IDIOSYNCRATIC RISK AND THE CROSS-SECTION OF REIT RETURNS

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Table of Contents

Acknowledgement.......................................................................................... i
Table of Contents ........................................................................................ ii
Summary ....................................................................................................... v

Chapter 1  Introduction ................................................................................. 1
  1.1 Motivation ............................................................................................ 1
  1.2 Research Questions and Research Plans ............................................ 4
  1.3 Possible Contributions ........................................................................ 7
  1.4 Organization ....................................................................................... 9

Chapter 2  Literature Review...................................................................... 10
  2.1 Historical Pattern of Idiosyncratic Risk ............................................. 10
  2.2 Asset Pricing on Common Stock Market ........................................... 12
    2.2.1 Development of Asset Pricing Models ......................................... 12
    2.2.2 A Detailed Review of Factor Models ......................................... 16
    2.2.3 Empirical Studies of Idiosyncratic Risk on Common Stock Market ........................................................................... 18
  2.3 REIT Pricing ....................................................................................... 26
    2.3.1 REIT Pricing at Index Level ......................................................... 26
    2.3.2 REIT Pricing at Firm Level ......................................................... 27
    2.3.3 Idiosyncratic Risk in REIT Stocks ............................................. 29

Chapter 3  Research Design ......................................................................... 31
  3.1 Standard Fama-MacBeth Regression Method ..................................... 31
  3.2 Estimating Variables ......................................................................... 33
    3.2.1 Size, Value and Momentum ...................................................... 33
    3.2.2 Lagged Market Risk and Idiosyncratic Risk in Spirit of
Chapter 4  Historical Pattern of Observed Idiosyncratic Risk in REIT Market ....................... 46

4.1 Empirical Measurement of Observed Idiosyncratic Risk ....46
4.2 Historical Pattern of Observed Idiosyncratic Risk on REIT Market ................................................................. 48
4.3 Controlling for the Effect of Outlier Observations ..............49
4.4 Controlling for the Sample Size ............................................ 50
4.5 Explanations to the Downward Trend of Observed Idiosyncratic Risk .................................................................52
    4.5.1 Size of Individual REIT Becomes Larger and Larger ........52
    4.5.2 Idiosyncratic Risk is Countercyclical .................................53

Chapter 5  Cross-Sectional Return Tests ...................... 57

5.1 Conditional Idiosyncratic Risk and the Cross-Section of REIT Returns ................................................................. 57
5.2 Interact with Various Cross-Sectional Effects ................. 62
    5.2.1 Interact with Size and Value Effects ............................... 65
    5.2.2 Interact with Momentum Effect ..................................... 68
    5.2.3 Controlling for Different Types of REITs .......................... 69
5.3 Robust Tests ........................................................................... 71
    5.3.1 Estimate Conditional Idiosyncratic Risk Relative to CAPM .. 71
    5.3.2 Sub-period Test ............................................................... 72
# Chapter 6 Profitability of Idiosyncratic Risk Strategy .... 77

6.1 Profitability of Idiosyncratic Risk Strategy ...........................................77

6.1.1 A Trading Strategy .............................................................................77

6.1.2 Idiosyncratic Risk Profit ....................................................................79

6.1.3 Sub-sample Analysis ...........................................................................81

6.2 Effect of Momentum on Idiosyncratic Risk Profits .........................84

# Chapter 7 Conclusions ...................................................................... 89

7.1 Research Objectives .............................................................................89

7.2 Key Findings, Possible Contributions and Policy Implications .........89

7.3 Limitations of the Research .................................................................92

7.4 Recommendations for Future Research .........................................93

# Bibliography ..............................................................................................95

# Appendix A: Examples of REITs with Low or High Idiosyncratic Risk .......105
Summary

This study seeks to trace the historical pattern of idiosyncratic risk of individual REITs and to examine whether idiosyncratic risk can explain the monthly cross-sectional returns of REIT stocks.

Based on a sample of 149 REITs traded on the US capital market, we observe that the average idiosyncratic risk of individual REIT stocks has drifted downwards between 1990 and 2005, which is contrary to the upward trend observed in common stocks. This declining trend can be attributed to the dramatic increase in the average size of REITs after 1990. We also observe that the idiosyncratic risk of REITs exhibits a countercyclical pattern. In particular, the idiosyncratic risk of REITs is particularly low during the bullish market between 1995 and 1998. We also observe that the countercyclical pattern is asymmetric: idiosyncratic risk decreases marginally in good times, but in bad times, it escalates very quickly.

Despite its declining trend, conditional idiosyncratic volatility is a significant factor in explaining the cross-sectional returns of REIT stocks, which suggests that under-diversified investors are compensated for their inability to hold well-diversified portfolios. The explanatory power of idiosyncratic risk remains robust after we control for three other well-known asset pricing anomalies, namely size, $B/M$ and momentum effects. It is also robust to alternative asset pricing models used to derive the conditional idiosyncratic volatility of the individual REITs as well as to categorization of data over different sub-periods.

The evidence that idiosyncratic risk is priced is an important contribution of the
current study. Whilst this finding is inconsistent with the prescription of CAPM and modern portfolio theory that only market risk matters (because idiosyncratic risk can be completely diversified away), it is consistent with Merton’s (1987) proposition that idiosyncratic risk should be priced because investors often hold under-diversified portfolios (rather than market portfolios) in the presence of incomplete information. An important implication of this result is that in addition to systematic risk, managers should also consider idiosyncratic risk when estimating the required return or cost of capital on individual stocks or assets. The results also have practical applications for portfolio formation and performance evaluation. As was shown, a portfolio manager could have realized exceptional returns with a strategy that tilts towards stocks with high conditional volatility. This is good news for real estate as an asset class which tends to have high idiosyncratic risk. Similarly, portfolio returns should be benchmarked against returns of portfolios with matching idiosyncratic risk.

Another striking result of our empirical tests is that once idiosyncratic risk is controlled for in the asset-pricing model, the influence of size and \( \frac{B}{M} \) on REIT cross-sectional returns become insignificant. The explanatory power of a third pricing anomaly, namely the momentum effect, remains robust in the presence of idiosyncratic risk. Idiosyncratic risk appears to have absorbed the influence of these two common factors which have become standard in asset pricing models. In their influential paper, Fama-French (1992) propose that size and \( \frac{B}{M} \) proxy for risk factors in returns, related to relative earning prospects that are priced in expected returns. Our empirical evidence suggests that the common risk factor proxied by size and \( \frac{B}{M} \) may be none other than the omitted conditional
idiosyncratic risk in previous asset pricing models. The correlation analysis indicates that smaller and value REITs tend to have higher idiosyncratic risk.

Finally, we find significant monthly profits of idiosyncratic risk around 0.4%, which is about 40% of that of momentum strategy by Chui, Titman and Wei (2003). This result is robust to categorization of data over different sub-periods, and different market conditions. Further, we also find that momentum have significant positive effect on the idiosyncratic risk profit, and after taking both momentum and idiosyncratic risk into account, we can achieve a profit of about 50% more than the momentum profit by Chui, Titman and Wei (2003).
Chapter 1  Introduction

The volatility of a stock can be decomposed into market and firm-specific volatility, with the former commonly known as systematic risk and the later as idiosyncratic risk. Compared to the plethora of studies on the relationship between systematic risk and asset returns, the role of idiosyncratic volatility in asset pricing has been largely ignored in the literature. This is hardly surprising, given that the traditional capital asset pricing model (CAPM; Sharp, 1964; Lintner, 1965; Black, 1972) prescribes that only the non-diversifiable systematic risk matters in asset pricing. Idiosyncratic risk, on the other hand, should not matter because it can be completely diversified away according to modern portfolio theory. Nevertheless, researchers and investors alike have recently started to pay more attention to idiosyncratic risk. While it is true that idiosyncratic risk can be eliminated in a well diversified portfolio, it has also been highlighted that most investors care about the firm-specific risk because they do not hold diversified portfolios, either because of wealth constraints or by choice (Xu and Malkiel, 2003). Furthermore, the pricing of options and warrants would require knowledge of total volatility, which includes both market as well as idiosyncratic risks.

1.1 Motivation

So far, no study has investigated the relationship between expected returns of REIT stocks and conditional idiosyncratic volatility at the firm-level. At the aggregate level, the returns of common stock, bonds and real estate have been employed in a number of studies to explain REIT returns. The proportion of returns not accounted
for by these three risk factors has, however, been rising over time (from 1979 to 1998, see Clayton and MacKinnon, 2003), which highlights the growing significance of idiosyncratic risk in explaining REIT returns.

A detailed study on the idiosyncratic risk of REITs is also timely as REIT managers shift towards a more focused investment strategy. Whilst the benefits of corporate focus versus diversification are well documented in the REIT literature (see Capozza and Seguin, 1999), we still do not understand its implications on stock returns and risk. In a recent study on listed real estate corporations in the US, British, French, Dutch and Swedish markets, Boer, Brounen and Veld (2005) observe that although the firm’s systematic risk is not affected by corporate specialization, there is a strong positive relationship between corporate focus and firm-specific risk. In other words, firm-specific risk increases with the degree of corporate focus.

Moreover, by focusing on a single sector (REIT in our case), we are able to filter out any sector specific idiosyncratic volatility. Consequently, a study on the cross-sectional returns of firms operating in the same sector would allow an examination of the role of firm-specific idiosyncratic risk without worrying about potential contamination from any industry-effect. Chui, Titman and Wei (2003) also point out that by holding the asset class constant, they can better understand the different determinants of expected returns.

Further, real estate assets and property-related stocks, such as REITs and property stocks, are exposed to more idiosyncratic risk due to the inherently localized and
segmented nature of the real estate space markets. To illustrate, Figure 1 tracks and decomposes the return volatility of REIT stocks between 1990 and 2005. In this study, we use return volatility to proxy for the risk, which is often done in various empirical studies, although it should be noted that risk and return volatility are not the same. The idiosyncratic risk is estimated as Ang et al (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals. Total volatility is defined as the standard deviation of the returns over the same period. It shows that the overall return volatility of the sector is dominated by idiosyncratic risk, which constitutes, on average, 88.5% of the total volatility exhibited by REIT stocks over the study period. Although diversifiable, this dominant status of idiosyncratic risk motives us to examine whether idiosyncratic risk can explain the cross-section of REIT returns when investors always hold under-diversified portfolios.
Figure 1: Idiosyncratic Risk as a Proportion over Total Volatility

The figure shows the proportion of idiosyncratic risk over the total volatility in REIT stocks between January 1990 and December 2005. The idiosyncratic risk is estimated as follows: In every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals. Total volatility is defined as the standard deviation of the returns over the same period.

### 1.2 Research Questions and Research Plans

Motivated by the dominant status of idiosyncratic risk in total risk, in this study, we seek to examine the role of idiosyncratic risk in REIT pricing. Our research is framed by three research questions:

1. What is the historical pattern of idiosyncratic risk of individual REIT stocks publicly traded in the U.S. since 1990?

2. Whether conditional idiosyncratic risk of individual REIT stocks is significantly related to their monthly cross-sectional returns? If yes, what is the joint role of conditional idiosyncratic risk and other well-known asset pricing anomalies, like size, value and momentum effects?

3. If conditional idiosyncratic risk is priced in REIT market, can we...
construct a trading strategy to make a profit from this finding? And what are the effects of momentum on idiosyncratic risk profits?

Our study sample covers 149 REITs, which were publicly traded in the U.S. between 1990 and 2005. According to Ang et al. (2006), we measure the observed idiosyncratic volatility of individual REIT stocks relative to the standard Fama and French (FF, 1993) three-factor model based on their daily returns over the previous month. Similar to Fu (2005), we transform the standard deviation of daily return residuals to monthly return residuals by multiplying the daily standard deviation by the square root of 22, the average number of monthly trading days. Then, the equal-weighted and value-weighted averages of observed idiosyncratic risk of individual REIT stocks are computed to track the historical pattern of idiosyncratic risk. After ranking on the observed idiosyncratic risk, we exclude 5% observations at each end in every month to control the outlier effect. Besides, we also reconstruct the observed idiosyncratic volatility series using only the 42 original REITs that have been trading continuously since January 1990 to test the possibility that the observed trend is simply the result of an increased number of REITs in the sample. Finally, we examine the trend of average REIT size during the study period and the countercyclical property of idiosyncratic risk, which may be the possible explanations to the historical trend of idiosyncratic risk that we find on the REIT market.

The cross-sectional relationship between idiosyncratic volatility and their expected returns is then analyzed. First, Exponential Generalized Auto-Regressive Conditional Heteroskedasticity (EGARCH) models are employed to control for the
time-varying nature of idiosyncratic risk. Second, month-by-month Fama and MacBeth (FM, 1973) regressions of the cross-section of REIT returns on conditional idiosyncratic volatility are estimated in order to examine their relationships. Besides, three well-known asset pricing anomalies, namely size, value and momentum effects, will be added one at a time into the month-by-month cross-sectional regressions in order to examine their joint effects with conditional idiosyncratic volatility and market risk in explaining the cross-sectional expected returns of REIT stocks. Finally, due to the different risk-return characteristics of equity REITs and mortgage REITs, we add a dummy variable for mortgage REIT in the regression to test whether the type of REITs has a significant effect on the role of idiosyncratic risk.

Motivated by the significant role of conditional idiosyncratic risk in the cross-section of REIT returns, we will construct idiosyncratic risk trading strategies to see whether we can make profits from this finding. We divide all REITs into 5 portfolios based on conditional idiosyncratic risk with 8 to 30 REITs in every quintile. These portfolios are equal-weighted and will be held for 12, 24 and 36 month respectively. Portfolio 1 (5) is the portfolio of stocks with lowest (highest) conditional idiosyncratic risk. The idiosyncratic risk portfolio we examine is the zero-cost, high-minus-low portfolio (portfolio “5-1”). The excess returns of idiosyncratic risk portfolios will then be regressed on the Fama-French three-factor model to see whether we can earn abnormal idiosyncratic risk profits. Besides, to test whether momentum has a significant effect on the idiosyncratic risk profits, we employ 3*3 double-sort method with 5 to 17 REITs in every double-sorted portfolio: at the end of each month, all REITs are divided into three
equal groups based on the momentum and then each of these momentum-sorted
groups are further divided into three equal groups based on their conditional
idiosyncratic risk. Zero-cost high-minus-low idiosyncratic risk portfolios in each
momentum group are constructed. Further, we construct a
“momentum-idiosyncratic risk” portfolio by deducting the idiosyncratic risk
portfolio in the small momentum group from that in the large momentum group.
The excess returns of “momentum-idiosyncratic risk” portfolios will also be
regressed on the Fama-French three-factor model to see whether momentum has a
significant effect on the idiosyncratic risk profits.

1.3 Possible Contributions

To our knowledge, this study may be the first one which finds that idiosyncratic
risk dominates the total risk of individual REIT stocks during the whole study
period. And it motivates this study directly. Besides, this study also finds that
idiosyncratic risk of individual REIT stocks has declined over the study period,
which is contrary to the findings on the common stock market. This finding is also
contrary to that of Clayton and MacKinnon (2003), who find that idiosyncratic risk
of REIT is rising from 1979 to 1998, but at index level, not firm level.

Meanwhile, since market risk ceases to be significant since 1960s on common
stock market\(^1\), this study proposes another risk factor, conditional idiosyncratic risk,
to improve the understanding of risk-return relationship in REIT industry, which is
also robust to three famous risk anomalies, namely size, value and momentum.

\(^1\) See Fama and French (1992a), “we find that the relation between beta and average return disappears during
the more recent 1963 – 1990 period.” p.428.
This suggests that investors are compensated for their inability to hold the market portfolios. To our knowledge, this is the first study to examine the role of idiosyncratic risk in explaining the cross-section of REITs returns.

Moreover, the explanatory power of size and value effects dissipated when idiosyncratic risk was controlled for the regression models, while the momentum effect was robust to the inclusion of idiosyncratic risk. Hence, another contribution of this study is that the strong size and value effects observed in previous studies could merely be picking up the effects of omitted idiosyncratic risk in the asset pricing models. Further, since size and value factors both have no residual explanatory power, our asset pricing model with conditional idiosyncratic risk is well-specified. It also provides us another perspective to understand the Fama-French three-factor model. Previous studies which did not include the idiosyncratic risk may be biased.

Finally, we find a significant profit of idiosyncratic risk trading strategy, which is persistent in different sub-periods, and different market conditions (up or down, stable or volatile). Further, we find positive effects of momentum on the idiosyncratic risk profits: idiosyncratic risk profits are larger in REITs with larger past returns. After taking both momentum and idiosyncratic risk effects into account, we can make 50% more abnormal profits than the momentum strategy by Chui, Titman and Wei (2003).
1.4 Organization

The remainder of this study is organized as follows. Chapter 2 reviews the literature on asset pricing on common stock market and the pricing of REIT stocks. Chapter 3 provides the details of the Fama-MacBeth regression method employed to do the cross-sectional return tests and GARCH-type models used to estimate the conditional market risk and idiosyncratic risk. The details of the data employed in this study are also included. The historical pattern of idiosyncratic risk in the US REIT market between 1990 and 2005 is tracked in Chapter 4. Chapter 5 tests the relationship between cross-sectional expected returns and the conditional idiosyncratic risk of individual REIT stocks. The robustness of the results in the presence of three common market anomalies, in different market models, and in different sub-periods is also examined. Chapter 6 attempts to examine whether investors can make abnormal profit by constructing REIT portfolios based on their idiosyncratic risk. The effect of momentum on idiosyncratic risk profits is also examined. Chapter 7 concludes.
Chapter 2  Literature Review

This chapter will place its importance on the literature related to our research questions. First, we will focus on the literature about the historical trend of idiosyncratic risk both on common stock market and REIT market. Second, a comprehensive literature review on asset pricing on common stock market will be conducted. The development of asset pricing models is reviewed and the position of idiosyncratic risk in asset pricing theory is then identified. Beside, the theory of idiosyncratic risk is also elaborated. Since Fama-French three-factor model is widely used in this research, a more detailed review about factor models is conducted, which is followed by the empirical studies of idiosyncratic risk pricing, and the problems in these studies. Third, on REIT market, the asset pricing models will be reviewed at index level and firm level respectively, which is followed by what have done about idiosyncratic risk within REIT literature.

2.1 Historical Pattern of Idiosyncratic Risk

Campbell, Lettau, Malkiel and Xu (2001), who first find the time-series increase trend phenomenon of idiosyncratic risk in common stock market, use an innovative approach to decompose the variance of common stocks into three components: market volatility, industry volatility and idiosyncratic volatility. This method circumvents the estimation of firm specific betas, which always cause estimation difficulties. However, this procedure is not designed to estimate the firm specific risk for individual stocks; instead, they estimate the idiosyncratic risk at the aggregate level. Similarly, Clayton and Mackinnon (2003) examine the relative
importance of stock, bond and real estate factors in explaining the REIT returns. They decompose the variance of the REIT returns into the relative components derived from market wide common stock, bond and real estate industry, and take the variance of the regression residuals as idiosyncratic variance. Also, they find there is a dramatic increase over time in the idiosyncratic variance in 1990s that is not explained by any of the factors, and the possible explanations they provide are that the increased idiosyncratic volatility could be due to an increased degree of informational efficiency in the market for REITs (as firm specific information is better incorporated into the prices); it could also be due to (possibly irrational) herding behavior on the part of institutions.

At the firm level, Bennett, and Sias (2005) find a time-series increase trend of idiosyncratic risk and attribute it to the changes in the market weights of “riskier” industries, changes in the relative role of small stocks in the market. Brown and Kapadia (2005) also argue that the documented increase in idiosyncratic risk in the post war era is due to the new listing effect: firms that list later in the sample have persistently higher idiosyncratic volatility than firms that list earlier. Fink, Fink, Grullon and Weston (2005) also find the time-series increase trend of idiosyncratic risk. They argue that the rise in firm specific risk can be explained by the interaction of two reinforcing factors: a dramatic increase in the number of new listings and a simultaneous decline in the age of the firm at IPO; since the equity of young firms typically represents a claim on cash flows that are further into the future, it is not surprising that the idiosyncratic risk of the typical public firm has increased over this time period. Wei and Zhang (2006) argue that of the upward trend in the equally weighted average variance of returns, about one-third is
attributed to the existing firms and about two-thirds is attributed to newly listed firms. For the value weighted variance of returns, the division is roughly half and half. Xu and Malkiel (2003) further suggest that the rising idiosyncratic risk is attributed to more institutional ownership and high expected earning growth. In summary, one of the most important reasons attributed to the increased idiosyncratic risk is that there are more and more small and young companies listed on the market.

2.2 Asset Pricing on Common Stock Market

2.2.1 Development of Asset Pricing Models

The traditional CAPM theory of Sharp (1964), Lintner (1965), and Black (1972) suggests that only the market risk should be incorporated into the asset price while idiosyncratic risk should not be priced because it can be completely diversified away. The validity of CAPM depends on the assumptions of complete information, no transaction cost, and rational economic behavior. But in reality, some of these assumptions apparently do not hold. In his AFA presidential address, Robert C. Merton (1987) points out that “financial models based on frictionless markets and complete information are often inadequate to capture the complexity of rationality in action.” Empirically, the CAPM meets great challenge in explaining the cross-section of expected stock returns. In their influential paper in 1992, Fama and French found that market risk lost their explanatory power since 1960s. Because of the diminishing influence of the traditional CAPM, according to Fama and French (2004), financial economists have worked in several directions to
improve it.

The first route is to extend the one period CAPM to an inter-temporal setting. The ICAPM begins with a different assumption about investor objectives. In the CAPM, investors care only about the wealth their portfolios produces at the end of the current period. In the ICAPM, investors are concerned not only with their end-of-period payoff, but also with the opportunities they will have to consume or invest the payoff. Thus, when choosing a portfolio at time \( t-1 \), ICAPM investors consider how their wealth at \( t \) might vary with future state variables, including labor income, the prices of consumption goods and the nature of portfolio opportunities at \( t \), and expectations about the labor income, consumption and investment opportunities to be available after \( t \) (e.g. Merton, 1973; Lucas, 1978; and Cox, Ingersoll and Ross, 1985). But ICAPM makes little improvement in explaining the cross-section of the expected stock returns.

Fama, and French (1993) take a more indirect approach, namely the “three-factor model”, which perhaps is more in the spirit of Ross’s (1976) arbitrage pricing theory. They argue that though size and book-to-market equity ratio are not themselves state variables, the higher average returns on small stocks and high book-to-market equity stocks reflect unidentified state variables that produce un-diversifiable risks in returns that are not captured by the market returns and are priced separately from market risk (E.g. Fama, and French (1992, 1993, 1996, 2000), Daniel, and Titman, 1997). From a theoretical perspective, the main shortcoming of the three-factor is its empirical motivation. The small-minus-big (SMB) and high-minus-low (HML) explanatory returns are not motivated by
predictions about state variables of concern to investors.

The third one is the momentum effect of Jegadeesh and Titman (1993). Stocks that do well relative to the market over the last three to twelve months tend to continue to do well for the next few months, and stocks that do poorly continue to do poorly. This momentum effect is distinct from the value effect captured by book-to-market equity ratio and other risk factors. Moreover, the momentum effect is left unexplained by the three-factor model as well as the CAPM.

Besides the above three improvements reviewed by Fama and French (2004), more importantly, Merton (1987) proposed a capital market equilibrium model with incomplete information, in which he argued that idiosyncratic risk should be priced because investors always held under-diversified portfolios instead of market portfolios. In his model, information is not free, and investors have to pay some price to learn and follow the information of securities, making it not optimal to track the information of all the securities in the market. These investors only know a subset of the securities in the market and construct their portfolios from these known securities and as a result, they only hold under-diversified portfolios. Specifically, the model predicts that expected stock returns are positively related the idiosyncratic risk and size, but are negatively related to investor base. Assuming the under-diversification of the investor portfolios, Levy (1978) and Malkiel and Xu (2006) also find a positive relation between idiosyncratic risk and the cross-section of expected stock returns.

Besides information costs, transaction costs also prevent investors from holding a
well-diversified portfolio. Bloomfield, Leftwich and Long (1977) indicate that transaction costs increase with the number of the stocks in the portfolio. So, there is a trade off between the transaction costs and the benefit of further diversification. In addition, institutional investors may not be able to hold well-diversified portfolios due to contract reasons. Moreover, many investors will often deliberately structure their portfolios to accept considerable idiosyncratic risk in an attempt to pursue extraordinary returns, like informed investors, arbitrageurs.\footnote{In addition, there are a number of other factors that could also attribute to why investors hold undiversified portfolios. They include market segmentation, taxes, and imperfect divisibility of securities. (Merton, 1987; p. 488)}

According to Malkiel and Xu (2006), these investors, which they call “constrained investors”, will hold undiversified portfolios. They argue that the “unconstrained investors” will also hold undiversified portfolios, because it is the total holdings from these two groups of investors that make up the whole market. Since the relative per capita supply will be higher for those stocks that the constrained investors only hold in very limited amounts, the prices of these stocks must be relatively low, and an idiosyncratic risk premium can be rationalized to compensate investors for the over supply of these assets. Meanwhile, another institution can also been gained if some investors are constrained from holding all securities, the “available” market portfolio that unconstrained investors can hold will be less diversified than the actual market portfolio. When individual investors use the “available” market portfolio to price individual securities, the corresponding risk premium will be higher than those under the CAPM where all investors are able to hold the actual market portfolio. Thus, idiosyncratic risk would be priced in the market.

Shleifer and Vishny (1997) emphasize the importance of idiosyncratic risk from
the perspective of undiversified arbitrageurs, who determine the equilibrium excess stock returns. They argue that the theoretical underpinnings of the efficient markets approach to arbitrage are based on a highly implausible assumption of many diversified arbitrageurs. In reality, arbitrage resources are heavily concentrated in the hands of a few investors that are highly specialized in trading a few assets, and are far from diversified. As a result, these investors care about total risk, and not just systematic risk. Since the equilibrium excess returns are determined by the trading strategies of these investors, looking for systematic risk as the only potential determinant of pricing is inappropriate. Idiosyncratic risk as well deters arbitrageurs, whether it is fundamental or noise trader idiosyncratic risk. Further, they suggest that idiosyncratic risk probably matters more to specialized arbitrageurs since it can not be hedged and arbitrageurs are not diversified. Their research also provides a different approach to look at the asset pricing anomalies. Specifically, they expect anomalies to reflect not some exposure of securities to difficult-to-measure macroeconomic risks, but rather, high idiosyncratic return volatility of arbitrage trades needed to eliminate the anomalies. Consistent with Shleifer and Vishny (1997), Ali et al. (2003) also suggest that risk associated with the volatility of arbitrage returns deters arbitrage activity and is an important reason why the book-to-market effect exists.

2.2.2 A Detailed Review of Factor Models

According to Fama and French (1992), Banz (1981) finds that market equity, $ME$ (price times shares outstanding), adds to the explanation of the cross-section of average returns provided by market risks, and the market equity is significant
negatively related to cross-section of average stock returns. Moreover, Bhandari (1988) finds that leverage helps explain the cross-section of average stock returns in tests that include size ($ME$) as well as beta, and the there is a positive relation between leverage and average returns that is not captured by SLB. Another contradiction of the SLB model is the positive relation between book-to-market equity ratio and average return documented by Statman (1980) and Rosenberg, Reid and Lanstein (1985), who find that average returns of U.S. stocks are positively related to the ratio of a firm’s book value of common equity, $BE$, to its market value, $ME$. Besides, Basu (1983) argues that earnings-price ratios ($E/P$) help explain the cross-section of average returns on U.S. stocks in tests that also include size and beta. $E/P$ is likely to be higher for stocks with higher risks and expected returns. Finally, Fama-French (1992) test the joint role of market equity, book-to-market equity ratio, leverage and earnings-price ratio, and find the combination of market equity and book-to-market equity ratio seems to absorb the roles of leverage and $E/P$ in average stock returns. Since these empirical regularities can not be explained within the current asset pricing paradigm, they are widely regarded as anomalous.

However, in his critique of size-related anomalies, Berk (1995) shows that firm size will, in general, explain part of the cross-section of expected returns left unexplained by an incorrectly specified asset pricing model. His model shows that market value is negatively correlated with all the risk factors and so long as an omitted risk factor is unrelated to the firm’s operating size, market value will be negatively correlated with the omitted risk factor. The intuition underlying the theory is best illustrated using the following thought experiment proposed by Berk.
Consider a one-period economy in which all investors trade off risk and return. Assume that all firms in this economy are exactly the same size; that is, assume that the expected value of every firm’s end-of-period cashflow is the same. Since the riskiness of each firm’s cashflow is different, the market value of each firm must also differ. Given that all firms have the same expected cashflow, riskier firms will have lower market values and so, by definition, will have higher expected returns. Thus, even though all firms are the same size, if market value is used as the measure of size, then it will predict return”. This indicates that the reason for the relation between the anomaly variables and the expected return of the firm is not related to the operating characteristics these variables measure; rather, they predict expected return because of the theoretical risk premium contained in the market characteristics of these variables. Consequently, market value will always provide additional explanatory power in any test of an asset pricing model that omits relevant risk factors. Since the size-related variables pick up any unmeasured risks, he suggests that they can be used in cross-sectional tests to detect model misspecification. In particular, Berk (1995) suggests that size-related measures provide an indication of how much of the risk premium remains unexplained by the model being tested. If a specific asset pricing model claims to explain all relevant risk factors, then, at a minimum, it must leave any market value related measure with no residual explanatory power.”

2.2.3 Empirical Studies of Idiosyncratic Risk on Common Stock Market

The following Table 1 presents a brief summary of the key studies on the cross-sectional return tests of idiosyncratic risk, which focuses on the methodology
they employed and the key findings they reached. The first four papers are the most important and representative ones in this field and will be reviewed in detail.
Table 1: Empirical Studies on the Cross-Sectional Return Tests of Idiosyncratic Risk

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Key Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1973</td>
<td>Fama and MacBeth</td>
<td>use rolling window method to estimate the lagged IR (idiosyncratic risk) at portfolio level to proxy for the current one; use Fama-MacBeth regression method to do the cross-sectional return tests.</td>
<td>support CAPM that only systematic risk is priced; deny the role of idiosyncratic risk.</td>
</tr>
<tr>
<td>2005</td>
<td>Fu</td>
<td>use EGARCH model to estimate the conditional IR at firm level to proxy for the current one; use Fama-MacBeth regression method to do the cross-sectional return tests.</td>
<td>conditional idiosyncratic risk is positively related to the cross-section of expected stock returns; large firms have higher average returns than small firms after controlling for idiosyncratic risk.</td>
</tr>
<tr>
<td>2006</td>
<td>Malkiel and Xu</td>
<td>estimate the lagged IR at portfolio level to proxy for the current one; use Fama-MacBeth regression method to do the cross-sectional return tests.</td>
<td>idiosyncratic risk is positively related to the cross-section of expected stock returns.</td>
</tr>
<tr>
<td>2006 (a)</td>
<td>Ang et al.</td>
<td>use daily data of previous month to estimate the lagged IR at firm level to proxy for the current one; use portfolio method to do the cross-sectional return tests.</td>
<td>stocks with high idiosyncratic volatility have abysmally low average returns.</td>
</tr>
</tbody>
</table>
Continued:

<table>
<thead>
<tr>
<th>Year</th>
<th>Authors</th>
<th>Methodology</th>
<th>Key Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>Spiegel and Wang</td>
<td>use EGARCH model to estimate the conditional IR at portfolio level to proxy for the current one; use portfolio method to do the cross-sectional return tests.</td>
<td>stock returns are increasing with the level of idiosyncratic risk and decreasing in a stock’s liquidity; the impact of idiosyncratic risk is much stronger and often eliminates liquidity’s explanatory power.</td>
</tr>
<tr>
<td>2005</td>
<td>Chua et al.</td>
<td>use AR model to estimated the expected IR at firm level to proxy for the current one; use multiple regression model to do the cross-sectional return tests.</td>
<td>expected idiosyncratic risk is significantly and positively related to expected returns; unexpected idiosyncratic risk is positively related to unexpected returns.</td>
</tr>
<tr>
<td>2006</td>
<td>Jiang, Xu and Yao</td>
<td>use daily data of previous month to estimate the lagged IR at firm level to proxy for the current one; use both Fama-MacBeth regression method and portfolio method to do cross-sectional return tests.</td>
<td>idiosyncratic risk is inversely related to future earnings and earning shocks; return predictive power of idiosyncratic risk is induced by its information content on future earnings.</td>
</tr>
<tr>
<td>2006</td>
<td>Guo and Savickas</td>
<td>estimate the lagged IR at firm level to proxy for the current one; use portfolio method to do the cross-sectional return tests.</td>
<td>idiosyncratic variance correlates negatively with future stock returns; the cross-sectional idiosyncratic variance effect is related to the well documented book-to-market effect.</td>
</tr>
<tr>
<td>2006 (b)</td>
<td>Ang et al.</td>
<td>use daily data of previous month to estimate the lagged IR at firm level to proxy for the current one; use portfolio method to do the cross-sectional return tests.</td>
<td>the negative cross-sectional return effect of idiosyncratic risk is a global phenomenon; the global idiosyncratic risk effect is captured by a simple U.S. idiosyncratic risk factor.</td>
</tr>
</tbody>
</table>
Consistent with the CAPM model, early studies support the proposition that only systematic risk is priced. One classic study is Fama-MacBeth (1973), who denies the role of idiosyncratic risk in explaining the cross-section of expected stock returns. Employing the first 4 years of monthly return data, 20 portfolios are formed on the basis of ranked $\hat{\beta}_i$ for individual securities; the following 5 years of data are then used to re-compute the $\hat{\beta}_i$, and these are averaged across securities within portfolios to obtain 20 initial portfolios $\hat{\beta}_{p,t}$ for the risk-return test. The component $\hat{\beta}_i$ is updated yearly and the portfolios are rebalanced every four years. As a measure of the non-$\beta$ risk of security $i$, they use $s(\hat{\varepsilon}_i)$, the standard deviation of the least-square residuals $\hat{\varepsilon}_{i,t}$ from the market model, which also is updated annually. They run monthly regression of equally weighted returns on systematic risk and unsystematic risk using the following regression:

$$r_{p,t} = \gamma_0 + \gamma_1 \hat{\beta}_{p,t-1} + \gamma_2 \hat{\beta}_{p,t-1}^2 + \gamma_3 s_{p,t-1}(\hat{\varepsilon}_i) + \eta_{p,t}$$ (1)

Fama and MacBeth argue that if idiosyncratic risk is priced in the cross-section, the coefficient $\gamma_3$ should be positive and statistically significant. In order to control for the cross-sectional correlations among residuals, they introduce a unique test-statistic, which is computed by averaging the monthly estimated coefficients and divided by the time-series standard errors. Finally, they find that the average of $\hat{\gamma}_3$ is indistinguishable from zero and argue that idiosyncratic risk is not priced in the cross-section.
However, recent studies have produced conflicting results. For instance, Ang et al. (2006) observe that stocks with lower idiosyncratic volatilities have higher average returns, which they suggest is puzzling since it is inconsistent with any extant asset pricing theory. Using the same methodology as Fama-MacBeth over a different time period, Malkiel and Xu (2002) observe a weakly positive relation between idiosyncratic risk and the cross-section of expected stock returns. Fu (2005), on the other hand, finds a stronger positive relationship when more sophisticated generalized autoregressive conditional heteroskedasticity (GARCH) models are used to estimate idiosyncratic volatility. The positive relation is consistent with Merton’s (1987) argument that idiosyncratic risk is priced in an incomplete information world because investors usually hold under-diversified portfolios.

Ang et al. (2006) find a statistically significant negative relation between idiosyncratic risk and average returns that stocks with higher idiosyncratic risk have lower expected returns in the cross-section. They define the idiosyncratic risk relative to Fama-French three factor model and estimate it as the standard deviation of the daily residuals from the Fama-French three factor regression of the previous month. Based on the ranking of the estimated idiosyncratic risk, they form five equal size portfolios and examine the difference in the risk adjusted returns between the highest risk and lowest risk portfolios. They find that the differences are negative and statistically significant, thus they conclude that idiosyncratic risk is negatively priced in the cross-section. Their idiosyncratic volatility results are robust to controlling for size, value, liquidity, volume, dispersion of analysts’ forecasts, and momentum effects. Moreover, the idiosyncratic volatility effect is also robust to different formation periods for
computing idiosyncratic volatility and for different holding periods. Further, the
effect also persists in bull and bear markets, recessions and expansions, and
volatile and stable periods.

Malkiel and Xu (2006) find that idiosyncratic risk is positively priced in the
cross-section. They try different number of portfolios (both 20 and 50 portfolios),
equal-weighted and the value-weighted market returns to estimate $\hat{\beta}_i$, and both the
market model and the Fama-French three factor model to estimate the idiosyncratic
risks. Though their empirical results support the positive relation between
idiosyncratic risk and average returns, the evidence is statistically weak.

Fu (2005) identifies that there are three problems in these empirical studies. First,
all the above three researches under-estimate the time-series variation of
idiosyncratic risk. They either use the previous 60 monthly returns or the daily
returns of the previous month to estimate $\hat{\beta}_i$ and $s(\hat{\varepsilon}_t)$, which proxy for the
current month’s expected market risk and idiosyncratic risk respectively. Their
methods implicitly assume that time-series market risk and idiosyncratic risk
follow a random walk process and approximate the expected market risk and
idiosyncratic risk of the current month using their lagged values. However, we will
show later in the paper that the random walk hypothesis is rejected in the
time-series market risk and idiosyncratic risk, which indicates that their researches
involve measurement error.

The second problem is to examine the idiosyncratic risk at the portfolio level.
Malkiel and Xu (2006) only use the idiosyncratic risk of one of the beta/size
portfolios to which a stock belongs to proxy for that stock’s idiosyncratic risk, thus do not examine firm-level idiosyncratic risk. Idiosyncratic risk can be largely diversified away by holding a portfolio of stocks. This unique property differentiates idiosyncratic risk from market risk and other common factor risks. Therefore, although idiosyncratic risk has a significant impact on returns of firm level, it should not explain the cross-sectional variation of portfolio returns especially when the number of stocks in portfolios are considerably large. That Malkiel and Xu (2006) only find weak relation between idiosyncratic risk and average returns is at least partly due to the overlook of the diversifiable nature of idiosyncratic risk. As a result, they miss the significant effect of idiosyncratic risk on firm-level returns.

The third problem in their empirical method is the use of a portfolio approach. The drawback of the portfolio approach has already been pointed out by Roll (1977), who suggests that the portfolio formation process, by concealing possible return relevant security characteristics within portfolio averages, may make it difficult to reject the null hypothesis of no effect on security returns. Fu (2005) also shows that the correlation between beta and idiosyncratic risk is not perfect. The use of a portfolio approach, as in Fama and MacBeth (1973) and Malkiel and Xu (2006), aggravates the measurement errors problem and obscures the positive relation between average return and idiosyncratic risk.

In summary, prior studies that fail to find the evidence of the positive relation between idiosyncratic risk and expected return may have one or more of these three problems. One is that their models can not capture the substantial time-series
variation of idiosyncratic risk thus have great measurement errors which make the related coefficient estimates biased towards not rejecting the null hypothesis. The second is that prior researches ignore the diversification property of idiosyncratic risk, making the relation statistically weak. The last problem is the use of portfolio approach, concealing the return relevant security characteristics within portfolio averages. So, in this research, we plan to use exponential Generalized Auto-Regressive Conditional Heteroskedasticity (E-GARCH) models to estimate the conditional idiosyncratic risk, which can largely capture the time-series variation of idiosyncratic risk. Besides, we will estimate the idiosyncratic risk at the firm level. Furthermore, we will use the standard Fama-MacBeth (1973) regression method rather than portfolio approach, trying to make the return-related security characteristics affect on security returns. In the empirical results, we will show later that conditional idiosyncratic risk estimated by E-GARCH models are positively related to expected returns in the cross-section, which means that under-diversified investors are compensated for the inability to hold the well-diversified portfolio.

2.3 REIT Pricing

2.3.1 REIT Pricing at Index Level

A number of studies have suggested that variation in the expected returns of REITs over time is predictable. Using a multifactor latent variable model with time-varying risk premium, Liu and Mei (1992) find that expected excess returns for equity REITs are more predictable than stocks and bonds, which is due in part
to movements in the cap rate, a real estate business condition variable. They also find that equity REITs resemble small cap stocks and to a lesser extent large cap stocks but have less in common with bonds. Mei and Liu (1994) extend these results to include equity REITs as well as mortgage REITs and real estate stocks. In addition to a stock factor and a bond factor, Mei and Lee (1994) identify the presence of a real estate factor in explaining the REITs returns. Consistent with the empirical results on common stock market, Peterson and Hsieh (1997) indicate that risk premiums on equity REITs are significantly related to risk premiums on a market portfolio of stocks as well as to the returns on mimicking portfolios for size and book-to-market equity factors in common stock returns. Anderson et al. (2005) further divide small capital stocks into small capital value stocks and small capital growth stocks, and find that REITs have a significant small capital value component, while REIT return is not highly related to small capital growth stocks.

Clayton and Mackinnon (2003) examine the structural changes of the above stock, bond and real estate factors. They find that large cap stock factor declines dramatically in importance in the late 1980s. Concurrently, a significant small cap stock factor begins to be observed. During the 1990s, a significant real estate factor also emerges. And more importantly, there is also a substantial increase over time in idiosyncratic volatility in the REIT index, which is unexplained by any of the other factors.

2.3.2 REIT Pricing at Firm Level

In this section, we will review the literature on REIT pricing at firm level and the
importance will be placed on the role of beta, factor models and the momentum effect.

Firstly detecting the decline in equity REIT beta from 1974 to 1988, McIntosh, Liang, and Tompkins (1991) suggest that betas estimated with the aggregated coefficient estimator do not explain the differences in average REIT returns. One recent study by Conover et al. (2000) use a varying-risk beta model and get further evidence. They find that beta explains cross-sectional returns when betas are allowed to vary across bull markets while during bear-market months, no significant relationship is found between REIT betas and returns. This indicates that the role of systematic risk in explaining the cross-sectional REIT returns depends on the market conditions.

McIntosh, Liang, and Tompkins (1991) find a small-firm effect even after considering the possible causes as identified in the financial efficient markets literature. Hamelink and Hoesli (2004) use constrained cross-sectional regressions to disentangle the effects of various factors on international real state security returns. They find that value/growth factor is volatile and have a substantial effect on returns. Country factor is the dominant factor and the size is shown to have a negative impact on returns. And they also suggest that statistical factors derived by means of cluster analysis explain about one third of specific returns. Ooi, Webb and Zhou (2007) use extrapolation theory to explain the value anomaly in REIT market, and find that value REITs provide superior returns without exposing investors to high risks because investors over extrapolate past corporate results into the future. In addition, they find the value premium varies over time and the
magnitude of the premium is inversely associated with the market performance.

Chui and Wei (2001) find a bigger momentum effect in REIT market than common stock market during 1982 and 1997, and attribute it to the factor that REITs are less liquid and smaller in size than common stocks. In addition, Chui, Titman and Wei (2003a) suggest that the momentum effect during pre-1990 period is very weak while it becomes much stronger after 1990, which may be caused by the increase in valuation uncertainty due to significant changes in REITs’ organizational structures, ownership structures and business strategies surrounding 1990. They also find this momentum effect is robust to the inclusion of the Fama-French three factors. Further, Chui, Titman and Wei (2003b) consider simultaneously a number of determinants of REIT returns and find that momentum effect is the dominant predictor of REIT returns after 1990. Different from the common stock market, they find that momentum is stronger for the larger REITs rather than the smaller REITs.

2.3.3 Idiosyncratic Risk in REIT Stocks

Very few researches have paid attention to the idiosyncratic risk in REIT stocks. Clayton and Mackinnon (2003) decompose the volatility of REIT index into four parts: stock, bond, real estate and idiosyncratic risk. They find a dramatic increase over time in the idiosyncratic volatility that is not explained by any of the factors. Also, they give the possible explanation that the increase in the idiosyncratic volatility could be due to an increased degree of market efficiency in REIT market (as firm specific information is better incorporated into the REIT prices); it could
also be due to (possibly irrational) herding behavior on the part of institutions. Chaudhry, Maheshwari and Webb (2004) estimate the realized idiosyncratic risk at firm level relative to CAPM and examine the determinants of idiosyncratic risk. They find different determinants become significant in a dynamic setting when various time periods are examined, which may be because REITs are evolving organizations and their role is constantly changing in the market place. Moreover, they indicate that because of unique characteristics of REIT, idiosyncratic risk maybe important for understanding the risk and return relationship. Boer, Brounen and Veld (2005) also estimate the realized idiosyncratic risk at firm level relative to CAPM. They find that corporate focus tends to increase the firm-specific risk of a listed property company, while the impact on the systematic risk is less compelling. All these researches are examining the behavior the idiosyncratic risk.

In conclusion, on common stock market, there are mainly four different streams of asset pricing models, and asset pricing model with idiosyncratic risk may be the most promising one. Existing empirical studies of idiosyncratic risk on cross-sectional return tests get mixed results can be attributed to their different methodologies employed. While on REIT market, to our knowledge, no research has been done to study the relationship between idiosyncratic risk and REIT returns. Given that systematic risk lost its explanation power in the cross-section of expected REIT returns, it is important for us to find other risk factors to explain the cross-section of expected REIT returns.
Chapter 3  Research Design

Upon doing a comprehensive literature review and then identifying the targeted research questions, in this chapter, more emphasis will be placed on discussing the research design and the set-up of the empirical models. First, the empirical models to do the cross-sectional return tests as well as the research hypotheses will be set up; then, the research will go on to the description of the dependent variable and independent variables, and how to estimate them. Finally, the details of the sample data used in this research will be described.

3.1 Standard Fama-MacBeth Regression Method

There are essentially two ways to examine the cross-sectional relationship between a risk factor and expected stock returns in the literature. The first way is to pool the stocks into different equal-sized portfolios (according to their ranking based on the risk factor). The returns of the two extreme portfolios are then examined to determine if they are statistically different. Ang et al (2006), for example, divide the stocks into five equal size portfolios according to their estimated idiosyncratic risk in the previous month. They then compare the risk-adjusted returns between the highest risk and lowest risk portfolios and found the difference to be statistically significant, thereby concluding that idiosyncratic risk is priced. As is discussed earlier in this study, the drawback of the portfolio approach has already been pointed out by Roll (1977), who suggests that the portfolio formation process, by concealing possible return relevant security characteristics within portfolio averages, may make it difficult to reject the null hypothesis of no effect on security.
returns. Moreover, this methodology has limited scope in examining the interactive
effects of different risk factors on average stock returns. For example, to allow for
variation in beta that is unrelated to firm size, Fama-French (1992) subdivide each
size deciles into ten portfolios on the basis of pre-ranking betas for individual
stocks. This results in 100 size-beta portfolios.

The second approach, which is employed for the current study, relies on the
Fama-MacBeth (1973) regression methodology where the following
cross-sectional regression is run for each month of the sample period:

$$r_{i,t} = \gamma_{0,t} + \sum_{k=1}^{K} \gamma_{k,t} X_{k,i,t} + \varepsilon_{i,t}, \quad i = 1, 2, \ldots, N_t, \quad t = 1, 2, \ldots, T$$  \hspace{1cm} (2)

where $r_{i,t}$ is the excess return on security $i$ in month $t$. $X_{k,i,t}$ are the
explanatory variables of the cross-sectional expected returns, such as beta, size,
book-to-market equity ratio, past return, and idiosyncratic risk. The disturbance
term, $\varepsilon_{i,t}$, captures the deviation of the realized return from its expected value. $N_t$
denotes the number of securities in the cross-sectional regression of month $t$,
which varies from month to month. In our case, the number of securities, $N_t$,
ranges from 42 to 149; and the maximum number of months, $t$, is 192. The most
important parameter in Equation (2) is $\hat{\gamma}_{k,t}$, which has the following mean and
variance:

$$\bar{\gamma}_{k,t} = \frac{1}{T} \sum_{t=1}^{T} \hat{\gamma}_{k,t}$$  \hspace{1cm} (3)
The $t$-statistic is the average slope ($\bar{\gamma}_{k,t}$) divided by its time-series standard error, which is the square root of the variance of $\hat{\gamma}_{k,t}$ divided by $T$:

$$ t(\bar{\gamma}_{k,t}) = \frac{\bar{\gamma}_{k,t}}{\sqrt{VAR(\hat{\gamma}_{k,t})/T}} $$

If under-diversified investors are compensated for their inability to hold well-diversified portfolios, the conditional idiosyncratic risk would be positively related to cross-sectional returns of the securities. And the $t$-statistic will reject the null hypothesis that the coefficient of conditional idiosyncratic risk are zero.

### 3.2 Estimating Variables

#### 3.2.1 Size, Value and Momentum

Firm size is measured by the market value of common equity ($ME$), which we computed as the product of monthly closing price and the number of shares outstanding for June of year $t$, and is updated monthly. Book-to-market equity ratio ($BE/ME$) is represented by the fiscal-year-end book value of common equity divided by the calendar-year-end market value of common equity. Due to the annual frequency of book equity, this variable is updated yearly. Further, to ensure that the
accounting variables are known before the returns they are used to explain, we follow Fama-French (1992) to match the accounting data for all fiscal yearends in calendar year \( t-1 \) with the returns for July of year \( t \) to June of year \( t+1 \). \( ME \) and \( BE/ME \) are transformed to natural logarithm because they are significantly skewed. To proxy for the momentum effect, we construct the variable \( Ret(-2,-13) \), the cumulative return calculated over the past the 12 months beginning in the second to last month, where \( t \) presents the current month. The return of \( t-1 \) month is excluded to avoid any spurious association between the prior month return and the current month return caused by thin trading or bid-ask spread effect, which may cause returns to exhibit first order serial correlations.

### 3.2.2 Lagged Market Risk and Idiosyncratic Risk in Spirit of Fama-MacBeth (1973)

The lagged market risk and idiosyncratic risk used when we qualitatively replicate what Fama-MacBeth (1973) have done on the REIT market is estimated in the spirit of Fama-MacBeth (1973) using their 60-months rolling window method. Every month, previous 60 months excess returns of individual REITs are regressed on the market model, and the lagged market risk of this month is the regression slope of the market model, while the idiosyncratic risk of this month is the standard deviation of the regression residuals. This procedure rolls every month.

### 3.2.3 Lagged Idiosyncratic Risk of Ang et al. (2006)

When we qualitatively replicate what Ang et al. (2006) have done on the REIT
market, the lagged idiosyncratic risk is estimated as in Ang et Al. (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals of the previous month.

3.2.4 Random Walk Tests of Market Risk and Idiosyncratic Risk

As Fu (2005) pointed out, from the theoretical perspective, the relationship between risk and returns should be contemporaneous. Investors get paid by returns only for bearing risk in the period that the returns are measured. While empirically, researches of cross-sectional returns often use the lagged firm characteristic variables to proxy for the expected value. For example, Fama and French (1992) use market equity and book-to-market equity ratio of the last year to explain the cross-section of the monthly returns of the current year. Chordia et al. (2001) employ the lagged share turnover to explain the cross-section of the expected returns. By definition, firm characteristics are fairly persistent, and we do not expect them to change substantially in a short interval. Accordingly, we may assume that firm characteristics follow a random walk process, that is, the best forecast of the next period value is the value of the current period. However, it is not appropriate for the market risk and idiosyncratic risk of the REITs. Table 2 presents the results of the random walk tests of market risk and idiosyncratic risk. Similar to Fu (2005), we first summarize the descriptive statistics of the time-series idiosyncratic risk for each firm and then present the mean statistics across all the REITs. The mean auto-correlation coefficients are 0.86, 0.90 and 0.39 respectively at the first lag and decay slowly, which suggests that the market risk and
idiosyncratic risk of individual REIT are non-stationary. Besides, the Ljung-Box Q-statistic and P-value both on average reject the random walk hypothesis of market risk and idiosyncratic risks at 1%, 1% and 5% level respectively. This indicates that using lagged market risk and idiosyncratic risk to approximate the expected ones could lead to severe measurement errors in variables, and the relationship between risk and return is not contemporaneous. The inference based on such studies may not be reliable.

**Table 2: Random Walk Tests of Monthly Beta and Idiosyncratic Risk**

This table summarizes the random walk test statistics of individual REIT’s market risk and idiosyncratic risk. The beta and idiosyncratic risk (Panel B) are estimated in the spirit of F-M (1973), but at individual REIT level. We run the 60-month time-series regression of the REIT’s returns on the current value weighted market returns to get the beta, which is rolled forward. Idiosyncratic risk (Panel B) is the standard deviation of the residuals of the 60-month rolling window market model regressions. Idiosyncratic risk (Panel C) is estimated as in Ang et al. (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals of the previous month. We first estimate the random walk test statistics of every REIT, and then compute the mean statistics across all the REITs.

<table>
<thead>
<tr>
<th>Lags</th>
<th>1</th>
<th>2</th>
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<th>7</th>
<th>8</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Random walk test for beta (F-M,1973)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AC</td>
<td>0.86</td>
<td>0.74</td>
<td>0.65</td>
<td>0.59</td>
<td>0.53</td>
<td>0.48</td>
<td>0.43</td>
<td>0.40</td>
<td>0.30</td>
<td>0.27</td>
</tr>
<tr>
<td>Q-statistic</td>
<td>85.72</td>
<td>159.75</td>
<td>225.94</td>
<td>285.71</td>
<td>340.10</td>
<td>389.52</td>
<td>434.56</td>
<td>475.72</td>
<td>578.37</td>
<td>606.37</td>
</tr>
<tr>
<td>P-value</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Panel B: Random walk test for idiosyncratic risk (F-M,1973)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AC</td>
<td>0.90</td>
<td>0.80</td>
<td>0.72</td>
<td>0.65</td>
<td>0.58</td>
<td>0.52</td>
<td>0.47</td>
<td>0.43</td>
<td>0.33</td>
<td>0.30</td>
</tr>
<tr>
<td>Q-statistic</td>
<td>89.88</td>
<td>169.78</td>
<td>241.59</td>
<td>306.52</td>
<td>365.40</td>
<td>418.72</td>
<td>467.19</td>
<td>511.31</td>
<td>620.79</td>
<td>650.72</td>
</tr>
<tr>
<td>P-value</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Panel C: Random walk test for idiosyncratic risk (Ang et al. 2006)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AC</td>
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<td>0.30</td>
<td>0.26</td>
<td>0.21</td>
<td>0.18</td>
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<td>0.17</td>
<td>0.14</td>
<td>0.14</td>
<td>0.14</td>
</tr>
<tr>
<td>Q-statistic</td>
<td>29.33</td>
<td>49.80</td>
<td>66.65</td>
<td>80.16</td>
<td>92.04</td>
<td>103.69</td>
<td>114.27</td>
<td>123.66</td>
<td>151.24</td>
<td>159.39</td>
</tr>
<tr>
<td>P-value</td>
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<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.04</td>
<td>0.05</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Note: AC is autocorrelation coefficients; Q-statistic is Ljung-Box Q-statistic with 12 lags; P-value is the lowest significance level at which random walk hypothesis can be rejected.
In the above paragraph, we find that market risk does not follow a random walk process, but is time variant. Now, the issue is to find an appropriate method to estimate the time variant beta. A number of different models have been developed in the recent literature to capture the time variation of the beta, and generally, three of them are widely applied, which are: (a) an augmented market model technique suggested by Schwert and Seguin (1990); (b) the Kalman Filter approach; and (c) the bivariate generalized ARCH model. In a recent study, Brooks, Faff and McKenzie (2002) compare the relative performance using a set of monthly Morgan Stanley country index data from 1970 to 1995. In-sample forecasts test of the performance of these models to generate conditional beta indicates that the bivariate generalized ARCH model generate the lowest forecast error and then outperform the other two models.

Moreover, the GARCH beta usually exhibits extremely large values or “spikes” which are significantly larger than average beta. McKenzie et al. (2000) examine this phenomenon generated by bivariate GARCH model in order to establish whether they are a response by the market to the arrival of the news or alternatively as a result of a model picking up a noise from the means. Using daily data for a sample of U.S. deposit taking institutions over the period 1976 to 1994, they finally find that these extreme observations are economically induced, which implies that bivariate GARCH model can better capture the time variation of the beta.
Furthermore, according to Engle and Gonzalez-Rivera (1991), who argue that assuming any other probability distribution function will not violate the spirit of the analysis, the estimates of the GARCH model are still consistent, even if the assumption of normality for the distribution of a series is violated.

Above all, bivariate GARCH model does have some superiority in estimating the conditional market risk, and also can capture the economically induced time variation caused by financial accidents, information disclosure, and market policies. Besides, it is less affected by the violation of normality assumption. Therefore, in this research, a bivariate GARCH (BEKK (1, 1)) model will be employed to estimate the time-varying market risk.

First, the mean of the excess return series is assumed to follow an AR(1) model, which can be specified as follow in the vector form:

\[
\begin{pmatrix}
    r_{i,t} \\
r_{m,t}
\end{pmatrix} =
\begin{pmatrix}
c_i \\
c_m
\end{pmatrix} +
\begin{pmatrix}
\gamma_i \\
\gamma_m
\end{pmatrix}
\begin{pmatrix}
r_{i,t-1} \\
r_{m,t-1}
\end{pmatrix} +
\begin{pmatrix}
\varepsilon_{i,t} \\
\varepsilon_{m,t}
\end{pmatrix}
\]  

(6)

Where \(r_{i,t}\) denotes the excess return of individual REIT, and \(r_{m,t}\) is the excess return of the general stock market. \(c_i\) and \(c_m\) are the constant term in the mean equation, and \(\gamma_i\) and \(\gamma_m\) are the autoregressive parameters. \(\varepsilon_{i,t}\), \(\varepsilon_{m,t}\) | \(\psi_{t-1}\) ∼ \(N(0, \sigma_i^2)\), that is to say \(\varepsilon_{i,t}\) and \(\varepsilon_{m,t}\) are conditioned by the complete information set \(\psi_{t-1}\) and are normally distributed with zero mean and a conditional variance matrix \(\sigma_i^2\), which may be described as:
\[ \sigma_i^2 = \begin{pmatrix} \sigma_{ii,t} & \sigma_{im,t} \\ \sigma_{mi,t} & \sigma_{mm,t} \end{pmatrix} \]  

(7)

And in this research, a GARCH-BEKK (1, 1) model, which allows for the dynamic dependence between the volatility series, has been employed to specify this conditional variance matrix as follow:

\[
\begin{pmatrix} \sigma_{ii,t} & \sigma_{im,t} \\ \sigma_{mi,t} & \sigma_{mm,t} \end{pmatrix} = \begin{pmatrix} c_{ii} & c_{im} \\ c_{mi} & c_{mm} \end{pmatrix} \begin{pmatrix} c_{ii} & c_{mi} \\ c_{mi} & c_{mm} \end{pmatrix} + \begin{pmatrix} \phi_{ii} & \phi_{im} \\ \phi_{mi} & \phi_{mm} \end{pmatrix} \begin{pmatrix} \alpha_{i,t-1}^2 & \alpha_{i,t-1}a_{m,t-1} \\ \alpha_{m,t-1}^2 & \alpha_{m,t-1}a_{m,t-1} \end{pmatrix} \begin{pmatrix} \phi_{ii} & \phi_{im} \\ \phi_{mi} & \phi_{mm} \end{pmatrix} + \begin{pmatrix} \varphi_{ii} & \varphi_{im} \\ \varphi_{mi} & \varphi_{mm} \end{pmatrix} \begin{pmatrix} \sigma_{ii,t-1} & \sigma_{im,t-1} \\ \sigma_{mi,t-1} & \sigma_{mm,t-1} \end{pmatrix} \begin{pmatrix} \varphi_{ii} & \varphi_{im} \\ \varphi_{mi} & \varphi_{mm} \end{pmatrix}
\]  

(8)

3.2.6 Conditional Idiosyncratic Risk

The previous section verifies that idiosyncratic risk changes over time and does not follow a random walk process. While the static OLS model has been extensively used in the idiosyncratic risk literature, it can not easily capture time variation nature which exists in a stock’s variance. In order to capture this time variation property, some autoregressive conditional heteroskedasticity models are used to estimate the conditional idiosyncratic risk. Engle (1982) proposes the autoregressive conditional heteroskedasticity (ARCH) model to capture the time variation of a time series with changing volatility. It proves to be an effective way to model the time-series behavior of many economic variables, especially the financial time series data. The ARCH models are attractive because the mean and variance equations are estimated jointly and it implicitly assumes that investors update their estimates of the mean and variance of returns each period using newly disclosed information in last period’s returns. Bollerslev (1986) extends the ARCH
model to GARCH model, which provides a more flexible structure to capture the
dynamic behavior of conditional variance. However, these two models both
assume that positive and negative return shocks have the same effects on the
volatility, which is not the case in the real financial market. In consideration of this
problem, Nelson (1991) proposes an exponential GARCH model to capture this
asymmetric effect of volatility, namely that an unexpected drop in prices (bad news)
increases predictable volatilities more than an unexpected increase in prices (good
news) of similar magnitude does. More importantly, EGARCH models do not
require restricting parameter values to avoid negative variance as do other ARCH
or GARCH models. Ding, Granger and Engle (1993) put forward another model,
namely asymmetric power GARCH model, to capture this asymmetric effect,
which allows a more flexible power form in variance equation.

A number of researches have compared the alternative GARCH specifications.
Pagan and Schwert (1990) fit different models to monthly U.S. stock returns and
find that Nelson’s EGARCH model is the best in overall performance. Engle and
Ng (1993) test the specifications of time-series volatility models using Lagrange
Multiplier tests. They also conclude that Nelson’s EGARCH specification best
capture the asymmetric effect of conditional volatilities. So, in this research,
EGARCH \((p, q)\) models are chosen to estimate the conditional idiosyncratic
volatility, where \(1 \leq p, q \leq 2\). The explicit functions are as follows:

\[
R_{it} - r_t = \alpha_t + \beta_t (R_{mt} - r_t) + s_t \cdot \text{SMB}_t + h_t \cdot \text{HML}_t + \varepsilon_{it} \quad \varepsilon_{it} \sim N(0, \sigma_{it}^2) \quad (9)
\]

\[
\ln \sigma_{it}^2 = \alpha_t + \sum_{j=1}^{p} b_{ij} \ln \sigma_{it-j}^2 + \sum_{k=1}^{q} c_{ik} \left\{ \theta \left( \frac{\varepsilon_{it-k}}{\sigma_{it-k}} \right) + \gamma \left[ \frac{\varepsilon_{it-k}}{\sigma_{it-k}} \right] - \left( \frac{2}{\pi} \right)^{1/2} \right\} \quad (10)
\]
We describe the monthly excess return process by the Fama-French three factor model as in equation (9), which means that we measure idiosyncratic risk relative to Fama-French three factor model due to its ubiquity in empirical financial studies and the relative failure of CAPM in explaining the cross-sectional returns. Term 
\[ \gamma \left[ \frac{E_{t,k}}{\sigma_{t,k}} \right] \left( \frac{2}{\pi} \right)^{1/2} \] is used to capture the asymmetric effect, and when \( \gamma < 0 \), the return volatility increases after a stock price drop. We define the idiosyncratic risk as the square root of conditional variance \( \sigma^2 \), which is the function of the past \( p \)-period of residual variance and \( q \)-period of shocks as specified by equation (10). Permutation of these orders yield four different EGARCH models: EGARCH (1,1), EGARCH (1,2), EGARCH (2,1) and EGARCH (2,2). We estimate the time-series conditional idiosyncratic volatility of each individual REIT using all these four EGARCH models and select the best one which: (1) is convergent within 500 iterations; and (2) yields the lowest Akaike Information Criterion (AIC). The estimated conditional idiosyncratic volatility will be used in the month-by-month cross-sectional regressions of individual REITs.

### 3.3 Data

This study uses the monthly data of the real estate investment trusts (REITs) that are traded on U.S. capital markets from 1990 to 2005. The return, price and number of shares outstanding data are collected from the Center for Research in Security Prices (CRSP) and the accounting data, like stockholder’s equity total, balance sheet deferred tax and investment tax credit, and book value of preferred stock, are collected from the CRSP/COMPUSTAT merged database’s annual
industrial files of income statement and balance-sheet data, which is also maintained by CRSP. Every REIT we used has more than 5 years’ trading to ensure the efficiency of GARCH estimation; we also exclude the REITs that do not trade for more than two continuous months; finally, due to the use of logarithm on the variable, we drop the REITs with negative book equity. Finally, we get 149 REITs in this research.

However, there are two exceptions with respect to the frequency and range of the data: first, when we estimate the lagged idiosyncratic risk of Ang et al. (2006), we use the daily REIT excess returns instead of monthly ones; second, due to the adoption of 60-months rolling window method when we estimate the lagged market risk and idiosyncratic risk in spirit of Fama-MacBeth (1973), the range of the data is extended to 1985 – 2005.

3.4 Definitions and Descriptive Statistics of all the Variables

Table 3 reports the definitions and descriptive statistics of all the variables in this study. Excess returns have the mean of 1.06% and the standard deviation of 8.55%, indicating that the excess returns fluctuate greatly. Consistent with the literature, GARCH beta exhibits extremely large value relative to OLS beta. Specifically, GARCH beta has the maximum value of 20.9597, while OLS beta has the maximum value of only 3.0342, and the standard deviation of GARCH beta is about one time bigger than that of OLS beta.

The mean of logarithm value of market capitalization (in million) is 5.6346, and
those for book-to-market equity ratio is -0.2704, which means REITs are on average smaller in size relative to the common stocks, and REITs are mostly growth stocks. After taking logarithm value of these two variables, the level of skewness is largely reduced, which can be seen from the skewness values of these two variables: -0.5625 and -0.8000 respectively. The mean of past 12-month cumulative return is 0.1751, and the standard deviation is 0.3514, indicating it fluctuates greatly over the time.

The IR(F-M) is estimated using 60-months rolling window method, which hypothesizes that investors will use previous 60 months’ information to predict the current month’s idiosyncratic risk. It also uses the lagged value to proxy for the current one assuming idiosyncratic risk follows a random walk process. The result is that the idiosyncratic risk estimated in the spirit of Fama-MacBeth (1973) has the smallest range and standard deviation, implying that it can not capture the time variation of idiosyncratic risk effectively. IR(Ang) is estimated using the previous daily excess returns, which assumes that investors will use the previous 1 month’s information to predict the current month’s idiosyncratic risk. Similar to IR(F-M), it also implicitly assumes that idiosyncratic risk follows a random walk process, which, however, can not hold in reality. Finally, E(IR) uses all the information till time $t$ (current period) to estimate the conditional idiosyncratic risk, which hypothesizes that investors predict the current month’s idiosyncratic risk based on all the past information, and it is rational in the real world. The mean of conditional idiosyncratic risk is slightly low than other two measures. The range and standard deviation of E(IR) allows large time-variation of idiosyncratic risk.
Besides, the number of observation is only 14751 in rows BETA and IR(F-M) compared with others of 20353 because of the use of 60-months rolling window method.
Table 3: Descriptive Statistics for the Pooled Sample of Each Variable

The table reports the descriptive statistics for the pooled sample of each variable from January 1990 to December 2005.

**ER(%)**: monthly percentage excess return, which is the total return net of the one-month T-bill rate.

**BETA**: estimated in the spirit of Fama-MacBeth (1973) using 60-month rolling window method.

**E(BETA)**: one month ahead expected market risk, which is estimated using bivariate GARCH (1,1) model.

**Ln(ME)**: natural logarithm of market equity (price times number of shares outstanding), which is computed in June of year t and updated monthly.

**Ln(BE/ME)**: natural logarithm of book-to-market equity. BE is the stockholder’s book equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock, and is for each REIT’s latest fiscal year end of calendar year t-1. The BE/ME ratio is measured using market equity ME in the end of December of year t-1 and is updated annually.

**Ret(-2,-13)(%)**: the cumulative return calculated over the past 12 months beginning in the second to last month.

**IR(F-M)**: estimated in the spirit of Fama-MacBeth (1973) using 60-month rolling window method.

**IR(Ang)**: estimated as in Ang et al. (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals of the previous month. Moreover, we transform the standard deviation of daily return residuals to a monthly return residual by multiplying the daily standard deviation by the square root of 22, the average number of trading days in one month.

**E(IR)**: one month ahead expected idiosyncratic risk estimated using exponential GARCH model relative to Fama-French (1992) three factor model.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Std Dev</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>No. Obs</th>
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</thead>
<tbody>
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<td>ER</td>
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</tr>
<tr>
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<td>6.3506</td>
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<td>-0.5625</td>
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<tr>
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<td>-0.8000</td>
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<td>110.2237</td>
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</table>
Chapter 4 Historical Pattern of Observed Idiosyncratic Risk in REIT Market

Since the seminal work by Campbell, Lettau, Malkiel and Xu (2001), who first find the time-series increase trend phenomenon of idiosyncratic risk in common stock market, there are a number of researches starting to pay attention to this topic and the importance of idiosyncratic risk in academic field keeps rising. However, very few researches on this topic are conducted on the REIT market. Clayton and Mackinnon (2003) examine the relative importance of stock, bond and real estate factors in explaining the REIT returns, and they also find there is a dramatic increase over time in the idiosyncratic variance in 1990s that is not explained by any of the factors. But, they estimate the idiosyncratic risk at the index level, not at the firm level. In this chapter, we will examine the historical pattern of idiosyncratic risk of individual REIT stocks from 1990 to 2005. Besides, we will test our results by controlling for the effects of outlier observations and the sample size. Finally, we will also try to give the possible explanations to the historical trend of idiosyncratic risk that we find on the REIT market.

4.1 Empirical Measurement of Observed Idiosyncratic Risk

Theoretically, idiosyncratic risk equals the return innovation’s standard deviation beyond what investors expected given that period’s market returns. But the models have nothing to say about how the market generates its expectation regarding the innovation’s variance and thus do not provide an empirical solution to this problem.
Moreover, as is pointed out by Malkiel and Xu (2006), it is very difficult to interpret the residuals from the market model as solely reflecting idiosyncratic risk. One can always argue that these residuals simply represent omitted factors. Therefore, we can only assert that the residuals from a market model measure idiosyncratic risk in the context of that model. Given the failure of the CAPM to explain the cross-sectional returns and the relative success of the Fama-French three factor model in the empirical financial application, we assume that Fama-French three factor model is the model used by the market and measure idiosyncratic risk relative to this model.

Consistent with Ang et al. (2006), we measure the idiosyncratic risk of an individual REIT as follows. In every month, daily excess returns of individual REIT are regressed on the daily Fama-French three factors: (1) the market excess return \((R_m - r_f)\); (2) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks \((SMB, \text{small minus big})\); and (3) the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks \((HML, \text{high minus low})\):

\[
R_{i,t} - r_f = \alpha_i + \beta_{1,t} (R_m, t - r_f) + s_{i,t} SMB_t + h_{i,t} HML_t + \epsilon_{i,t} \quad (11)
\]

\(\tau\) is the subscript for the day, \(t\) is the subscript for the month, \(\tau \in t, i\) is the subscript for individual REIT, and \(\beta_{1,t}, s_{i,t}\) and \(h_{i,t}\) are factor loadings. The daily three factor data are downloaded from Kenneth R. French’s website. We perform the time-series regressions for each REIT in each month. The observed idiosyncratic risk of individual REIT is computed as the standard deviation of the
regression residual of that month. Further, similar to Fu (2005), we transform the standard deviation of daily return residuals to monthly return residuals by multiplying the daily standard deviation by the square root of 22, the average number of monthly trading days.

4.2 Historical Pattern of Observed Idiosyncratic Risk on REIT Market

In order to track the historical movements in the idiosyncratic volatility of the overall REIT market, we take the average idiosyncratic risk across all the individual REITs for each month using equally-weighted (EW) and value-weighted (VW) measures. The two volatility series are presented in Figure 2. Whilst the average idiosyncratic risk of the REIT stocks fluctuates greatly from time to time, several patterns are discernible from Figure 2. First, the volatility series shows a visible downward drift over the study period, which is contrary to that observed for common stocks (see Xu and Malkiel, 2003; Bennett and Sias, 2005; Fink et al., 2005; Wei and Zhang, 2006). In particular, the average idiosyncratic risk of the REITs stocks fell from 9.3% at the beginning of the study period to 4.7% by the end of the study period, representing a 50% decrease in the idiosyncratic risk of individual REITs between 1990 and 2005. Second, the value-weighted measures are lower than the equal-weighted ones in almost all months, indicating that small REITs tend to have higher idiosyncratic risk than large REITs.
Figure 2: Time-series Average Observed Idiosyncratic Risk

The figure shows the equal-weighted and value-weighted average observed idiosyncratic risk from January 1990 to December 2005. The idiosyncratic risk is estimated as in Ang et. Al (2006): in every month, excess daily returns of each individual REITs are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REITs is the standard deviation of the regression residuals. Moreover, we transform the standard deviation of daily return residuals to a monthly return residual by multiplying the daily standard deviation by the square root of 22, the average number of trading days in one month.

4.3 Controlling for the Effect of Outlier Observations

To ensure that the observed patterns in the volatility series are not driven by outliers, we re-compute the two series by excluding 5% observations at both ends of the distribution. The time trend for the reconstructed series is reported in Figure 3, which is similar to that observed in Figure 2. The results show that the observed patterns are not adversely influenced by extreme observations.
Figure 3: Time-series Average Observed Idiosyncratic Risk with 5% Outliers Excluded on Each End

The figure shows the equal-weighted and value-weighted average observed idiosyncratic risk with 5% outliers excluded on each end. The idiosyncratic risk is estimated as in Ang et al. (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals. Moreover, we transform the standard deviation of daily return residuals to a monthly return residual by multiplying the daily standard deviation by the square root of 22, the average number of trading days in one month.

4.4 Controlling for the Sample Size

It should be noted that the composition of REITs in our sample is not static over the study period, rising from 42 in January 1990 to 146 in December 2005. Table 4 presents the median value of three financial attributes, namely size, B/M ratio and financial leverage of REITs in our sample at the start and at the end of the study period. The table shows that between 1990 and 2005, the median market capitalization of the 42 REITs in our initial sample grew by 7.57 times, from US$59.34 million to US$508.37 million, whilst the median B/M declined from 1.096 to 0.586. This implies that the median REIT has not only grown larger, but it has
also transformed from a value stock to become more of a growth stock. Over the same period, the financial ratio of the median REIT has increased from 0.946 to 1.875. Comparing the financial attributes of the initial 42 REITs with that of the full sample (146 REITs), REITs that were listed subsequent to 1990 generally employ more debt in their capital structure. They are also bigger in terms of market capitalization as compared to the original 42 REITs.

**Table 4: Financial attributes of REITs in the sample**

This table presents the median value of three financial attributes, namely size, book-to-market equity ratio and financial leverage of the REITs in the sample at the start (January 1990) and at the end (December 2005) of the study period. The initial sample comprises 42 REITs, whilst the full sample comprises 146 REITs. Change refers to how many times the particular financial attribute has changed between 1990 and 2005.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Full Sample (146 REITs)</th>
<th>Initial sample (42 REITs)</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (ME) (US $ M)</td>
<td>1,061.14</td>
<td>59.34</td>
<td>508.37</td>
</tr>
<tr>
<td>Book-to-market equity</td>
<td>0.538</td>
<td>1.096</td>
<td>0.586</td>
</tr>
<tr>
<td>Debt-equity ratio</td>
<td>2.069</td>
<td>0.946</td>
<td>1.875</td>
</tr>
</tbody>
</table>

In order to test the possibility that the trend observations in Figure 2 are simply the result of an increased number of REITs in the sample, we reconstruct the idiosyncratic volatility series using only the 42 original REITs that have been trading continuously since January 1990. The resulting series presented in Figure 4 show similar trends as observed earlier in Figure 2. The results indicate that the observed time trend of the idiosyncratic volatility in the REIT market between 1990 and 2005 is not driven by the addition of more new REITs over the study period.
Figure 4: Observed Idiosyncratic Risk of REITs (Initial Sample of 42 REITs)

The figure shows the equal-weighted and value-weighted average observed idiosyncratic risk from January 1990 through December 2005. The REITs included are the 42 REITs that have been traded on the U.S. market since January 1990. The idiosyncratic risk is estimated as in Ang et. Al (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals. Moreover, we transform the standard deviation of daily return residuals to a monthly return residual by multiplying the daily standard deviation by the square root of 22, the average number of trading days in one month.

4.5 Explanations to the Downward Trend of Observed Idiosyncratic Risk

4.5.1 Size of Individual REIT Becomes Larger and Larger

In Figure 2, the value-weighted measures are lower than the equal-weighted ones in almost all months, indicating that small REITs tend to have higher idiosyncratic risk than large REITs. We can also find it in the statistically significant negative simple cross-sectional relation between size and idiosyncratic risk in the later section of this study. So, the observed decreasing trend of idiosyncratic risk can be
at least partly attributed to the dramatic increase in the average size of REITs after 1990. The average market capitalization of publicly traded REITs grew from just below US$ 100 million prior to 1991 to above US$ 1.5 billion in 2004 (Ooi, Webb and Zhou, 2007). Active acquisition and merger activities in the REIT market during the 1990s also resulted in REITs that were separately listed previously (and hence, their idiosyncratic risks separately measured) being merged into a single entity; thus, resulting in a lower combined idiosyncratic risk (see Campbell et al., 2001; Campbell, Petrova and Sirmans, 2003). Chaudhry, Maheshwari and Webb (2004) explain that larger REITs are more likely to be geographically diversified and hence, they would be more insulated from fluctuations in the market prices of the underlying real estate properties than smaller firms, which are unable to achieve such a level of diversification.3

**Figure 5: Trend of Average Market Capitalization (1990 – 2005)**

![Graph showing trend of average market capitalization from 1990 to 2005.](image)

Source: NAREIT Web Site, 2006

### 4.5.2 Idiosyncratic Risk is Countercyclical

3 Besides size, Chaudhry, Maheshwari and Webb (2004) also observe that efficiency, liquidity and earnings variability are important determinants of idiosyncratic risk of REITs.
Figure 6 shows a countercyclical pattern in the idiosyncratic volatility of REITs, which is consistent with Campbell et al. (2001). In particular, the idiosyncratic risk of REITs is particularly low between 1995 and 1998, which were characterized by bullish market sentiment as reflected by the steadily rising NAREIT index. In contrast, sudden spikes in the average volatility were registered in late 1990-early 1991, September 1998 and April 2004, which coincided with periods of decline in the broad REIT market. Given the robust growth of the REIT sector in recent years, it is not surprising that the idiosyncratic volatility of the sector has declined, as noted earlier. The idiosyncratic volatility of REITs can be expected to rise when the market sentiment settles to a realistic level. It is also interesting to note that the countercyclical pattern is asymmetric: idiosyncratic volatility decreases marginally in good times, but in bad times, it escalates very quickly. Campbell et al. (2001) suggest that the countercyclical behavior of volatility has important implications for diversification of risk at different stages of the business cycle. Because market volatility is substantially higher in recessions, they argue that even a well diversified portfolio is exposed to more volatility when the economy turns down. Because industry and firm-level volatility also increase in economic downturns, they further argue that increase in volatility is stronger for an undiversified portfolio. Consequently, they propose that diversification is more important and requires more individual stock holdings to achieve when the economy turns down.
Figure 6: Time-series Average Observed Idiosyncratic Risk Compared with NAREIT Index

The figure shows the equal-weighted and value-weighted average observed idiosyncratic risk and the monthly percentage change of NAREIT Index from January 1990 to December 2005. The idiosyncratic risk is estimated as in Ang et al. (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals. The NAREIT Index is collected from NAREIT web site. Moreover, we transform the standard deviation of daily return residuals to a monthly return residual by multiplying the daily standard deviation by the square root of 22, the average number of trading days in one month.

Summarily, in this chapter, we find a decreasing trend of idiosyncratic risk at the firm level on the REIT market, which is contrary to the increasing trend that has been found on the common stock market. And this downward trend continues to hold after we control the effect of outlier observations and the sample size during the study period. This indicates that the correlations between individual REIT stocks become larger and investors can achieve the same diversification level by using relatively fewer REITs than before. Besides, we find that this downward trend of idiosyncratic risk is due to the fact that the size of individual REITs is keeping rising during our study period and idiosyncratic risk is negatively related to the firm size. Moreover, this downward trend of idiosyncratic risk can also be attributed to the countercyclical property of idiosyncratic risk when the REIT
market is keeping rising during our study period. Further, we find that the
countercyclical property of idiosyncratic risk is also asymmetric: idiosyncratic
volatility decreases marginally in good times, while in bad times, it increases very
quickly. This implicates that investors should use much more REITs achieve the
same diversification effect during the down market than up market.
Chapter 5  Cross-Sectional Return Tests

After examine the historical pattern of the observed idiosyncratic risk, in this chapter, we will go on to test whether conditional idiosyncratic risk of individual REIT stocks is significantly related to their monthly cross-sectional returns because our empirical investigation indicates that idiosyncratic risk dominates the total risk of individual REIT returns between 1990 and 2005. First, besides qualitatively replicating what Fama-MacBeth (1973) and Ang et al. (2006) have done using REIT data, we do the cross-sectional return test of conditional idiosyncratic risk as well as conditional market risk. In section 2, we test the role of conditional idiosyncratic risk after controlling for various cross-sectional effects, three of which are the famous risk anomalies found on the common stock market, namely size, value and momentum effects, and the rest one is a dummy variable for mortgage REIT because mortgage REITs have different risk-return characteristics from equity REITs. Also, we examine the effects of size, value and momentum after controlling the conditional idiosyncratic risk. In section 3, we further do some robust tests by using different market model (CAPM) to derive the conditional idiosyncratic risk of the individual REITs as well as categorizing the data over different sub-periods.

5.1 Conditional Idiosyncratic Risk and the Cross-Section of REIT Returns

As is discussed in the literature review section, there are mixed empirical results in the common stock market although in the Merton (1987)’s theoretical asset pricing
model with incomplete information, idiosyncratic risk should be positively priced to compensate rational investors for the inability to hold the market portfolio. Previous studies fail to find the positive relationship between idiosyncratic risk and expected returns because their models of idiosyncratic risk can not capture the substantial time-variation or not estimate the idiosyncratic risk at firm level. In this section, similar to Fu (2005), we will first qualitatively replicate these empirical tests in the REIT industry, and then compare them with those of conditional measures. The empirical results are presented in table 5.
Table 5: Fama-MacBeth Regressions of REIT Excess Returns on Beta and Idiosyncratic Risk

The following table presents the time-series averages of the slopes in the monthly cross sectional regressions using the standard Fama-MacBeth (1973) methodology. The number in the parenthesis is the $t$-statistic value of the corresponding coefficients, which is the average slope divided by its time-series standard error. The dependent variable is the percentage monthly excess return. C refers to the regression intercept. Beta(F-M) and IR(F-M) are both estimated in the spirit of Fama-MacBeth (1973) using 60-month rolling window method. IR1(Ang) is estimated as in Ang et al. (2006): in every month, excess daily returns of each individual REIT are regressed on the Fama-French three factors and the monthly idiosyncratic risk of the REIT is the standard deviation of the regression residuals of the previous month. IR2(Ang) is the contemporaneous version of IR1(Ang). E(BETA) is one month ahead expected market risk, which is estimated using bi-variate GARCH (1,1) model. E(IR) is one month ahead expected idiosyncratic risk estimated using exponential GARCH model relative to Fama-French (1992) three factor model.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>C</th>
<th>BETA(F-M)</th>
<th>IR(F-M)</th>
<th>IR1(Ang)</th>
<th>IR2(Ang)</th>
<th>E(BETA)</th>
<th>E(IR)</th>
<th>$R^2$(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Replicate F-M (1973) in U.S. REIT market</td>
<td>1</td>
<td>0.0065*</td>
<td>-0.0043</td>
<td>0.0465</td>
<td></td>
<td></td>
<td></td>
<td>10.49</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.81)</td>
<td>(-0.94)</td>
<td>(0.82)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Panel B: Replicate Ang et al. (2006) in U.S. REIT market</td>
<td>2</td>
<td>0.0082***</td>
<td>0.1324</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.26</td>
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<tr>
<td></td>
<td></td>
<td>(2.72)</td>
<td>(0.97)</td>
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<td></td>
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<tr>
<td></td>
<td>3</td>
<td>0.0044</td>
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<td>0.3562**</td>
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<td></td>
<td>8.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.54)</td>
<td></td>
<td>(2.37)</td>
<td></td>
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</tr>
<tr>
<td>Panel C: F-M regressions on E(BETA) and E(IR)</td>
<td>4</td>
<td>0.0107***</td>
<td></td>
<td>-0.0013</td>
<td></td>
<td></td>
<td></td>
<td>6.65</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.72)</td>
<td></td>
<td>(-0.39)</td>
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</tr>
<tr>
<td></td>
<td>5</td>
<td>0.0043</td>
<td></td>
<td></td>
<td>0.0898**</td>
<td></td>
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<td>8.04</td>
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<tr>
<td></td>
<td></td>
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<tr>
<td></td>
<td>6</td>
<td>0.0045</td>
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<td>-0.0027</td>
<td>0.1028**</td>
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<td>12.88</td>
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<tr>
<td></td>
<td></td>
<td>(1.59)</td>
<td></td>
<td>(-0.94)</td>
<td>(2.38)</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * Significance at 10 percent level; ** Significance at 5 percent level; *** Significance at 1 percent level.

Model 1 qualitatively replicates the work of Fama-MacBeth (1973). Beta(F-M) and IR(F-M) are both estimated in the spirit of Fama-MacBeth (1973) using 60-month rolling window method. Like them, we have not found a significantly positive relation between idiosyncratic risk and expected returns. The coefficient estimate is 0.0465 but not statistically significant. However, different from them,
we also have not found a significantly positive coefficient slope for beta variable, whose coefficient estimate is -0.0043 but the value of corresponding $t$-statistic is only -0.94, which means market risk is not priced in the REIT market, and the investors holding REITs with large market risk can not earn significant excess returns from those holding REITs with small market risk.

Model 2 qualitatively replicates what Ang et al. (2006) has done. IR1(Ang) is estimated as in Ang et. al (2006). However, we do not find significantly negative relation between lagged idiosyncratic risk and expected returns. Instead, in our empirical result, the coefficient estimate is 0.1324 and not statistically significant.

Model 3 examines the contemporaneous association between return and observed idiosyncratic risk, which, the variable IR2(Ang), is the contemporaneous version of IR1(Ang). According to Fu (2005), technically we are not able to make inferences about expected returns from this regression due to the potential correlation between the error of expected return ($r_t - E(r_t)$) and the error of conditional idiosyncratic risk ($IR - E(IR)$), it can still serve as a reference for comparison. The coefficient of IR2(Ang) is 0.3562 and statistically significant at 5% level. There is a significantly positive relationship between realized return and contemporaneous idiosyncratic risk. The results of this regression still can provide us additional confidence on the positive relation between expected return and expected idiosyncratic risk.

Model 4 to 6 examine the role of expected market risk and expected idiosyncratic risk in explaining the cross-section of expected REIT returns. On the influence of beta on the expected returns of REITs, the regression results reported in Table 5
show a relatively flat relationship with the average slope of expected beta not significantly different from zero. This indicates that market beta does not help to explain the cross-sectional return of REITs between 1990 and 2005 even when it is the only explanatory variable in the asset pricing model (Model 4). The insignificant coefficient persists when we include expected idiosyncratic risk as an additional explanatory variable in the monthly FM regressions (Model 6). The results, although contradictory to the prediction of the CAPM theory, are consistent with numerous studies which recorded the diminishing influence of beta on average stock returns (Reinganum, 1981; Lakonishok and Shapiro, 1986; Fama and French, 1992; and Fu, 2005). They are also consistent with McIntosh, Liang and Tompkins (1991), who find that the beta does not explain the differences in average REIT returns.

On the other hand, the average slope of conditional idiosyncratic volatility is positive and statistically significant in Model 5 and Model 6, indicating that REITs with higher expected idiosyncratic risk do earn higher average returns. In particular, the coefficient estimate is 0.0898 and statistically significant at the 5% level in Model 5. The result continues to hold after we control for conditional market risk in Model 6. Indeed, the inclusion of $E(\text{IR})$ in the regression model results in the average R-square almost doubled (from 6.65% for Model 4 to 12.88% for Model 6) and the value of the constant term decreases and becomes not statistically different from zero. Furthermore, the effect of idiosyncratic risk on expected returns are economically significant. The magnitude of the average slope in Model 6 indicates that the monthly return is expected to increase by 1.028% with every 10% increase in idiosyncratic risk.
5.2 Interact with Various Cross-Sectional Effects

In the last section, we find conditional idiosyncratic risk is positively priced. However, conditional idiosyncratic risk may just picking up other effects of risk factors. So, in this section, we will examine the explanatory power of idiosyncratic risk in the presence of three other well-known pricing anomalies, namely size, value and momentum effects. The small premium effect was first highlighted by Banz (1981) who observes that market value of common equity ($ME$), not only adds to the explanation of the cross-section of average returns provided by market risks, but is significantly negatively related to stock returns. Stattman (1980) and Rosenberg, Reid and Lanstein (1985), who were among the first to document the premium attached to value stocks, find that average returns of U.S. stocks are positively related to the ratio of a firm’s book value of common equity to its market equity ($B/M$).\(^4\) Jegadeesh and Titman (1993) further observe that over an intermediate horizon of three to twelve months, past winners, on average, continue to outperform past losers. They went on to argue that past returns can be used to predict future returns. This proposition is now better known as the “momentum effect” in the literature. These three variables were added one at a time into the month-by-month cross-sectional regressions in order to examine their joint effect with conditional idiosyncratic volatility and market risk in explaining the expected returns of REIT stocks. Finally, due to the different risk-return characteristics of equity REITs and mortgage REITs, we do a sub-sector test (Equity or Mortgage REITs) by adding a dummy variable for mortgage REIT in the regression. The

\(^4\) Although other studies have identified other factors that affect cross-sectional stock returns, such as leverage (Bhandari, 1988) and earnings-price ratio (Basu, 1983), FF (1992) test the joint role of market equity, book-to-market equity (BE/ME) ratio, leverage and earnings-price ratio (E/P), and conclude that the combination of market equity and book-to-market equity ratio seems to absorb the roles of leverage and E/P in average stock returns.
regression results are reported in Table 6. In order to avoid giving extreme observations a heavy weight in the cross-section regressions, we set the smallest and largest 1% of the explanatory variables (except the dummy variable) equal to the next smallest or largest values.
Table 6: Average Slopes (t-statistics) from Month-by-Month Regressions of REIT Returns on Beta, Idiosyncratic Volatility, Size, Value and Momentum Factors and a Dummy Variable for Mortgage REITs

The average slope is the time-series average of the monthly regression slopes, and the \( t \)-statistic is the average slope divided by its time-series standard error. Firm size, ln(ME), is measured in June of year \( t \) and updated monthly (price times shares outstanding). BE is the stockholder’s book equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock, and is for each REIT’s latest fiscal year end of calendar year \( t-1 \). The BE/ME ratio is measured using market equity ME in the end of December of year \( t-1 \). In the monthly regressions, these values of the explanatory variables for individual REITs are matched with the excess returns for the months from July of year \( t \) to June of year \( t+1 \). The gap between the accounting data and the excess returns ensures that the accounting data are available prior to the corresponding excess returns. Ret(-2,-13), which proxies the momentum effect, is the cumulative return calculated over the past 12 months beginning in the second to last month. This measure was computed excluding the data of the immediate prior month in order to avoid any spurious association between the prior month data and the current month data caused by thin trading or bid-ask spread effects. D(M) is a dummy variable for mortgage REIT to control the effect of different type of REITs.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>C</th>
<th>E(BETA)</th>
<th>ln(ME)</th>
<th>ln(BE/ME)</th>
<th>Ret(-2,-13)</th>
<th>E(IR)</th>
<th>D(M)</th>
<th>R² (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size-effect</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>7A</td>
<td>0.0168***</td>
<td>-0.0013*</td>
<td>4.14</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.85)</td>
<td>(-1.70)</td>
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</tr>
<tr>
<td>7B</td>
<td>0.0166***</td>
<td>-0.0007</td>
<td>9.83</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>7C</td>
<td>0.0077**</td>
<td>-0.0024</td>
<td>14.36</td>
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<td></td>
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<td>Value-effect</td>
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<td>8A</td>
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<td>8B</td>
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<td>0.0128**</td>
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<td>9C</td>
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<td>Sub-sector test</td>
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<td>10</td>
<td>0.0064*</td>
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<td>(1.76)</td>
<td>(-1.16)</td>
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</tr>
</tbody>
</table>

Note: *, **, and *** denotes significance at the 10% level, 5% and 1% level, respectively.
5.2.1 Interact with Size and Value Effects

The positive relation between REIT returns and conditional idiosyncratic risk continues to hold after the inclusion of new variables, namely, size and $B/M$. Specifically, the coefficients of conditional idiosyncratic risk in model 7C and 8C are 0.0858 and 0.0845 respectively, both are statistically significant at 5% level. This means the positive idiosyncratic risk effects are robust and not just picking up the effects of these two risk factors. Conversely, the average slope for beta consistently remains statistically insignificant, which reconfirm the insignificant role of market risk in explaining the cross-sectional REIT returns.

Models 7A, 7B and 7C focus on the small size-effect and examine its interactive effect with conditional idiosyncratic risk. The average slope of -0.13% and -0.12% for $ME$ in Model 7A and 7B, respectively, are significant at the 10% level. This indicates that small REITs earn higher returns than larger REITs, which is consistent with extant evidence in the finance and real estate literature (Banz, 1981; McIntosh, Liang, and Tompkins, 1991). Compared with the corresponding empirical results of the common stocks, like Fama-French (1992), where size is significant at 1% level, the size effect is relatively weaker on the REIT market. The possible explanation may be found in Merton (1987), who argues that it is not the size of the firm relative to national wealth that matters, but instead, the size of the firm relative to the aggregate wealth of the investors in the firm. When the REIT investors (mainly institutional investors) are relatively more homogeneous in terms of the wealth than investors on the common stock market (mainly individual investors), the size effect will be less significant. However, when conditional idiosyncratic risk is added to the regression (Model 7C), the average slope on $ME$
loses its statistical significance. This suggests that the small size-effect dissipates once idiosyncratic risk is taken into account.

Models 8A, 8B and 8C similarly focus on the premium associated with value stocks and examine its interactive effect with conditional idiosyncratic risk. The average slope of 0.33% and 0.38% for $B/M$ in Model 8A and 8B are statistically significant at the 10% and 5% level, respectively. This result is consistent with Ooi, Webb, and Zhou (2007), who find that value REITs tend to earn higher excess returns than growth REITs. Also, we compare it with that of the common stock market and find that the value effect is less significant on the REIT market (10% level) than on the common stock market (1% level, see Fama and French, 1992). The possible explanation is that as postulated by Chan and Chen (1991) and Fama and French (1992) that the risk captured by value factor is the relative distress risk, this distress risk may not be prominent on the REIT market due to the unique dividend policy of REITs that more than 90% income should be distributed as cash dividend, which makes REITs behave more like bonds, and the persistent bullish market during 1990 to 2005. Ong, Ooi, and Sing (2000) also point out that if property funds would be able to make the generous payouts that are made in the US, the risk-return characteristic of the property fund will then be much akin to that of a bond instrument. Since the distress risk of the bond is relatively smaller than that of the stock, the value factor proxy for the distress risk will be less significant on the REIT market. However, just as we have observed earlier for the small-size effect, the value effect disappears once idiosyncratic volatility is added to the regression (Model 8C).
The disappearing return premiums associated with small firm and value stocks after the addition of idiosyncratic risk is not unique. Chui, Titman and Wei (2003) find that the small-firm and high B/M effects do not exist on the REITs market at least after 1990. Fu (2005) also reaches a similar result of the value factor for common stocks traded in NYSE, AMEX and NASDAQ during the period from 1963 to 2002. How can the disappearing influence of the size and value factors in the presence of idiosyncratic volatility be explained? We think that size and $B/M$ may be capturing the omitted effects of idiosyncratic risk in models 7A, 7B, 8A and 8B, which is also consistent with Berk (1995), who argues that so long as this misspecification does not imply a positive relation between operating size and the return predicted by the model, the logarithm of market value will be inversely correlated with the part of return not explained by the model.

To further examine the interactive relationships between size-related measures and idiosyncratic risk, Table 7 reports the pair-wise Pearson Correlations for the explanatory variables in our regression model. Not surprising, idiosyncratic risk and market risk are positively related. $B/M$ is strongly correlated with $ME$ (-0.49). Both variables, in turn, are strongly correlated with conditional idiosyncratic volatility, -0.35 for $ME$ and 0.30 for $B/M$, indicating that smaller and value REITs tend to have higher idiosyncratic risk. This suggests that most of the relation between size and expected returns is due to the strong negative correlation between $ME$ and conditional idiosyncratic risk. Similarly, the relation between $M/B$ and expected returns is due to the strong positive correlation between $B/M$ and conditional idiosyncratic risk.
Table 7: Cross-Sectional Pearson Correlations

The time-series means of the cross-sectional Pearson correlations between the variables defined in Table 3 are presented. The significance level is decided according to the $t$-statistics computed by the time-series means of the cross-sectional Pearson correlations divided by the corresponding time-series standard error.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Ln(ME)</th>
<th>Ln(BE/ME)</th>
<th>Ret(-2,-13)</th>
<th>E(IR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E(BETA)</td>
<td>0.11***</td>
<td>0.06***</td>
<td>-0.07***</td>
<td>0.14***</td>
</tr>
<tr>
<td>Ln(ME)</td>
<td>-0.49***</td>
<td>0.12***</td>
<td>-0.35***</td>
<td></td>
</tr>
<tr>
<td>Ln(BE/ME)</td>
<td></td>
<td>0.00</td>
<td>0.30***</td>
<td>-0.06***</td>
</tr>
</tbody>
</table>

Note: *** significant at 1% level.

5.2.2 Interact with Momentum Effect

Similar to the robustness of idiosyncratic risk effect to the size and value effects that we observe in the last section, the positive relation between REIT returns and conditional idiosyncratic risk continues to hold after controlling the momentum effect. Specifically, the coefficient of conditional idiosyncratic risk in model 9C is 0.0831, and the value of corresponding $t$-statistic is 2.01, which means that the monthly return is expected to increase by 0.831% with every 10% increase in idiosyncratic risk after adjusting other three risk factors, namely size, value and momentum. However, the average slope for beta still remains statistically insignificant.

The average slope for the $Ret(-2,-13)$ variable in Model 9A and Model 9B is 1.28% and 1.34%, respectively. Both are statistically significant at the 5% and 1% level, respectively. This indicates that momentum has a strong influence on REIT returns, which is consistent with the findings of Chui, Titman and Wei (2003).
However, unlike the small-size and value premium, the coefficient for momentum continues to be significant when we add conditional idiosyncratic volatility and other risk factors in the regression (Model 9C). When estimated jointly, the coefficients for momentum and idiosyncratic risk are 0.1370 and 0.0831, respectively. Both are statistically significant. We will further examine their interactive effects in the context of the trading strategy in Chapter 6.

### 5.2.3 Controlling for Different Types of REITs

Besides, we take a sub-sector test to see whether the significance of idiosyncratic risk persists in these two sub-sectors due to the differences between equity REITs and mortgage REITs, which may have some effect on the role of idiosyncratic risk. First, besides other risk factors, mortgage REITs are exposed to default and prepayment risks, which may make them not behave as pure equity REITs. Second, there is a general agreement in the REIT literature that of the three types of REITs (namely equity, mortgage and hybrid), equity REITs have outperformed mortgage REITs in terms of their risk-adjusted excess returns at least since the early 1970s ( see Han and Liang (1995) and Peterson and Hsieh (1997) for evidence on this issue). Meanwhile, research also indicates that equity REITs consistently have less market risk than mortgage or hybrid REITs. Above all, there seems to be different risk-return characteristics between equity REITs and mortgage REITs, which motivate us to do this sub-sector analysis to test the hypothesis that idiosyncratic risk may have different roles in equity REITs and mortgage REITs.

We add a dummy variable for mortgage REITs in the regression to test this effect,
see model 10 on Table 6. There are two reasons why we add a dummy variable into the regression rather than do the regressions in these two sub-sectors respectively as follows: first, the number of mortgage REITs varies between 2 and 19 during the study period, which does not reach the minimal required number of efficient regression. This means we could not do the regression in the mortgage sub-sector. Second, using a dummy variable does not need to divide the whole sample into two sub-samples, and the coefficient of other variables, like market risk, size, value, momentum and idiosyncratic risk will be estimated using the whole sample data, which makes this regression result more comparable to other regression results.

The empirical result indicates that, contrary to our hypothesis, the significance of idiosyncratic risk is robust to different type of REITs, since the coefficient of the dummy variable for mortgage REITs is only 0.0016 and not statistically significant, while that of idiosyncratic risk increases from 0.0831 to 0.0947 and the corresponding value of $t$-statistic increases from 2.01 to 2.23.

In all the above tests in Table 6, we use the E(BETA), while the Fama-French three factor model use BETA(F-M), which means that E(IR) may be picking up some omitted variable effect relating to the BETA(F-M). To clear this concern, we rerun the model 7c, 8c, 9c and 10 using BETA(F-M) instead of E(BETA). The empirical results show that Fama-French three factors continue to be not statistically different from zero in all these four regressions, and the momentum effect and conditional idiosyncratic risk are always statically significant. This means that E(IR) has not pickup up omitted effect of BETA(F-M).
5.3 Robust Tests

5.3.1 Estimate Conditional Idiosyncratic Risk Relative to CAPM

In the previous section, we measure conditional idiosyncratic volatility relative to the Fama-French three-factor model. To examine the robustness of our empirical results, we also estimate the conditional idiosyncratic risk relative to the CAPM as follows:

\[
R_{it} - r_t = \alpha_i + \beta_i (R_{mt} - r_t) + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma^2_{it})
\]  

\[
\ln \sigma^2_{it} = \alpha_i + \sum_{j=1}^{p} b_{ij} \ln \sigma^2_{i,t-j} + \sum_{k=1}^{q} c_{ik} \left\{ \theta \left( \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right) + \gamma \left( \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right)^{1/2} \right\}
\]

The only difference is that we here use CAPM model to describe the monthly excess return process (equation 8), which means we estimate idiosyncratic risk relative to CAPM model. The regression results are reported in Table 8, which show that the findings of the current study are robust to the alternative asset pricing model employed to derive the conditional idiosyncratic risk of REITs. In particular, there still exists a statistically significant positive relation between conditional idiosyncratic risk and average REIT returns, which is also robust to the inclusion of other explanatory variables, like size, book-to-market equity ratio and momentum effect; further, when controlling for the conditional idiosyncratic risk, size and book-to-market equity ratio lose their explanation power in the cross-section of expected REIT returns, while the momentum factor remain significant.
Table 8: Average Slopes (t-statistics) from Month-by-Month Regressions of REIT Returns on Beta, Idiosyncratic Volatility (CAPM-based), Size, Value and Momentum Factors

The average slope is the time-series average of the monthly regression slopes for January 1990 through December 2005, and the $t$-statistic is the average slope divided by its time-series standard error. E(BETA) is the one month ahead expected market risk, which is estimated using a bi-variate GARCH (1,1) model. E(IR)(CAPM) is one month ahead expected idiosyncratic risk estimated using an exponential GARCH model relative to CAPM. Firm size, ln(ME), is measured in June of year $t$ and updated monthly (price times shares outstanding). BE is the stockholder’s book equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of the preferred stock, and is for each REIT’s latest fiscal year end of calendar year $t-1$. The BE/ME ratio is measured using market equity ME in the end of December of year $t-1$ and is updated monthly. In the monthly regressions, the values of the explanatory variables for individual REITs are matched with the excess returns for the months from July of year $t$ to June of year $t+1$. The gap between the accounting data and the excess returns ensures that the accounting data are available prior to the corresponding excess returns. Ret(-2,-13), which proxies the momentum effect, is the cumulative return calculated over the past the 12 months beginning in the second to last month. This measure was computed excluding the data of the immediate prior month in order to avoid any spurious association between the prior month data and the current month data caused by thin trading or bid-ask spread effects.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>C</th>
<th>E(BETA)</th>
<th>ln(ME)</th>
<th>ln(BE/ME)</th>
<th>Ret(-2,-13)</th>
<th>E(IR)</th>
<th>$R^2$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0107***</td>
<td>-0.0013</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.65</td>
</tr>
<tr>
<td></td>
<td>(4.72)</td>
<td>(-0.39)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.0043</td>
<td></td>
<td></td>
<td></td>
<td>0.0832*</td>
<td></td>
<td>7.92</td>
</tr>
<tr>
<td></td>
<td>(1.45)</td>
<td></td>
<td></td>
<td></td>
<td>(1.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.0045*</td>
<td>-0.0024</td>
<td></td>
<td></td>
<td>0.1028**</td>
<td></td>
<td>12.79</td>
</tr>
<tr>
<td></td>
<td>(1.66)</td>
<td>(-0.82)</td>
<td></td>
<td></td>
<td>(2.38)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7C</td>
<td>0.0066*</td>
<td>-0.0017</td>
<td>-0.0004</td>
<td></td>
<td>0.0870**</td>
<td></td>
<td>15.76</td>
</tr>
<tr>
<td></td>
<td>(1.95)</td>
<td>(-0.59)</td>
<td>(-0.61)</td>
<td></td>
<td>(2.01)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8C</td>
<td>0.0060*</td>
<td>-0.0020</td>
<td>-0.0003</td>
<td>0.0004</td>
<td>0.0888**</td>
<td></td>
<td>17.03</td>
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<tr>
<td></td>
<td>(1.76)</td>
<td>(-0.67)</td>
<td>(-0.44)</td>
<td>(0.33)</td>
<td>(2.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9C</td>
<td>0.0060*</td>
<td>-0.0013</td>
<td>-0.0008</td>
<td>-0.0008</td>
<td>0.0141***</td>
<td>0.0888**</td>
<td>20.64</td>
</tr>
<tr>
<td></td>
<td>(1.73)</td>
<td>(-0.44)</td>
<td>(-1.17)</td>
<td>(-0.66)</td>
<td>(3.28)</td>
<td>(2.08)</td>
<td></td>
</tr>
</tbody>
</table>

Note: *, **, and *** denotes significance at the 10% level, 5% and 1% level, respectively.

5.3.2 Sub-period Test

To examine the persistence of our empirical results over different time periods, we
divide our study period into two equal sub-periods covering 120 months each as follows; January 1990 through December 1999, and January 1996 through December 2005. Note that the two sub-periods, 1990-1999 and 1996-2005, include overlapping years from 1996 to 1999 to provide sufficient length of time for the sub-period tests. In their influential paper on testing the CAPM model, FM (1973) conclude that on average there is a statistically observable positive relationship between return and beta based on the significant beta coefficient observed for their overall sample period. Even though the beta coefficients are not significant in 7 out of the 9 sub-periods they examined, they explained that due to the substantial month-to-month variability of the parameters of the risk-return regressions, a longer time-period is required before the coefficients of beta yield sufficiently large $t$-value (page 624). Consequently, subsequent researchers such as Chui, Titman and Wei (2003) and Ang et al. (2006) have carried out sub-period tests using at least ten years’ data. Month-by-month regressions are carried out based on the following two estimation models:

\begin{align}
r_{it} &= c + \gamma_4 \text{Ret}(-2,-13)_{it} + \gamma_5 E(IR)_{it} + \epsilon_{it} \\
&= c + \gamma_1 E(\beta)_{it} + \gamma_2 \ln(ME_{it}) + \gamma_3 \ln(B/M_{it}) + \gamma_4 \text{Ret}(-2,-13)_{it} + \gamma_5 E(IR)_{it} + \epsilon_{it}
\end{align}

Model (14) is a more parsimonious model for REIT returns incorporating only the two significant factors, namely past returns and idiosyncratic volatility, whilst Model (15) incorporates all the risk factors, namely beta, firm size, B/M, past returns and idiosyncratic volatility.

The average slope of the monthly regressions for the full and sub-samples are
presented in Table 9. Consistent with the results obtained for the full sample period, the influence of beta, size and B/M on the cross sectional REIT returns are muted in the two sub-periods once idiosyncratic risk is added to the asset pricing model. The sub-period results further support the conclusion that momentum effect and idiosyncratic volatility are consistently significant factors in explaining the cross-section of REIT returns. Comparing the explanatory power of past returns over the two sub-periods, we observe that the momentum effect has diminished in the later sub-period, i.e. January 1996 through December 2005. Conversely, we observe a stronger relationship with conditional idiosyncratic risk and expected REIT returns in the second sub-period. Thus, the results show that our earlier conclusions are robust across different sub-periods.

Further, to test the sensitivity of our results to the length of the sample period, the redo the regression of model 15 using the data ranging from 11 to 15 years, and find that our results are consistent in all these different sample periods, which means the significant role of conditional idiosyncratic risk is robust to different length of sample periods. (The regression results not presented here)
Table 9: Average Slopes (t-statistics) from Month-by-Month Regressions of REIT Returns on Beta, Idiosyncratic Volatility, Size, Value and Momentum Factors

The table presents the time series averages of FM slopes for two equal sub-periods (January 1990 – December 1999 and January 1996 – December 2005) from two regressions: (a) the cross-section of excess REIT returns on momentum factor and idiosyncratic risk; (b) the cross-section of excess REIT returns on conditional beta, size, book-to-market equity ratio, momentum factor and conditional idiosyncratic risk. The numbers in the parenthesis are the t-statistic values of the corresponding coefficients, which is the average slope divided by its time series standard errors.

Firm size ln(ME) is measure in June of year $t$ and updated monthly (price times shares outstanding). BE is the stockholder’s book equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock, and is for each REIT’s latest fiscal year end of calendar year $t-1$. The BE/ME ratio is measured using market equity ME in the end of December of year $t-1$ and is updated annually. In the monthly regressions, these values of the explanatory variables for individual REITs are matched with the excess returns for the months from July of year $t$ to June of year $t+1$. The gap between the accounting data and the excess returns ensures that the accounting data are available prior to the corresponding excess returns. Ret(-2,-13), which proxies the momentum effect, is the cumulative return calculated over the past the 12 months beginning in the second to last month. This measure was computed excluding the data of the immediate prior month in order to avoid any spurious association between the prior month data and the current month data caused by thin trading or bid-ask spread effects.

<table>
<thead>
<tr>
<th>Period</th>
<th>01/90-12/05(192 months)</th>
<th>01/90-12/99(120 months)</th>
<th>01/96-12/05(120 months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Mean</td>
<td>St.dev</td>
<td>t-stat</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.0033</td>
<td>0.04</td>
<td>1.05</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td>0.0122</td>
<td>0.06</td>
<td>3.02</td>
</tr>
<tr>
<td>$\gamma_5$</td>
<td>0.0789</td>
<td>0.60</td>
<td>1.84</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>-0.0020</td>
<td>0.04</td>
<td>-0.68</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>-0.0007</td>
<td>0.01</td>
<td>-0.94</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td>0.0002</td>
<td>0.02</td>
<td>0.18</td>
</tr>
<tr>
<td>$\gamma_5$</td>
<td>0.0131</td>
<td>0.06</td>
<td>3.19</td>
</tr>
<tr>
<td>$\gamma_6$</td>
<td>0.0891</td>
<td>0.58</td>
<td>2.14</td>
</tr>
</tbody>
</table>

Note: critical value of t-stat: 2.58 (1% level); 1.96 (5% level); 1.65 (10% level)
In conclusion, in this chapter, we find that conditional idiosyncratic risk is positively priced in the cross-section of the REIT returns. Moreover, the significant positive relationship between conditional idiosyncratic risk and the REIT returns is robust to the other three famous risk anomalies, namely size, value and momentum, which means conditional idiosyncratic risk effect is not just picking up the effects of these three factors and investors holding REITs with high idiosyncratic risk can still earn excess returns after adjusting for these three factors. However, once idiosyncratic risk is controlled for in the asset pricing model, the size and value factors cease to be significant. This suggests that these two popular anomalies associated with firm size and value stocks may only be capturing the omitted effects of conditional idiosyncratic risk, which is consistent with the finding of the famous work by Berk (1995). The explanatory power of a third pricing anomaly, namely the momentum effect, remains robust in the presence of idiosyncratic risk. Moreover, the significant role of conditional idiosyncratic risk continues to hold after we add a dummy variable into the regression to control for the effect of different type of REITs, which means idiosyncratic risk effect is robust to different type of REITs. Further, the empirical results also show that the significant role of conditional idiosyncratic risk is robust to the alternative asset pricing model to derive the conditional idiosyncratic risk and categorization of data over different sub-periods.
Chapter 6 Profitability of Idiosyncratic Risk Strategy

Given the empirical regression results that conditional idiosyncratic risk is significantly priced during 1990 – 2005, we will construct idiosyncratic risk trading strategies to see whether we can make profits from this finding. Moreover, momentum factor not only can predict expected REIT returns, but also have significant cross-section relation with conditional idiosyncratic risk, which motivate us to examine the effect of the momentum factor on the idiosyncratic risk profits.

6.1 Profitability of Idiosyncratic Risk Strategy

6.1.1 A Trading Strategy

To form idiosyncratic risk portfolios, at the beginning of each month, all the REITs in our sample will be ranked in ascending order according to conditional idiosyncratic risk of the current month, and then be divided into five equal portfolios. There is a tradeoff between meaningfulness of characteristic-sorted portfolios and the drawback of the portfolio method, which is concealing possible return relevant security characteristics within portfolio averages, pointed by Roll (1977). The more portfolios, the less meaningfulness of characteristic-sorted portfolios, and less drawback of the portfolio method. Chui, Titman and Wei (2003) also point out: “we require at least 21 REITs in any month during our sample period to be meaningful to form characteristic-sorted portfolios. To reach a balance, we divide them into 5 portfolios with 8 to 30 REITs in every quintile. Portfolio 1
(5) is the portfolio of stocks with lowest (highest) conditional idiosyncratic risk. The idiosyncratic risk portfolio we examine is the zero-cost, high-minus-low portfolio (portfolio “5-1”).

These portfolios are equal-weighted because the number of REITs in every quintile is very limited, and the sizes of REITs vary greatly across all these 149 REITs (take December 2005 for example, from 3 to 17213 million), so only one REIT with large size can dominate the mean excess return of that portfolio, which means value-weighted portfolios may change the real relationship between conditional idiosyncratic risk and REIT returns when firm sizes are negatively related to conditional idiosyncratic risks and excess returns. In this research we choose equal-weighted portfolios, which is also comparable to the regression method. And it is also the case when we examine the effects of firm characteristics on idiosyncratic risk profits.

Besides, we choose 12, 24 and 36 months holding periods as our trading strategies because: first, according to Chan, Erickson and Wang (2003), REITs stock market might be less efficient than the common stock market as a whole because historically the behavior of REITs stocks returns has been most similar to that of small stocks and securities analysts are much less likely to follow them; besides, according to Chan, Erickson and Wang (2003), the information on the value of the properties owned by REITs can be difficult to obtain, and even more difficult when a REIT holds a diversified portfolio. The less efficiency of the REIT market suggests that REITs react to the new information more slowly and take a longer period to incorporate the information into their prices, which motives us to choose
longer holding periods of 12, 24 and 36 months. Second, the GARCH model we employed in estimating the conditional idiosyncratic risk has the uniqueness that it uses all the information till time $t$ to estimate the conditional idiosyncratic risk, and the choices of 12, 24 and 36 months holding periods will be more commensurate with the estimation period of conditional idiosyncratic risk than shorter holding periods; last, as professional practice, institutional investors, the main investors in REIT market, will pursue long-term return, which makes our trading strategies more practically meaningful.

To increase the power of our tests, similar to Ang et al. (2006), we construct overlapping portfolios. Take 12 months holding period strategy for example, each month we construct the quintile portfolios based on the conditional idiosyncratic risk of that month; similarly, we form the quintile portfolios based on the conditional idiosyncratic risk of one month prior, and so on up to 11 months prior. We then compute the simple average of these 12 portfolios, hence each quintile portfolio changes $1/12^{th}$ of its composition portfolio.

### 6.1.2 Idiosyncratic Risk Profit

Table 10 reports the profits of a simple idiosyncratic risk strategy, using all the REITs with the means of each quintile portfolios equal-weighted. Panel A reports the idiosyncratic risk profits based on the raw excess returns. From the last column we can find that the differences in raw excess returns between quintile portfolios 5 and 1 have the value of 0.45, 0.44, and 0.41 every month respectively over three different holding periods, which are all statistically significant, indicating that the
average returns of portfolios with high idiosyncratic risk are consistently higher than those of portfolios with low idiosyncratic risk. Moreover, the magnitude of differences in raw excess returns decreases with the length of holding periods.

In addition to the raw excess returns, we also estimate the risk-adjusted returns of the portfolios represented by the alphas of the Fama-French three-factor regression as follows:

\[
R_{t,i} - r_t = \alpha_i + \beta_1(R_m,t - r_t) + s_iSMB_t + h_iHML_t + \epsilon_{t,i}
\]

The risk-adjusted returns are presented in Panel B of Table 10. The results indicate that the risk-adjusted returns of the idiosyncratic risk portfolios are quite similar with the raw excess returns presented in the Panel A of Table 10, with the magnitude and the significance level only slightly decreased. This means the raw excess returns achieved by idiosyncratic risk strategy are not due to other risk factors, at least the Fama-French three factors. Specifically, the risk-adjusted returns achieved by idiosyncratic risk strategies are statistically significant with values of 0.42%, 0.41% and 0.39% every month respectively over three different holding periods. Compared with the momentum profits by Chui, Titman and Wei (2003), the magnitude of our idiosyncratic risk profit is around 40% of their momentum profits. However, as model 9C indicates that idiosyncratic risk and momentum effects both have significant role in explaining the cross-section of REITs returns, when we take both of these two effects into account, we can make larger trading profits than we only trade on momentum effect. This will be explained in detail in the next section.
Table 10: Profits of a Simple Idiosyncratic Risk Strategy

Panel A reports the average monthly excess returns (in percentage) of idiosyncratic risk portfolios, and the numbers in the parenthesis are robust Newey-West (1987) $t$-statistics, which can correct the serial correlation caused by overlapping portfolios. We have three strategies with 12, 24 and 36 months’ holding periods respectively. Portfolios are formed every month, based on the conditional idiosyncratic risk estimated using GARCH-type model. Portfolio 1 (5) is the portfolio of stocks with lowest (highest) expected idiosyncratic risk. The portfolio “5-1” is the zero-cost, high-minus-low portfolio.

Panel B reports the risk-adjusted returns of the idiosyncratic risk portfolios, and the numbers in the parenthesis are robust Newey-West (1987) $t$-statistics. Excess returns of idiosyncratic risk portfolios are regressed on the Fama-French three factors, namely the market factor ($MKTRF$), the size factor ($SMB$) and the value factor ($HML$). The intercepts of the Fama-French three-factor regressions are the risk-adjusted return, which is also called alphas. The sample period is from January 1990 to December 2005.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>1 low</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5 high</th>
<th>5-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 months</td>
<td>0.82</td>
<td>1.06</td>
<td>0.86</td>
<td>0.79</td>
<td>1.27</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>(5.06)</td>
<td>(6.16)</td>
<td>(4.30)</td>
<td>(3.40)</td>
<td>(3.67)</td>
<td>(1.89)</td>
</tr>
<tr>
<td>24 months</td>
<td>0.75</td>
<td>1.00</td>
<td>0.78</td>
<td>0.69</td>
<td>1.18</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>(5.14)</td>
<td>(7.30)</td>
<td>(4.52)</td>
<td>(3.34)</td>
<td>(4.16)</td>
<td>(2.45)</td>
</tr>
<tr>
<td>36 months</td>
<td>0.68</td>
<td>0.96</td>
<td>0.71</td>
<td>0.59</td>
<td>1.09</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>(5.31)</td>
<td>(8.58)</td>
<td>(4.82)</td>
<td>(3.19)</td>
<td>(4.35)</td>
<td>(2.76)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Panel A: Idiosyncratic Risk Profits (Based on Raw Excess Returns)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Panel B: Idiosyncratic Risk Profits (Based on Risk-Adjusted Returns)</td>
</tr>
<tr>
<td></td>
<td>6.1.3 Sub-sample Analysis</td>
</tr>
</tbody>
</table>

Similar to Ang et al. (2006), in this section, we will test the robustness of the idiosyncratic risk profits achieved in Table 10 over different sub-samples, which are reported in Table 11. First, we divided the whole period into two equal
sub-periods (1990 – 1997, and 1998 – 2005) to test the persistence of the idiosyncratic risk profits. Idiosyncratic risk profits have the values of 0.46 and 0.33 respectively in these two period and both are statistically significant. Moreover, consistent with the sub-period regression results in Chapter 5, in the second sub-period, the idiosyncratic risk profits decrease in the magnitude, but increase in the statistical significance level, which means idiosyncratic risk profits are stronger in the second sub-period.

In Chapter 4, we find a counter-cycle pattern of idiosyncratic risk and the asymmetric effect of this property, which motivates us to test the possibility that idiosyncratic risk effects may be due to the asymmetry of return distributions during market cycles: REITs stocks with high idiosyncratic risk may have normal average returns during the up markets, and their high returns may mainly occur during down market periods. We check this hypothesis by examining the idiosyncratic risk profits conditioning on up markets and down markets respectively. Months with positive NAREIT Index returns are allocated to the up market (121 months) while others to the down market (71 months). The empirical investigation indicates that during the up (down) market, the F-F alpha of the high-minus-low portfolio is 0.46 (0.32), and both the F-F alphas of the high-minus-low portfolios in up and down markets are statistically significant at 1% level. This implies that payoffs from the idiosyncratic risk strategy are robust to the overall performance of the market, which is also consistent with Shilling (2003), who finds that real estate investors appear to be no more than uncertain about expected future returns after a decrease in price and fall in return than after an increase in price and return. Moreover, contrary to our hypothesis, the
magnitude and the strength of idiosyncratic risk profits are even larger during the up market, which means investors trading on idiosyncratic risk can earn higher excess return during the up market, and the possible reason is that during the down market REITs investors may experience larger capital losses.

Another potential possibility is that idiosyncratic risk effect is concentrated during the most volatile periods of the REIT market. We test it by computing the FF-3 alphas of the high-minus-low portfolios during the stable and volatile periods, which are the lowest and highest 20% of absolute returns of the NAREIT index respectively. During the stable market, the FF-3 alpha of the high-minus-low portfolio is 0.49 and statistically significant at 1% level; however, contrary to our initial hypothesis, the FF-3 alpha of the high-minus-low portfolio during the volatile market is only 0.26 and not statistically significant. This indicates that assuming more firm-specific risks in an unstable market may not yield any significant abnormal returns to investors adopting the idiosyncratic risk trading strategy. One possible explanation is that during the volatile market, the relative role of market risk is rising, while that of idiosyncratic risk is decreasing.

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5 Similarly, Ang et al. (2006) also find more strong effect of idiosyncratic risk in stable periods than volatile periods; however, they also find significant effect of idiosyncratic risk in volatile periods. And the possible reason is that their research does not control the industry effect and consequently their measure of idiosyncratic risk has more information than ours.
Table 11: Idiosyncratic Risk Effects over Different Sub-samples

The table reports the Fama-French (1992) alphas of 36 months holding period, with robust Newey-West (1987) t-statistics in the parentheses to correct the serial correlation caused by overlapping holding periods. The column “5-1” refers to the difference of FF-3 alphas between portfolios 5 and portfolios 1 with the highest and lowest conditional idiosyncratic risk respectively. The stable and volatile periods refer to the months with the lowest and highest 20% absolute value of the NAREIT index return respectively. The full sample period is January 1990 to December 2005.

<table>
<thead>
<tr>
<th>Sub-periods</th>
<th>Ranking on Expected Idiosyncratic Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 low</td>
</tr>
<tr>
<td>Jan 1990 - Dec 1997</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>(1.58)</td>
</tr>
<tr>
<td>Jan 1998 - Dec 2005</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>(8.00)</td>
</tr>
<tr>
<td>Up Market</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>(6.93)</td>
</tr>
<tr>
<td>Down Market</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>(6.09)</td>
</tr>
<tr>
<td>Stable Market</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>(3.95)</td>
</tr>
<tr>
<td>Volatile Market</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>(3.49)</td>
</tr>
</tbody>
</table>

6.2 Effect of Momentum on Idiosyncratic Risk Profits

We already mentioned in the previous section that since idiosyncratic risk and momentum are both significantly priced in the cross-section of REIT returns, taking both of these two effects into account may generate more trading profits than trading on only one factor. Motivated by this, in this section, we will examine the effect of momentum on idiosyncratic risk profit.

At the end of each month, all REITs are divided into three equal groups based on the momentum and then each of these momentum-sorted groups are further...
divided into three equal groups based on their conditional idiosyncratic risk. As
noted before, there is a tradeoff between meaningfulness of characteristic-sorted
portfolios and the drawback of the portfolio method, which is concealing possible
return relevant security characteristics within portfolio averages, pointed by Roll
(1977). To reach a balance, we employ 3*3 double-sort method with 5 to 17 REITs
in every double-sorted portfolio. Zero-cost high-minus-low idiosyncratic risk
portfolios in each momentum group are constructed. Further, to test the momentum
effect on the idiosyncratic risk, we construct a “momentum-idiosyncratic risk”
portfolio by deducting the idiosyncratic risk portfolio in the small momentum
group from that in the large momentum group, which is reported in the last column
of Table 12. The mean returns of each portfolio are equal-weighted.

Table 12 reports the momentum effect on idiosyncratic risk trading profits, and
only two of these factors are significant in the cross-section regressions.
Idiosyncratic risk trading profits are strongest in the large momentum group, while
in other two groups, idiosyncratic risk trading profits are much weaker. The
zero-cost idiosyncratic risk portfolios of large momentum have significant excess
returns of 1.43%, 1.59% and 1.68% over those of small momentum in three
different holding periods respectively; moreover, these excess returns can not be
explained away by Fama-French three factors, which means momentum has a
significant positive effect on idiosyncratic risk trading profits: REIT stock with
higher past returns can achieve larger idiosyncratic risk trading profits.
Furthermore, the magnitude and strength of this effect are both increasing with the
length of holding periods.
Besides, as can been seen from the last column of Table 12, after taking both idiosyncratic risk and momentum effects into account, the monthly risk-adjusted trading profits are 1.47%, 1.62% and 1.70% respectively over the three different holding periods, which are roughly the sum of our idiosyncratic risk profits and the momentum profits achieved by Chui, Titman and Wei (2003). This suggests that compared with the momentum profits by Chui, Titman and Wei (2003), investors can earn even more excess returns (around 50%) after taking idiosyncratic risk effect into account as well.
Table 12: Momentum Effect on Idiosyncratic Risk Profits

Panel A reports the average monthly excess returns (in percentage) of portfolios sorted first on 12-month lagged returns and then on conditional idiosyncratic risk. Every month, all the REITs are divided into three equal groups, small to large, based on their 12-month lagged returns. Stocks in each group are further divided into three equal groups, low to high, based on their conditional idiosyncratic risk of that month. These portfolios are held for 12, 24, and 36 months respectively and are overlapping portfolios that consists of the portfolios of the previous 11, 23, and 35 months and the current one respectively. The returns of the portfolios are equal-weighted. The idiosyncratic risk portfolios are zero-cost, high-minus-low portfolios. In order to correct the serial correlation in returns induced by overlapping holding periods, the \( t \)-statistics reported in the parenthesis are Newey-West ones. Panel B shows the average monthly risk-adjusted returns (in percentage) of the above double-sorted portfolios. Excess returns are regressed on the Fama-French three-factor, namely the market factor (\( MKTRF \)), the size factor (\( SMB \)) and the value factor (\( HML \)). The intercepts of the Fama-French three-factor regressions are the risk-adjusted return, which is also called alphas. The sample period is from January 1990 to December 2005.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Small</th>
<th>Media</th>
<th>Large</th>
<th>Large minus Small</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 low</td>
<td>3 high</td>
<td>3-1</td>
<td>1 low</td>
</tr>
<tr>
<td><strong>Panel A: Based on Raw Excess Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 months</td>
<td>0.97</td>
<td>0.77</td>
<td>-0.20</td>
<td>0.96</td>
</tr>
<tr>
<td>(3.17)</td>
<td>(4.05)</td>
<td>(-1.05)</td>
<td>(5.09)</td>
<td>(3.24)</td>
</tr>
<tr>
<td>24 months</td>
<td>0.90</td>
<td>0.69</td>
<td>-0.21</td>
<td>0.94</td>
</tr>
<tr>
<td>(4.12)</td>
<td>(4.66)</td>
<td>(-1.82)</td>
<td>(6.96)</td>
<td>(3.12)</td>
</tr>
<tr>
<td>36 months</td>
<td>0.83</td>
<td>0.62</td>
<td>-0.21</td>
<td>0.91</td>
</tr>
<tr>
<td>(4.34)</td>
<td>(5.20)</td>
<td>(-2.03)</td>
<td>(8.27)</td>
<td>(2.97)</td>
</tr>
<tr>
<td><strong>Panel B: Based on Risk-Adjusted Returns</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 months</td>
<td>0.84</td>
<td>0.66</td>
<td>-0.18</td>
<td>0.89</td>
</tr>
<tr>
<td>(2.73)</td>
<td>(3.73)</td>
<td>(-0.92)</td>
<td>(4.56)</td>
<td>(2.53)</td>
</tr>
<tr>
<td>24 months</td>
<td>0.81</td>
<td>0.64</td>
<td>-0.18</td>
<td>0.90</td>
</tr>
<tr>
<td>(3.44)</td>
<td>(4.18)</td>
<td>(-1.40)</td>
<td>(6.14)</td>
<td>(2.40)</td>
</tr>
<tr>
<td>36 months</td>
<td>0.78</td>
<td>0.60</td>
<td>-0.18</td>
<td>0.89</td>
</tr>
<tr>
<td>(3.74)</td>
<td>(4.64)</td>
<td>(-1.63)</td>
<td>(7.36)</td>
<td>(2.28)</td>
</tr>
</tbody>
</table>
In summary, we can make significant profits from the finding in Chapter 5 that conditional idiosyncratic risk is significantly priced in the cross-section of REIT returns. On average, when we hold the zero-cost, high-minus-low idiosyncratic risk portfolio, we can earn 0.42%, 0.41% and 0.39% monthly risk-adjusted (Fama-French three factors) excess returns over 12, 24 and 36 months holding periods respectively. This trading profit is robust to categorization of data over different sub-periods, and different market conditions: up or down, stable or volatile. Further, we also find that momentum have significant positive effect on the idiosyncratic risk profit, and after taking both momentum and idiosyncratic risk into account, we can achieve abnormal profit of about 50% more than the momentum profit by Chui, Titman and Wei (2003).
Chapter 7 Conclusions

Upon doing the empirical analysis of this study, in this chapter, we will conclude this study by highlighting the research objectives and research plans, key findings and possible contribution and policy implications, and limitation of this study and recommendations for the future study.

7.1 Research Objectives

Motivated by the dominant status of idiosyncratic risk in total risk, in the current study, we aim to examine the role of idiosyncratic risk in REIT pricing. Firstly, we seek to track the historic idiosyncratic volatility pattern of individual REIT stocks publicly traded in the US between 1990 and 2005. Secondly, we examine whether conditional idiosyncratic volatility of individual REIT stocks is significantly related to their monthly cross-sectional returns. Finally, we construct trading strategy based on conditional idiosyncratic risk to see whether we can make abnormal profits.

7.2 Key Findings, Possible Contributions and Policy Implications

Our empirical results indicate that although idiosyncratic risk dominates the total risk of individual REIT stocks, idiosyncratic risk of individual REIT stocks has declined over the study period, which is contrary to the findings on the common stock market. This result is not driven by the outliers or the continuous listing of more REITs during the study period. Instead, we give two explanations: first, the
average size of REITs experiences dramatic increase during the study period, and the idiosyncratic risk is negatively related to the REIT size; second, idiosyncratic risk is countercycle, and the REIT market experienced a persistent increase trend from 1990 to 2005.

More importantly, conditional idiosyncratic volatility is a significant factor in explaining the cross-sectional returns of REIT stocks, which suggests that investors are compensated for their inability to hold the market portfolio. The positive relationship between conditional idiosyncratic risk and the cross-section of average REIT returns continue to persist after the inclusion of other asset pricing anomalies, such as size, B/M and momentum effects. It is also robust to alternative asset pricing models used to derive the conditional idiosyncratic volatility of the individual REITs as well as to categorization of data over different sub-periods. Since market risk ceases to be significant since 1960s on common stock market, this study proposes another risk factor, conditional idiosyncratic risk, to improve the understanding of risk-return relationship in REIT industry. To our knowledge, this is the first study to examine the role of idiosyncratic risk in explaining the cross-section of REITs returns.

The evidence that idiosyncratic risk is priced is an important finding of the current study. Whilst this finding is inconsistent with the prescription of CAPM and modern portfolio theory that only market risk matters (because idiosyncratic risk can be completely diversified away), it is consistent with Merton’s (1987) proposition that idiosyncratic risk should be priced because investors often hold under-diversified portfolios (rather than market portfolios) in the presence of
incomplete information. An important implication of this result is that in addition to systematic risk, managers should also consider idiosyncratic risk when estimating the required return or cost of capital on individual stocks or assets. The results also have practical applications for portfolio formation and performance evaluation. As was shown, a portfolio manager could have realized exceptional returns with a strategy that tilts towards stocks with high conditional volatility. This is good news for real estate as an asset class which tends to have high idiosyncratic risk. Similarly, portfolio returns should be benchmarked against returns of portfolios with matching idiosyncratic risk.

Another striking result of our empirical tests is that once idiosyncratic risk is controlled for in the asset-pricing model, the influence of size and $B/M$ on REIT cross-sectional returns become insignificant. The FM regression results show significant small-size and value premium when $ME$ and $B/M$ are used alone or together with market beta to explain REIT returns. However, the observed premium is not robust to the inclusion of idiosyncratic risk in the pricing model. The explanatory power of a third pricing anomaly, namely the momentum effect, remains robust in the presence of idiosyncratic risk. Idiosyncratic risk appears to have absorbed the influence of these two common factors which have become standard in asset pricing models. In their influential paper, FF (1992) propose that size and $B/M$ proxy for risk factors in returns, related to relative earning prospects that are priced in expected returns. Our empirical evidence suggests that the common risk factor proxied by size and $B/M$ may be none other than the omitted conditional idiosynchratic risk in previous asset pricing models. Further, according to Berk (1995), since these size-related variables always explain any unmeasured
risk, they can be used as a measure of how much of the risk premium remains unexplained by the model being tested. In particular, if a specific asset pricing model claims to explain all relevant risk factors, then, at a minimum, it must leave any market value related measure with no residual explanatory power. In our tests, size and book-to-market equity ratio both have no residual explanatory power, therefore, in this sense, our asset pricing model with conditional idiosyncratic risk is well specified. It also provides us another perspective to understand the Fama-French three-factor model. Previous studies which did not include the idiosyncratic risk may be biased.

Finally, we find significant idiosyncratic risk profits, which are not caused by other risk factors, at least Fama-French three factors, namely market, size and value factors. Moreover, this result is robust to categorization of data over different sub-periods, and different market conditional: up or down, stable or volatile. Further, we find significant positive effects of momentum on the idiosyncratic risk profits: idiosyncratic risk effect is stronger for REITs with higher past returns rather than REITs with lower past returns. After taking both momentum and idiosyncratic risk effects into account, we can make 50% more abnormal profits than the momentum strategy by Chui, Titman and Wei (2003).

7.3 Limitations of the Research

Data may be the first limitation of this study as most of other empirical studies. To meet the requirement of the number of REITs for the cross-sectional regression, we choose 1990-2005 as our research sample, which may be not enough to examine
the historical pattern of idiosyncratic risk. Besides, the number of REIT is very limited, especially in the early time of the sample period, which makes the trading strategy of that period not meaningful or efficient.

Second, in this research, we estimate idiosyncratic risk relative to Fama-French three-factor model and CAPM respectively. As is pointed out by Malkiel and Xu (2006), it is very difficult to interpret the residuals from the market model as solely reflecting idiosyncratic risk. One can always argue that these residuals simply represent omitted factors. Therefore, we can only assert that the residuals from a market model measure idiosyncratic risk in the context of that model.

7.4 Recommendations for Future Research

First, as noted in the last section, 16-years sample period may be not enough to examine the historical pattern of idiosyncratic risk. Therefore, we can extend the sample period to reexamine this phenomenon.

Second, according to Chui, Titman and Wei (2003), in the early 1990s, the REIT market expanded considerably, and there was a fundamental change in the REIT market that occurred sometime after 1990, which include the changes in management style, changes in ownership structure, an increased flow of information and the evolution of the umbrella partnership REIT structure. Hence, the industry provides a nice experiment for understanding how changes in the structure of a market can affect the cross-sectional determinants of expected returns. Therefore, it is worthwhile to examine the dynamic role of conditional
idiosyncratic risk in the cross-section of REIT returns.
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Appendix A: Examples of REITs with Low or High Idiosyncratic Risk

Listed below are individual REITs that have consistently been allocated to Q1 (portfolios with low idiosyncratic risk) and Q5 (portfolios with high idiosyncratic risk). The selection is based on the possibility of each REIT that will be allocated to Q1 and Q5 over the sample period. REITs with low idiosyncratic risk have the probability of above 0.5 allocated to Q1, whilst those with high idiosyncratic risk have the probability of above 0.5 allocated to Q5.

<table>
<thead>
<tr>
<th>Name of REITs</th>
<th>Prob</th>
<th>Name of REITs</th>
<th>Prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>WASHINGTON REIT</td>
<td>0.51</td>
<td>THORNBURG MORTGAGE INC</td>
<td>0.51</td>
</tr>
<tr>
<td>ALEXANDRIA R E EQUITIES INC</td>
<td>0.51</td>
<td>CAPITAL TRUST INC/MD</td>
<td>0.55</td>
</tr>
<tr>
<td>LIBERTY PROPERTY TRUST</td>
<td>0.52</td>
<td>JAMESON INNS INC</td>
<td>0.56</td>
</tr>
<tr>
<td>HOME PROPERTIES INC</td>
<td>0.56</td>
<td>AMERICAN COMMUNITY PPTYS TR</td>
<td>0.58</td>
</tr>
<tr>
<td>BRE PROPERTIES -CL A</td>
<td>0.56</td>
<td>DYNEX CAPITAL INC</td>
<td>0.58</td>
</tr>
<tr>
<td>SUN COMMUNITIES INC</td>
<td>0.57</td>
<td>WINTHROP REALTY TRUST</td>
<td>0.59</td>
</tr>
<tr>
<td>EQUITY ONE INC</td>
<td>0.60</td>
<td>INCOME OPPORTUNITY RLTY INVS</td>
<td>0.61</td>
</tr>
<tr>
<td>MID-AMERICA APT CMNTYS INC</td>
<td>0.66</td>
<td>HMG COURTLAND PROPERTIES</td>
<td>0.62</td>
</tr>
<tr>
<td>COLONIAL PROPERTIES TRUST</td>
<td>0.77</td>
<td>CRIIMI MAE INC</td>
<td>0.63</td>
</tr>
<tr>
<td>AMB PROPERTY CORP.</td>
<td>0.82</td>
<td>ISTAR FINANCIAL INC</td>
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</tr>
<tr>
<td>PITTSBURGH &amp; W VA RAILROAD</td>
<td>0.90</td>
<td>CEDAR SHOPPING CENTERS INC</td>
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</tr>
<tr>
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<td></td>
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<td>MERISTAR HOSPITALITY CORP</td>
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<tr>
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<td></td>
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<td></td>
<td>NOVASTAR FINANCIAL INC</td>
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