001, Explaining the cross-section of stock returns in Japan: factors or characteristics? *Journal of Finance* 56, 743-766.

[20] Dijk, Van M., 2011, Is size dead? A review of the size effect in equity returns, *Journal of Banking and Finance* 35, 3263-3274.

[21] Falkenstein, Eric G., 1996, Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings, *Journal of Finance* 51, 111-135.

[22] Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

[23] Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[24] Fama, Eugene F., MacBeth James, Risk, Return, and Equilibrium: Empirical Tests, 1973, *Journal of Political Economy* 81, 607-636.

[25] Fama, Eugene F., and Kenneth R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance* 51, 55-84.

[26] Frazzini, Andrea, and Lasse H. Pedersen, 2014, Betting Against Beta, *Journal of Financial Economics* 111, 1-25.

[27] Fu, Fangjian, 2009, Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91, 24-37.

[28] Galai, Dan and Ronald W. Masulis, 1976, The option pricing model and the risk factor of stocks, *Journal of Financial Economics* 3, 53-81.

[29] Grullon, Gustavo, Evgeny Lyandres and Alexei Zhdanov, 2012, Real Options, Volatility, and Stock Returns, *Journal of Finance* 67, 1499-1537.

[30] Guo, Hui, Haimanot Kassa, and Michael F. Ferguson, 2014, On the Relation between EGARCH Idiosyncratic Volatility and Expected Stock Returns, *Journal of Financial and Quantitative Analysis* 49, 271-296.

[31] Han, Bing, and Alok Kumar, 2013, Speculative Trading and Asset Prices,*Journal of Financial and Quantitative Analysis* 48, 377-404.

[32] Hong, Harrison G. and David Sraer, 2014, Speculative Betas, Working Paper, Princeton University.

[33] Horowitz, Joel L., Tim Loughran and N. E. Savin, 2000, Three Analyses of the Firm Size Premium, *Journal of Empirical Finance* 7, 143-153.

[34] Huang, Victor, Qianqiu Liu, Ghon Rhee, and Liang Zhang, 2010, Return Reversals, Idiosyncratic Risk, and Expected Returns, *Review of Financial Studies* 23, 147-168.

[35] Jagannathan, Ravi and Zhenyu Wang, 1996, The Conditional CAPM and the Cross-Section of Expected Returns, *Journal of Finance* 51, 3-53.

[36] Jiang, George, Danielle Xu, and Tong Yao, 2009, The Information Content of Idiosyncratic Volatility, *Journal of Financial and Quantitative Analysis* 44, 1-28.

[37] Johnson, Timothy, 2004, Forecast Dispersion and the Cross Section of Expected Returns, *Journal of Finance* 59, 1957-1978.

[38] Kim, Dongcheol, 1997, A reexamination of firm size, book-to-market, and earnings price in the cross-Section of expected stock returns, *Journal of Financial and Quantitative Analysis* 32, 463-489.

[39] Knez, Peter and Mark Ready, 1997, The robustness of size and book-to-market in cross-sectional regressions, *Journal of Finance* 52, 1355-1382.

[40] Kothari, S.P., Jay Shanken and Richard Sloan, 1995, Another Look at the Cross-Sectional Stock Returns, *Journal of Finance* 50, 185–224.

[41] Lewellena, Jonathan , and Nagelb Stefan, 2006, The conditional CAPM does not explain asset-pricing anomalies, *Journal of Financial Economics* 82, 289-314.

[42] Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13-37.

[43] Malkiel, Burton, and Yexiao Xu, 2002, Investigating the Behavior of Idiosyncratic Volatility, *Journal of Business* 76, 613-644.

[44] Merton, Robert C, 1973, An Intertemporal Capital Asset Pricing Model, *Econometrica* 41, 867-887.

[45] Pastor Lubos, and Veronesi Pietro, 2009, Learning in Financial Markets, *Annual Review of Financial Economics, Annual Reviews* 1, 361-381.

[46] Patton, Andrew and Michela Verardo, 2012, Does Beta Move with News? Firm-Specific Information Flows and Learning about Profitability, *Review of Financial Studies* 25, 2789-2839

[47] Sharpe, William, 1964, Capital Asset Prices: a Theory of Market Equilibrium under Conditions of Risk. *Journal of Finance* 19,425-442.

[48] Shumway, Tyler, 1997, The Delisting Bias in CRSP Data, *Journal of Finance* 52, 327-340.

Table 1: **Idiosyncratic Volatility and Beta Sorted Portfolio Returns**

This table shows the average stock returns for the 25 equal-weighted portfolios by first sorting individual stocks according to their beta estimates ($Beta_r$) and then according to their idiosyncratic volatilities IV_d. $Beta_r$ is estimated using the past 60 monthly returns as in Fama and French (1992); and IV_d is computed based on the daily residual stock returns in the past month with respect to the Carhart's four-factor model (see Ang et al, 2006). The sample period ranges from July 1963 to December 2010. $H - L$ represents the portfolio return difference between the highest and lowest portfolios. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Row{IV_d}; Column{$Beta_r$}					
	1(low)	2	3	4	5(High)	H-L
1(Low)	0.89	1.05	1.15	1.13	1.31	0.43*
	(5.65)	(6.96)	(6.31)	(5.58)	(4.77)	(1.85)
2	1.09	1.25	1.28	1.38	1.41	0.32
	(6.11)	(6.88)	(6.72)	(6.42)	(4.21)	(1.07)
3	1.21	1.33	1.37	1.52	1.38	0.17
	(5.85)	(6.92)	(6.35)	(5.53)	(3.97)	(0.58)
4	1.23	1.42	1.39	1.23	1.17	-0.06
	(5.57)	(6.25)	(5.54)	(4.09)	(3.16)	(-0.23)
5(high)	1.26	1.29	1.17	0.90	0.62	-0.64**
	(3.82)	(4.35)	(3.59)	(2.43)	(1.47)	(-2.24)
H-L	0.37	0.24	0.02	-0.23	-0.70**	
	(1.33)	(1.04)	(0.07)	(-0.82)	(-2.61)	

Table 2: **Summary Statistics**

This table provides summary statistics for variables used in this study. The sample period spans from July 1963 to December 2010. RET is the monthly. $Beta_r$ represents an individual stock's rolling beta estimated from a market model using the past 60-month stock returns. $Beta_p$ is the portfolio beta, estimated following Fama French (1992). $Beta_{(d,-1)}$ and $Beta_{(d,-3)}$ are the monthly rolling beta estimated using a stock's daily returns within either the last month or the last three months. IV_d is the monthly realized idiosyncratic volatility using the past month daily residual returns with respect to the Carhart's four-factor model (see Ang et al, 2006). IV_r is the rolling realized idiosyncratic volatility computed following Bali and Cakici (2009). $Ln(ME)$ is a stock's log market capitalization (ME) of the last June, and $Ln(BM)$ is the log of the fiscal year-end book value of equity divided by the calendar year-end market value of equity. $RET_{(-2,-7)}$ is the compounded gross return from months $t - 7$ to $t - 2$ (inclusive). $Illiq$ is the Amihud illiquidity measure defined in Amihud (2002) and calculated in year $t - 1$. $P25$ and $P75$ represent the 25% and the 75% percentile, respectively. To control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels.

	Mean	STD	P25	Median	P75
RET	0.012	0.159	-0.067	0.000	0.075
$Beta_r$	1.160	0.740	0.687	1.090	1.544
$Beta_p$	1.358	0.332	1.139	1.330	1.623
$Beta_{(d,-1)}$	0.737	1.374	0.066	0.666	1.368
$Beta_{(d,-3)}$	0.761	0.868	0.238	0.695	1.229
IV_d	0.127	0.108	0.060	0.096	0.157
IV_r	0.126	0.072	0.076	0.109	0.157
TV	0.151	0.121	0.075	0.118	0.186
$Ln(ME)$	11.515	2.154	9.918	11.362	13.001
$Ln(BM)$	-0.466	0.965	-0.989	-0.379	0.165
$RET_{(-2,-7)}$	0.078	0.431	-0.156	0.027	0.228
$Illiq$	0.056	0.242	0.000	0.002	0.020

Table 3: **Transition Probability Matrix of Beta**

This table shows the transition probability matrices of beta among different groups of stocks. They are estimated by first sorting individual stocks into five groups by their idiosyncratic volatility IV_d each month. All stocks are also sorted separately into three groups according to their $Beta_{d,-1}$ estimated using daily returns within a month to determine the breakpoints. Stocks in the lowest (highest) idiosyncratic volatility group are then sorted into three groups according to the beta breakpoints. Stocks in each beta-group are traced to the next period and are assigned into three groups according to their persistence adjusted beta. The transition probability matrix of beta changing from group i in month t to group j in month $t+1$ can then be calculated. Since stocks in each group in month t are uneven, the number reported in bracket is computed with respect to all stocks. Panels A and B report the probability matrix for lowest and highest idiosyncratic volatility groups, respectively.

	Panel A: Lowest IV_d Decile		
$Beta_{d,-1}$	Small	Median	Large
Small	0.33 (0.12)	0.47 (0.17)	0.20 (0.07)
Median	0.31 (0.14)	0.47 (0.21)	0.22 (0.10)
Large	0.26 (0.05)	0.42 (0.08)	0.32 (0.06)
	Panel B: Highest IV_d Decile		
Small	0.30 (0.12)	0.17 (0.07)	0.53 (0.21)
Median	0.40 (0.06)	0.20 (0.03)	0.40 (0.06)
Large	0.53 (0.24)	0.16 (0.07)	0.31 (0.14)

Table 4: **Relationship between Beta and Idiosyncratic Volatility**

This table presents the Fama-MacBeth regression results from regressing beta on the past beta and idiosyncratic volatility. The dependent variable is beta ($Beta_d$) estimated using daily stock returns within the month. IV_d is the idiosyncratic volatility measure estimated based on the daily residual stock returns from the past month with respect to the Carhart's four-factor model (see Ang et al, 2006). $Beta_{(d,-3)}$ is estimated using the past three month daily returns. $Beta_{d,-1} * IV_{d,-1}$ is the interaction term between the last period beta and idiosyncratic volatility. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: 1 Month	
	Model 1	Model 2
$Beta_{d,-1}$	0.242***	0.365***
	(10.35)	(11.80)
$Beta_{d,-1} * IV_{d,-1}$		-0.596***
		(-5.10)
	Panel B: 3 Months	
	Model 1	Model 2
$Beta_{d,-3}$	0.450***	0.560***
	(13.71)	(18.17)
$Beta_{d,-3} * IV_{d,-1}$		-0.562***
		(-3.53)

Table 5: **Sorted Portfolio Returns**

This table shows the average stock returns for the 25 equal-weighted portfolios. Portfolios in Panels A and B are formed by sorting individual stocks according to their beta estimates ($Beta_r$) and the book-to-market ratios (B/M) simultaneously. $Beta_r$ is estimated using the past 60 monthly returns as in Fama and French (1992). In Panel A, we use all stocks in the sample, while in Panel B we delete the four portfolio with the largest beta estimates and idiosyncratic volatilities (stocks in the lower right corner of Table 1). The sample period ranges from July 1963 to December 2010. $H-L$ represents the portfolio return difference between the highest and lowest portfolios. Portfolio returns are computed using equal weights. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Using Full Sample Row{B/M}; Column{$Beta_r$}					
	1(low)	2	3	4	5(High)	H-L
1(low)	0.75	0.95	0.81	0.75	0.70	-0.05
	(2.97)	(4.71)	(3.46)	(2.71)	(1.95)	(-0.21)
2	0.84	1.05	1.12	1.15	1.07	0.23
	(4.20)	(5.48)	(5.37)	(4.70)	(3.20)	(1.04)
3	1.09	1.21	1.30	1.23	1.43	0.33
	(5.39)	(6.36)	(5.89)	(4.87)	(4.38)	(1.30)
4	1.22	1.28	1.50	1.53	1.49	0.28
	(6.18)	(6.56)	(6.57)	(5.67)	(4.40)	(1.29)
5(high)	1.55	1.74	1.56	1.57	1.77	0.22
	(6.67)	(6.76)	(5.86)	(5.09)	(5.15)	(0.92)
H-L	0.81***	0.80***	0.75***	0.82***	1.07***	
	(4.23)	(4.86)	(3.80)	(4.24)	(4.94)	
	Panel B: Using Reduced Sample					
1	0.70	1.01	0.89	0.90	1.02	0.32*
	(2.67)	(4.89)	(4.41)	(3.74)	(3.63)	(1.73)
2	0.84	1.06	1.16	1.19	1.30	0.46***
	(4.00)	(5.31)	(5.99)	(5.41)	(4.91)	(2.78)
3	1.09	1.13	1.24	1.28	1.41	0.32**
	(5.37)	(6.18)	(5.92)	(5.98)	(5.75)	(2.12)
4	1.21	1.26	1.45	1.48	1.62	0.42***
	(5.88)	(6.77)	(6.85)	(6.42)	(6.40)	(2.96)
5	1.54	1.64	1.69	1.53	1.72	0.18
	(6.45)	(6.70)	(6.22)	(5.93)	(6.41)	(1.25)
H-L	0.84***	0.63***	0.79***	0.63***	0.69***	
	(4.06)	(3.58)	(4.48)	(3.15)	(3.12)	

Table 6: **Fama-MacBeth Regression Analysis for Individual Stocks**

This table presents the Fama-MacBeth regression results for monthly individual stock returns on different factors. These factors include $Beta_r$ estimated using the last 60 monthly returns, idiosyncratic volatility IV_d estimated based on the daily residual stock returns from the past month with respect to the Carhart's four-factor model (see Ang et al, 2006), the log market capitalization $Ln(ME)$ of the last June, the log of book-to-market $Ln(BM)$, the last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, and the Amihud illiquidity measure defined in Amihud (2002) $Illiq$. $Beta_r * IV_d$ is the interaction term between beta and idiosyncratic volatility. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels. Monthly returns are dividend and split-adjusted in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
IV_d	0.024			-0.047***	-0.005	0.002	-0.008
	(1.26)			(-4.98)	(-0.37)	(0.15)	(-0.59)
$Beta_r * IV_d$	-0.037***				-0.034***	-0.028***	-0.026***
	(-4.3)				(-4.14)	(-3.67)	(-3.45)
$Beta_r$	0.005***	0.001	0.001	0.002	0.006***	0.004***	0.004***
	(3.13)	(0.49)	(0.67)	(1.49)	(3.64)	(2.84)	(2.97)
$Ln(BM)$			0.003***	0.002***	0.002***	0.003***	0.002***
			(4.23)	(3.78)	(4.01)	(3.94)	(3.71)
$Ln(ME)$			-0.001	-0.001***	-0.001***	-0.001**	-0.001**
			(-1.63)	(-3.34)	(-3.27)	(-2.56)	(-1.98)
$RET_{(-1)}$						-0.065***	-0.065***
						(-8.86)	(-8.76)
$RET_{(-2,-7)}$						0.006**	0.006**
						(2.51)	(2.50)
$Illiq$							0.033**
							(2.53)

Table 7: **Fama-MacBeth Regression Analysis Using the Predicted Beta or Adjusted Beta**

This table presents the Fama-MacBeth regression results from regressing future returns on predicted beta or beta-reversal-adjusted beta. The predicted beta $\widehat{Beta}$ is computed based on Model 2 in Panel A of Table 4. The beta-reversal-adjusted beta $Beta_{adj}$ is estimated based on a two-factor model of Equation 12 that includes both the market and beta-reversal factors. $Beta_r$ is the rolling beta estimate from a market model using the last 60 monthly returns. Idiosyncratic volatility IV_d estimated based on the daily residual stock returns from the past month with respect to the Carhart's four-factor model (see Ang et al, 2006). Other control variables include the log market capitalization $Ln(ME)$ of the last June, the log of book-to-market $Ln(BM)$, the last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, and the Amihud illiquidity measure defined in Amihud (2002) *Illiq*. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels. Monthly returns are dividend and split-adjusted in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Panel A: Using Predicted Beta				
$\widehat{Beta}$	0.004**	0.007***	0.009***	0.008***	0.009***
	(2.34)	(3.12)	(4.24)	(3.93)	(4.19)
$Ln(BM)$		0.003***	0.003***	0.003***	0.003***
		(4.97)	(4.50)	(4.39)	(4.14)
$Ln(ME)$		-0.001**	-0.002***	-0.002***	-0.002***
		(-1.98)	(-4.01)	(-3.39)	(-2.95)
IV_d			-0.060***	-0.042***	-0.052***
			(-5.96)	(-4.58)	(-5.57)
$RET_{(-1)}$				-0.064***	-0.063***
				(-8.8)	(-8.73)
$RET_{(-2,-7)}$				0.005**	0.005**
				(2.13)	(2.10)
Illiq					0.038***
					(2.93)
	Panel B: Using Adjusted Beta				
$Beta_r$	0.001				
	(0.53)				
$Beta_{adj}$		0.002***	0.002***	0.002***	0.002***
		(2.94)	(3.20)	(3.73)	(4.05)
$Ln(BM)$	0.003***	0.003***	0.003***	0.003***	0.003***
	(4.31)	(4.19)	(3.70)	(3.93)	(3.47)
$Ln(ME)$	-0.001	-0.001	-0.002***	0.000	-0.001*
	(-1.60)	(-1.59)	(-3.32)	(-0.66)	(-1.96)
IV_d			-0.045***		-0.038***
			(-4.11)		(-3.61)
$RET_{(-1)}$				-0.063***	-0.063***
				(-8.70)	(-8.62)
$RET_{(-2,-7)}$				0.006**	0.005**
				(2.30)	(2.18)
Illiq				0.033**	0.039***
				(2.40)	(2.70)

Table 8: **Beta Reversal Factor vs. Betting-Against-Beta Factor**

This table presents coefficient estimates for the Beta Reversal (BR) factor and the Frazzini and Pedersen's (2012) Betting-Against-Beta (BAB) factor for the 25 ME and B/M sorted portfolio returns. In the time-series regression, we also control for the Carhart four factors, namely the market factor (MKTRF), the size factor (SMB), the book-to-market factor (HML), and the momentum factor (UMD). The left (right) panel of Panel A shows the coefficient estimate of the Beta Reversal (Betting-Against-Beta) factor when only the BR (BAB) factor is used with the Carhart factors. Panel B reports the coefficient estimates of both the BR and the BAB factors when both variables are used in the regression models. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Coefficient Estimates When Either the BR or BAB Factors Are Used									
	BR + Carhart 4 Factors					BAB + Carhart 4 Factors				
	1(low)	2	3	4	5(high)	1(low)	2	3	4	5(high)
1(low)	0.100***	0.025*	-0.022**	-0.033***	0.028**	-0.128***	-0.046*	0.043**	0.060***	0.079***
	(5.94)	(1.91)	(-2.14)	(-3.12)	(2.53)	(-3.90)	(-1.89)	(2.18)	(3.01)	(3.79)
2	0.030**	-0.054***	-0.059***	-0.057***	-0.023**	-0.077***	0.052**	0.072***	0.079***	-0.048**
	(2.39)	(-4.88)	(-5.74)	(-5.62)	(-2.09)	(-3.34)	(2.48)	(3.62)	(4.09)	(-2.30)
3	0.002	-0.037***	-0.061***	-0.047***	-0.029**	-0.061***	0.077***	0.108***	0.102***	-0.043
	(0.14)	(-2.90)	(-4.91)	(-3.81)	(-2.07)	(-2.80)	(3.19)	(4.59)	(4.42)	(-1.60)
4	0.029**	-0.058***	-0.050***	-0.017	-0.005	-0.083***	0.133***	0.132***	0.045*	-0.011
	(2.55)	(-4.40)	(-3.68)	(-1.37)	(-0.33)	(-3.88)	(5.38)	(5.29)	(1.87)	(-0.39)
5(high)	-0.018**	-0.045***	-0.021	-0.020*	0.062***	0.004	0.104***	0.055**	0.036*	-0.086***
	(-1.97)	(-4.05)	(-1.63)	(-1.80)	(3.65)	(0.23)	(5.00)	(2.26)	(1.71)	(-2.66)
	Coefficient Estimates When Both the BR and BAB Factors Are Used									
	BR Factor					BAB Factor				
1(low)	0.086***	0.017	-0.015	-0.022*	0.062***	-0.059	-0.031	0.029	0.041*	0.128***
	(4.42)	(1.17)	(-1.23)	(-1.84)	(4.98)	(-1.59)	(-1.1)	(1.25)	(1.77)	(5.46)
2	0.012	-0.054***	-0.052***	-0.047***	-0.049***	-0.069**	0.003	0.031	0.039*	-0.101***
	(0.81)	(-4.18)	(-4.34)	(-4.06)	(-3.91)	(-2.57)	(0.10)	(1.36)	(1.78)	(-4.26)
3	-0.020	-0.020	-0.042***	-0.024*	-0.052***	-0.084***	0.066**	0.077***	0.088***	-0.093***
	(-1.53)	(-1.38)	(-2.94)	(-1.74)	(-3.30)	(-3.30)	(2.33)	(2.86)	(3.30)	(-3.08)
4	0.009	-0.030**	-0.019	-0.007	-0.013	-0.078***	0.111***	0.119***	0.040	-0.029
	(0.67)	(-1.97)	(-1.25)	(-0.50)	(-0.73)	(-3.09)	(3.88)	(4.10)	(1.43)	(-0.87)
5(high)	-0.023**	-0.025**	-0.007	-0.016	0.053***	-0.021	0.079***	0.055*	0.019	-0.036
	(-2.16)	(-1.97)	(-0.49)	(-1.21)	(2.72)	(-1.03)	(3.25)	(1.93)	(0.75)	(-0.96)

Table 9: **Fama-MacBeth Regression Analysis Using the BAB-Adjusted Beta**

This table presents the Fama-MacBeth regression results from regressing future returns on the BAB (Betting-Against-Beta) factor adjusted beta, $Beta_{BAB}$. It is estimated based on a two-factor model that includes both the market and BAB factors. $Beta_r$ is the rolling beta estimate from a market model using the last 60 monthly returns. Idiosyncratic volatility IV_d estimated based on the daily residual stock returns from the past month with respect to the Carhart's four-factor model (see Ang et al, 2006). Other control variables include the log market capitalization $Ln(ME)$ of the last June, the log of book-to-market $Ln(BM)$, the last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, and the Amihud illiquidity measure defined in Amihud (2002) *Illiq*. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels. Monthly returns are dividend and split-adjusted in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5
$Beta_r$	0.001				
	(0.53)				
$Beta_{BAB}$		-0.001	-0.002	-0.001	-0.002
		(-0.73)	(-1.52)	(-0.91)	(-1.56)
$Ln(BM)$	0.003***	0.003***	0.002***	0.003***	0.002***
	(4.31)	(4.30)	(3.85)	(4.08)	(3.62)
$Ln(ME)$	-0.001	-0.001	-0.002***	-0.000	-0.001*
	(-1.60)	(-1.61)	(-3.31)	(-0.67)	(-1.97)
IV_d			-0.047***		-0.039***
			(-4.78)		(-4.09)
$RET_{(-1)}$				-0.067***	-0.066***
				(-8.80)	(-8.64)
$RET_{(-2,-7)}$				0.006**	0.006**
				(2.60)	(2.45)
Illiq				0.028**	0.036***
				(2.41)	(2.82)

Table 10: **Beta-Reversal-Adjusted Beta versus Option-implied Beta**

This table compares the explanatory power of our beta-reversal adjusted beta $Beta_{adj}$ with the option-implied beta (defined in the Section 3.2) $Beta_{opt}$ proposed by Buss and Vilkov (2012). Cross-sectional regression analysis on 50 beta sorted portfolios are used in Panel A, while pooled regression analysis with clustering on both firm and month is applied in Panel B. Portfolios are formed either by sorting individual stocks each month on either their beta-reversal adjusted beta, option-implied beta, or rolling monthly beta $Beta_r$. Panel C reports the percentage of individual stocks from the Buss and Vilkov's (2012) study that fall into the corresponding groups constructed using our full sample of stocks. Following Buss and Vilkov (2012), the sample used in Panel A covers $S\&P500$ firms from 1996 to 2009. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Replication of Buss and Vilkov's (2012) Results for 50 Portfolios					
	Model 1	Model 2	Model 3		
$Beta_{opt}$	0.0043***				
	(3.12)				
$Beta_{adj}$		0.0036***			
		(3.59)			
$Beta_r$			0.0028***		
			(3.21)		
Panel B: Pooled Regression with Cluster Adjustment					
	Model 1	Model 2	Model 3	Model 4	Model 5
$Beta_{opt}$	0.004**			0.001	
	(2.33)			(0.68)	
$Beta_{adj}$		0.005***		0.005***	0.005***
		(4.84)		(4.10)	(4.34)
$Beta_r$			0.002***		0.001
			(2.65)		(-0.14)
Panel C: Distribution of Buss and Vilkov's (2012) sample w.r.t. Our Sample					
	Column{$Beta_r$}; Row{IV_d}				
	1(low)	2	3	4	5(High)
1(low)	0.10	0.06	0.03	0.01	0.00
2	0.13	0.08	0.04	0.01	0.00
3	0.13	0.07	0.03	0.01	0.00
4	0.09	0.05	0.02	0.01	0.00
5(High)	0.06	0.03	0.01	0.01	0.00

Table 11: **Beta Reversal and the Wealth Effect**

This table presents the Fama-MacBeth regression results for the contemporaneous and predictive relations among a change in beta ($\Delta Beta_d$), change in idiosyncratic volatility (ΔIV_d), and change in firm size ($\Delta ln(ME_m)$). $Beta_d$ is estimated using daily returns in a month. $\Delta IV_{d,-1}$ and IV_d refer to the last and the current month's idiosyncratic volatility, respectively. $\Delta ln(ME_{m,-1})$ and $\Delta ln(ME_m)$ are the last and current month's firm size. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

Independent	$\Delta ln(ME_m)$ as Dep. Var.		$\Delta Beta_d$ as Dep. Var.				
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ΔIV_d	0.255***			1.760***	1.584***		1.535***
	(8.29)			(7.38)	(7.42)		(7.04)
$\Delta IV_{(d,-1)}$		-0.061***				-0.690***	-0.049
		(-4.36)				(-7.07)	(-0.78)
$\Delta ln(ME_m)$			0.526***		0.407***		0.408***
			(7.13)		(6.42)		(6.58)
$\Delta ln(ME_{(m,-1)})$						-0.301***	-0.178***
						(-4.89)	(-3.39)

Table 12: **Beta Reversal and Earnings Announcement**

This table presents the Fama-MacBeth regression results that differentiate the effect of earnings announcement. The sample period ranges from 1971 to 2010. The earnings announcement dummy Dum is set to 1 for the firm *without* an earnings announcement in month t, and 0 otherwise. The regressors include $Beta_r$ estimated using the last 60 monthly returns, idiosyncratic volatility IV_d estimated based on the daily residual stock returns from the past month with respect to the Carhart's four-factor model (see Ang et al, 2006), the log market capitalization $Ln(ME)$ for the last June, the log of book-to-market $Ln(BM)$, the last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, and the monthly Amihud illiquidity measure defined in Amihud (2002) $Illiq$. $Beta_r * IV_d$ is the interaction term between beta and idiosyncratic volatility. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels. Monthly returns are dividend and split-adjusted in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5
IV_r	0.012	-0.011	-0.012	-0.012	0.011
	(0.82)	(-1.15)	(-1.16)	(-1.18)	(0.82)
$Beta_r * IV_r$	-0.029***	-0.025***	-0.019***	-0.023***	-0.036***
	(-4.15)	(-4.32)	(-3.35)	(-4.06)	(-4.84)
$Beta_r$	0.004**	0.005***	0.004**	0.003**	0.004**
	(2.56)	(3.17)	(2.42)	(2.19)	(2.41)
$Ln(BM)$		0.003***	0.003***	0.003***	0.003***
		(4.06)	(3.68)	(3.57)	(3.55)
$Ln(ME)$		-0.001***	-0.001	-0.001**	-0.001**
		(-2.92)	(-1.55)	(-2.13)	(-2.08)
$RET_{(-1)}$			-0.065***	-0.065***	-0.065***
			(-7.72)	(-7.71)	(-7.74)
$RET_{(-2,-7)}$			0.004	0.004	0.004
			(1.56)	(1.52)	(1.51)
$Illiq$			0.021***	0.021***	0.022***
			(3.83)	(3.90)	(3.85)
Dum				-0.008***	-0.005***
				(-10.97)	(-4.78)
$Beta_r * IV_r * Dum$				0.008**	0.023***
				(2.03)	(2.91)
$IV_r * Dum$					-0.029***
					(-2.88)
$Beta_r * Dum$					-0.001
					(-1.25)

Table 13: **Relationship between Change in Beta and Firms' Characteristics**

This table presents the Fama-MacBeth regression results from regressing change in beta this month on firms' characteristics in the last month. These firms characteristics includes the log of book-to-market $Ln(BM)$ and the log of firm age $ln(Age)$. Other firms characteristics includes the change in firm's beta,$\Delta Beta$, defined as a difference between the current montht beta and the last month beta; the log market capitalization $Ln(ME)$ of the last June, last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, the Amihud illiquidity measure defined in Amihud (2002) $Illiq$. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and the 99.5% level. Monthly returns are dividend and split-adjusted, in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, $***$ denote significance level at the 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$Ln(ME)$	0.001***			0.0000			0.000
	(0.83)			(0.29)			(0.07)
$Ln(BM)$		0.004***			0.004***		0.004***
		(3.04)			(3.59)		(2.94)
$ln(Age)$			0.004**			0.004***	0.003***
			(2.57)			(3.24)	(2.76)
$\Delta Beta$	-0.492***	-0.492***	-0.492***	-0.492***	-0.492***	-0.492***	-0.492***
	(-164.83)	(-162.19)	(-161.82)	(-171.37)	(-169.86)	(-169.15)	(-173.43)
$RET_{(-1)}$				-0.052	-0.039	-0.044	-0.052
				(-0.96)	(-0.74)	(-0.83)	(-0.98)
$RET_{(-2,-7)}$				-0.029**	-0.031**	-0.029**	-0.032**
				(-2.25)	(-2.50)	(-2.45)	(-2.55)
$Illiq$				-0.224**	-0.113	-0.127	-0.210**
				(-2.10)	(-2.34)	(-1.53)	(-2.11)

Table 14: **Cross-sectional Regression Analysis with Alternative Beta Measures**

This table presents the cross-sectional regression results using an alternative beta measure. These measures include the portfolio beta $Beta_p$ estimated following Fama and French's (1992) method, and the rolling beta $Beta_{(d,-3)}$ estimated using the past three month daily returns. Other regressors include idiosyncratic volatility IV_d estimated based on daily residual returns with respect to the Carhart's four-factor model (see Ang et al, 2006), the log market capitalization $Ln(ME)$ for the last June, the log of book-to-market $Ln(BM)$, the last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, and the monthly Amihud illiquidity measure defined in Amihud (2002) *Illiq*. $Beta * IV_d$ is the interaction term between beta and idiosyncratic volatility. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels. Monthly returns are dividend and split-adjusted in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5
	Panel A: Portfolio Beta				
IV_d	0.046**		-0.047***	0.007	0.005
	(2.22)		(-4.84)	(0.46)	(0.32)
$Beta_p * IV_d$	-0.054***			-0.038***	-0.032***
	(-4.45)			(-3.65)	(-3.03)
$Beta_p$	0.009***	0.003	0.002	0.005**	0.005**
	(3.03)	(0.84)	(1.02)	(2.24)	(2.00)
$Ln(BM)$			0.002***	0.002***	0.002***
			(3.87)	(3.99)	(3.67)
$Ln(ME)$			-0.001***	-0.001***	-0.001*
			(-3.26)	(-3.09)	(-1.69)
$RET_{(-1)}$					-0.063***
					(-8.64)
$RET_{(-2,-7)}$					0.006**
					(2.21)
Illiq					0.032**
					(2.50)
	Panel B: Individual Beta Using Three Month Daily Returns				
IV_d	-0.007		-0.049***	-0.031***	-0.024***
	(-0.46)		(-5.21)	(-3.5)	(-2.62)
$Beta_{(d,-3)} * IV_d$	-0.019***			-0.024***	-0.021***
	(-3.81)			(-4.72)	(-4.41)
$Beta_{(d,-3)}$	0.003**	0.000	0.001	0.005***	0.004***
	(1.96)	(-0.36)	(1.46)	(3.74)	(3.07)
$Ln(BM)$			0.002***	0.002***	0.002***
			(3.79)	(3.93)	(3.58)
$Ln(ME)$			-0.002***	-0.002***	-0.001**
			(-3.1)	(-3.43)	(-2.19)
$RET_{(-1)}$					-0.062***
					(-8.5)
$RET_{(-2,-7)}$					0.005**
					(2.15)
Illiq					0.033**
					-2.58

Table 15: **Cross-sectional Regression Analysis with Total Volatility**

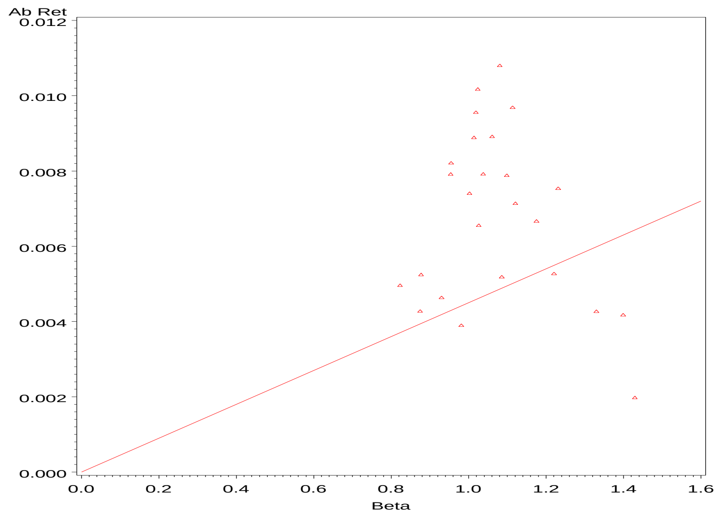
This table presents the cross-sectional regression results using total volatility. The regressors include $Beta_r$ estimated using the last 60 monthly returns, total volatility TV estimated based on daily residual return within the last month, the log market capitalization $Ln(ME)$ for the last June, the log of book-to-market $Ln(BM)$, the last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, and the monthly Amihud illiquidity measure defined in Amihud (2002) $Illiq$. $Beta_p * TV$ is the interaction term between beta and total volatility. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels. Monthly returns are dividend and split-adjusted in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4
TV	0.023	-0.040***	-0.001	-0.004
	(1.34)	(-4.38)	(-0.06)	(-0.32)
$Beta_r * TV$	-0.034***		-0.031***	-0.025***
	(-4.9)		(-4.81)	(-4.01)
$Beta_r$	0.006***	0.002*	0.006***	0.005***
	(3.86)	(1.74)	(4.51)	(3.68)
$Ln(BM)$		0.002***	0.002***	0.002***
		(3.78)	(4.02)	(3.71)
$Ln(ME)$		-0.001***	-0.001***	-0.001*
		(-3.21)	(-3.14)	(-1.81)
$RET_{(-1)}$				-0.065***
				(-8.72)
$RET_{(-2,-7)}$				0.006**
				(2.50)
$Illiq$				0.032**
				(2.50)

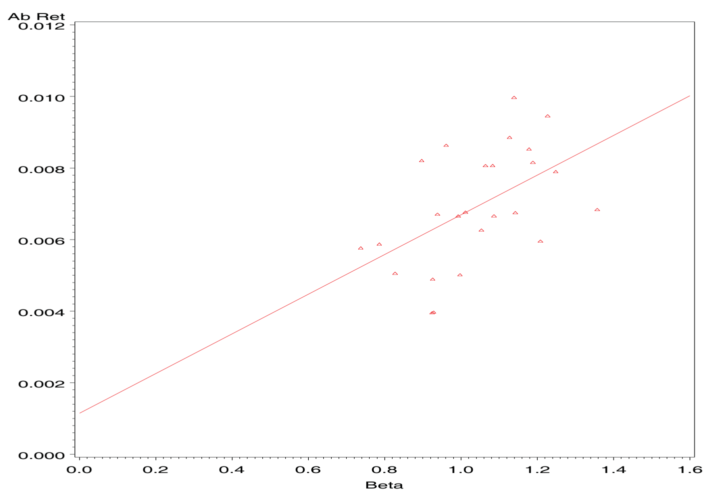
Table 16: **Cross-sectional Regression Analysis over Different Subsamples**

This table presents the Fama-MacBeth regression results for different stock exchanges and over different subsample periods. These regressors include $Beta_r$ estimated using the last 60 monthly returns, idiosyncratic volatility IV_d estimated based on the daily residual stock returns from the past month with respect to the Carhart's four-factor model (see Ang et al, 2006), the log market capitalization $Ln(ME)$ for the last June, the log of book-to-market $Ln(BM)$, the last month return $RET_{(-1)}$, the compounded gross return from months $t-7$ to $t-2$ (inclusive) $RET_{(-2,-7)}$, and the monthly Amihud illiquidity measure defined in Amihud (2002) $Illiq$. $Beta_p * IV_d$ is the interaction term between beta and idiosyncratic volatility. Results in Panel A are based on NYSE stocks only, while those in Panel B are based on Amex/NASDAQ stocks only. Regression equations in Panels C and D are for the first and second equally divided subsample periods, respectively. In order to control for the potential data errors and extreme values, all variables are winsorized at the 0.5% and 99.5% levels. Monthly returns are dividend and split-adjusted in percentages. The robust Newey West t-statistic is reported in the bracket. The symbols $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Panel A: NYSE				Panel B: AMEX&NASDAQ			
IV_d	0.022		-0.051***	-0.018	-0.01		-0.034***	-0.020
	(1.07)		(-5.03)	(-1.16)	(-0.83)		(-3.83)	(-1.52)
$Beta_r * IV_d$	-0.039***			-0.025***	-0.013***			-0.010**
	(-3.91)			(-2.75)	(-2.95)			(-2.06)
$Beta_r$	0.005***	0.001	0.001	0.004**	0.003**	0.00	0.002	0.003*
	(3.11)	(0.44)	(1.27)	(2.51)	(2.03)	(0.00)	(1.36)	(1.87)
$Ln(BM)$			0.002***	0.002***			0.004***	0.004***
			(3.28)	(3.15)			(5.49)	(4.91)
$Ln(ME)$			-0.001***	-0.001*			-0.001*	0.000
			(-3.06)	(-1.93)			(-1.83)	(-0.73)
$RET_{(-1)}$				-0.058***				-0.055***
				(-6.93)				(-9.48)
$RET_{(-2,-7)}$				0.007***				0.001
				(2.60)				(0.53)
$Illiq$				0.040***				0.019***
				(2.99)				(2.77)
	Panel C: 1963-1986				Panel D: 1987-2010			
IV_r	0.048		-0.067***	0.004	0.001		-0.027***	-0.019
	(1.40)		(-4.87)	(0.16)	(0.06)		(-2.95)	(-1.48)
$Beta_p * IV_r$	-0.060***			-0.045***	-0.015***			-0.008*
	(-4.51)			(-3.66)	(-3.13)			(-1.84)
$Beta_r$	0.007**	0.000	0.001	0.005**	0.004**	0.001	0.002	0.004**
	(2.47)	(0.03)	(0.58)	(2.21)	(1.98)	(0.75)	(1.60)	(2.00)
$Ln(BM)$			0.002**	0.002**			0.003***	0.003***
			(1.98)	(2.13)			(3.63)	(3.31)
$Ln(ME)$			-0.002***	-0.001*			-0.001**	-0.001
			(-2.67)	(-1.67)			(-2.42)	(-1.2)
$RET_{(-1)}$				-0.081***				-0.049***
				(-7.5)				(-7.77)
$RET_{(-2,-7)}$				0.010***				0.002
				(3.47)				(0.63)
$Illiq$				0.041*				0.025***
				(1.66)				(3.13)

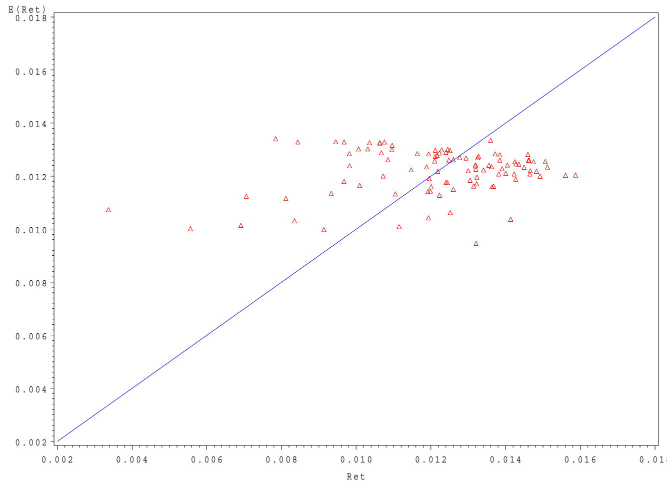


Panel A: Whole Sample

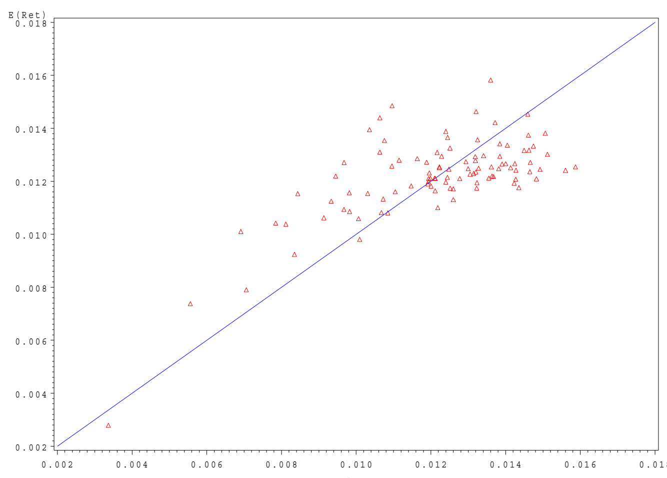


Panel B: Subsample

Figure 1: **Average Return versus Market Beta for the 25 Size and Book-to-Market Sorted Portfolios**
This graph presents the relation between beta and the expected return of the 25 size and book-to-market sorted portfolios. The expected return excess of risk-free rate is on the y axis and the market beta is on the x axis. The whole sample is used in Panel A, while partial sample described in Section 4.2 is used in Panel B.



Panel A: Without Controlling for Beta Reversal



Panel B: With Controlling for Beta Reversal

Figure 2: **Realized versus Expected Return Estimated for the 100 Beta and Idiosyncratic Volatility Sorted Portfolios**
This graph presents the relation between the realized and expected returns of the 100 beta-idiosyncratic volatility sorted portfolios. The expected return in Panel A is estimated from cross-sectional regression equations using rolling beta estimates and the realized idiosyncratic volatilities of individual stocks only, while the expected return in Panel B is estimated from cross-sectional regression equations using rolling beta estimates, the realized idiosyncratic volatilities, and the interaction between beta and idiosyncratic volatility of individual stocks (see Section 4.5). The expected return is on the y axis and the realized return is on the x axis.