ESSAYS ON ASSET PRICING AND DOWNSIDE RISK

A THESIS SUBMITTED FOR THE DEGREE
OF DOCTOR OF PHILOSOPHY

Usman Muhammed Umer

Eskişehir, 2017

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Graduate School of Social Sciences
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ABSTRACT

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This dissertation presents three essays on asset pricing and downside risk. The first chapter investigates whether the variation in asset returns can be captured by the association of returns with the conditional risk premia. I propose asset pricing models that distinguish market factor between upside and downside components. The central idea of these models is that investors care differently between downside losses and upside gains, and asset pricing models that distinguish downward market from upward trend appear to characterize investors' risk perception. The finding of the study shows that downside risk is an informative measure of risk, and asset pricing models that characterize the disappointment aversion of representative investors better explains the variation of equities, currencies, bonds, commodities and CDS returns.

The second chapter provides an empirical investigation of momentum in equity and currency markets. Momentum strategy offers higher Sharpe ratio than the market return. However, it exposes to huge crash risk following market rebound. I propose optimal risk management strategy to mitigate momentum crash based on hedging the time-varying risk exposure of momentum then scaling the hedged long-short portfolio by its forecasted semi-variance. This strategy remarkably mitigates momentum crash and provides higher positive returns in the crisis and tranquil periods. Looking at currency markets, huge crash risk is not prevalent in currency momentum. Idiosyncratic risk accounts for the main source of currency momentum risk.

The third chapter examines the existence of idiosyncratic risk premia in stock markets. The relationship between idiosyncratic risk and stock returns is subject to idiosyncratic risk measures. Average stock returns increase monotonically with the increase in the conditional idiosyncratic volatility. However, when one-month lagged idiosyncratic volatility used as a proxy of specific risk, a systematic pattern is not found. The conditional idiosyncratic volatility priced positively in a downside market. The overall result demonstrates that investors require a positive risk premium to hold stocks with high idiosyncratic risk.

Keywords: Risk premia, Downside risk, Momentum, Idiosyncratic risk, Asset pricing.

FINAL APPROVAL FOR THESIS

This thesis titled "**Essays on Asset Pricing and Downside Risk**" has been prepared and submitted by **Usman Muhammed UMER** in partial fullfillment of the requirements in "Anadolu University Directive on Graduate Education and Examination" for the PhD in **Department of Business Administration Program in Finance** has been examined and approved on 13/11/2017

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ÖZET

Doktora Tezi

FİNANSAL VARLIK FİYATLANDİRMASINDA KAYIP RİSKİ VE ÖNEMİ

Usman Muhammed Umer

İşletme Anabilim Dalı
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Anadolu Üniversitesi, Sosyal Bilimler Enstitüsü, Kasım 2017

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Tez çalışması varlık fiyatlama ile aşağı yönlü risk konularıyla ilgili üç araştırmayı içermektedir. Birinci bölümde, varlık getirilerinin koşullu risk primi ile belirlenebilmesi konuları araştırılmıştır. Aşağı yönlü riski ve yukarı yönlü risk unsurlarını içeren faktörlere dayalı varlık fiyatlama modelleri önerilmiştir. Modellerin temel noktası yatırımcıların aşağı yönlü riski ve yukarı yönlü kazançlar arasında farklı görüşlere sahip olduklarıdır. Bu bağlamda; aşağı yönlü ve yukarı yönlü trendleri belirleyen varlık fiyatlama modelleri yatırımcıların risk algılarını yansıtmaktadır. Araştırmanın bulguları; aşağı yönlü riskin, risk ölçütü olarak, bilgi verme özelliği gösterdiğini ve kaybetme korkusundan kaçınmaya yol açan yatırımcı davranışlarının esas alındığı varlık fiyatlama modellerinde pay senetleri, dövizler, tahviller, emtialar ve CDS getirilerdeki değişimi daha iyi açıkladığını göstermektedir.

İkinci bölüm pay senetleri ve döviz piyasalarında momentumun uygulamalı araştırmasını içermektedir. Momentum stratejisi piyasa getirisine göre daha yüksek Sharpe oranları sunmaktadır. Ancak, piyasa geri çekilmelerinde momentum stratejisi yüksek nakit riskine maruz kalmaktadır. Momentum çöküşlerini önleyecek en uygun risk yönetim stratejisi olarak, momentumun maruz kaldığı zaman değişkeni risklerine bağlı olarak hedging yapılması ve ardından semi-varyans öngörülerine bağlı uzun ve kısa pozisyon portföylerinin ölçeklendirilmesi önerilmiştir. Bu strateji, momentum çökmesini önemli ölçüde azaltmakta ve durgun dönemlerde ise daha fazla pozitif getiri kazanıldığı görülmüştür. Döviz piyasalarına bakıldığında momentum stratejisinde nakit riskinin olmadığı görülmektedir. Sistematik olmayan risklerin döviz kuru momentum riskin temel kaynağı olduğu görülmüştür.

Tezin üçüncü bölümünde sistematik olmayan risk priminin pay senedi piyasasında varlığı incelenmiştir. Sistematik olmayan risk ile pay senedi getirileri arasındaki ilişki sistematik olmayan riskin ölçümüne bağlıdır. Koşullu sistematik olmayan volatilitedeki artışla beraber, ortalama pay senetleri de tekdüze şekilde artmaktadır. Ancak, spesifik risk yerine sistematik olmayan volatilitenin bir ay gecikmeli değerleri kullanıldığında sistematik bir ilişki görülmemektedir. Koşullu varlık fiyatlama modellerinde aşağıyönlü riski olası piyasalarda sistematik olmayan volatilitenin pozitif olarak fiyatlandığı görülmüştür. Sonuç olarak, yatırımcılar yüksek sistematik olmayan riske sahip pay senetlerini elde tutmak için pozitif risk primi talep etmektedir.

Anahtar Kelimeler: Risk primi, Aşağı yönlü risk, Momentum, Sistematik olmayan risk, Varlık fiyatlama

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Dedicated to my parents

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby declare that this thesis is my own original work. All the information throughout the stages of preparation, data collection, analysis and presentation of my work has been in accordance with academic rules and ethical principles. I have cited and referenced the sources of all the data and information that could be obtained within the scope of this study and are not original to this work. I declare that this thesis has been scanned for plagiarism with "scientific plagiarism detection program" used by Anadolu University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

Usman Muhammed Umer

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ABBREVIATIONS

APT	Arbitrage Pricing Theory
CAPM	Capital Asset Pricing Model
CDS	Credit Default Swaps
DA	Disappointment Aversion
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
GMM	Generalized Method of Moments
IVOL	Idiosyncratic Volatility
MAE	Mean Absolute Pricing Error
SDF	Stochastic Discount Factor
VARHAC	Vector Autoregressive Heteroskedastic and Autocorrelation Consistent
WML	Winner-Minus-Loser

INTRODUCTION

The pricing of financial assets plays a vital role in the theory of finance and applications. Over the past half-century, it has witnessed considerable developments on how to price assets and determine what kind of risk eventually derive asset returns. Numerous researches attempted to develop distinct theoretical models that helps to understand the pricing mechanism in apparently complex financial markets. One of the first models that illustrates how to price assets was the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966). It links the cross-section of expected returns with the market, which is constant across periods of market upturn and downturns. Subsequent studies challenged the validity and applicability of this model. It led them to relax some unrealistic assumptions to become closer with the reality without drastically affecting the empirical predictions of the model. While others, extend the model by adding new factors and using different risk measures to explain the cross-section of asset returns precisely. Merton (1973) relaxes the single-time period assumption of CAPM with continuous-time framework to initiate the Intertemporal Capital Asset Pricing Model. This model relates the expected return of any asset to several state variables that eventually results a multi-factor model. Ross (1976) also propose Arbitrage Pricing Theory(APT), which claims that in asset pricing of no-arbitrage the expected return of an asset is linearly related to factors risk premia.

In the realm of capital asset pricing model, market is the only risk factor embedded in the asset returns, however the so-called anomaly literatures provide empirical evidence that other factors such as firm size, book-to-market value, momentum, profitability and investment dynamics also influences asset returns. Banz (1981) documents that stocks with lower market capitalization have higher risk adjusted average returns than stocks with higher market capitalization, he named it size effect. Another widely reported anomaly is value effect, stocks with high book-to-market value outperform the return of stocks with low book-to-market ratio (Rosenberg, Reid, and Lanstein, 1984, DeBondt and Thaler, 1985 and Lakonishok, Shleifer and Vishny, 1994). Jegadeesh and Titman (1993) also introduce the existence of momentum in asset returns, which is a tendency of asset's return to stay on its recent relative performance. Subsequently, Fama and French (1993) suggest a three-factor model to explain average returns by extending the basic CAPM to include size and book-to-market factors. In order to capture momentum and other anomalies, Carhart (1997) proposes a four-factor model by allowing the Fama and French three-factor model to incorporate momentum effect. Recently, Fama and French (2015) come with a five-factor model by including profitability and investment dynamics in their three-factor model to explain the variations in average returns.

While risk is considered as an essential deriving force of asset returns, there is no consistent method how to price risk and what kind of risk explain the cross-section of asset returns. Numerous risk proxies have been proposed by researchers to characterize the risk perception of investors. In this regard, the behavioral based approach suggests placing more weight on loss compared with gain to account for investors' loss aversion in the utility function. Loss aversion refers to the tendency of an agent to be more sensitive to loss than gain. The notion of loss aversion plays a central role in the prospects theory of Kahneman and Tversky (1979). They provide empirical evidence that agents place higher weight on loss than gain of the same amount of income. Tversky and Kahneman (1992) estimate the loss aversion coefficient of utility function and find a value close to 2, meaning that the disutility of losing something is twice as great as the pleasure associated with gaining it. Gul (1991) propose axiomatic Disappointment Aversion (DA) framework that allows asymmetric treatment of lottery outcomes where the threshold to the outcomes determined relative to endogenous expected certainty equivalent. Hence, outcomes below the certain equivalent treated as disappointments and receive a greater weight in the expected utility calculation of disappointment-averse individuals. Asset pricing studies based on these theories argues to put greater risk premium on downside risk in the capital market equilibrium.

Asymmetric relationship of asset returns with the market across upside and downside movements have been documented in several literatures. Ang and Chen (2002) reported that the correlation between stocks and aggregate market is much greater when the market moves down than it moves up. They also find greater asymmetric correlations for value, small and past loser firms. Similarly, Hong, Tu, and Zhou (2006) designed a model-free approach to examine the asymmetric dependence between portfolio returns and market. They find evidence of asymmetries for momentum and size portfolios. Moreover, they state the economic importance of considering asymmetries in the investment decision of investors with disappointment aversion preference. Ang, Chen, and Xing (2006) calculate downside and upside beta to characterize the sensitivity of stock returns to market movement. They show that stocks that covary strongly with downside market exhibit higher average returns, which implies that investors require extra premium for holding stocks with higher downside risk. Hence, asset pricing model with downside risk frameworks better explains the variation in stock returns. Lettau, Maggiori, and Weber (2014) also emphasize the importance of asymmetric pricing of upside and downside risk in a conditional market setting. They demonstrate that the downside risk capital asset pricing model better explains the return of multiple asset classes.

This thesis examines the cross-section of asset returns based on the risk perception of investors. It consists of three essays on asset pricing and downside risk. The first chapter investigates the relationship between risk and return, and assesses whether the cross-section of asset returns better explained using asset pricing models that characterize the risk aversion of representative investors. The predominant asset pricing models relates the expected return of an asset with the market risk, which is constant across periods of market upturn and downturns. However, these models may not better characterize the risk perception of the investors. In order to describe investors' perception towards risk, the behavioral based approaches suggest asymmetric treatment of downside risk from upside gain in the market equilibrium. I propose alternative asset pricing models that distinguish market factor between upside and downside components. The central idea of these models is that investors care differently between downside loss and upside gain, and asset pricing models that distinguish downward market from upward trend appear to characterize investors risk perception. I investigate the return of multiple asset classes such as equities, currencies, bonds, commodities and CDS. The efficiency of asset pricing models examined using Fama-MacBeth regressions and GMM approaches.

The second chapter provides empirical investigation of momentum in equity and currency markets. Numerous studies show the profitability of momentum strategy, buying recent winner and selling recent loser assets, in the short-run. However, given the pervasive and outstanding performance of momentum across many markets and asset classes, it exposes to huge crash risk. In this study, I examine the performance of momentum strategy using an extended time span and larger cross-section of currencies and equities. It allows to capture the variation in momentum across time and markets. Furthermore, I propose a novel approach to mitigate the risk of momentum crash. This approach is based on hedging the time-varying risk exposure of momentum then by scaling the hedged long-short portfolio using its forecasted semi-variance. The robustness of this risk management strategy examined relative to the market and other strategies in the tranquil and a period when plain momentum strategy experience worst losses. The risk exposure of currency momentum further investigated by decomposing the risk factor into systematic and idiosyncratic components.

The third chapter explore the existence of idiosyncratic risk premia in the cross-section of stock returns. In the sphere of traditional asset pricing framework, only systematic risk should be incorporated in the asset price and entails risk premium, but the exposure to idiosyncratic risk should not be compensated as it can be avoided in a well-diversified portfolio. This assumption holds if investors are alike and fully-diversify their portfolios. In reality, however, investors may not hold market portfolio for various reasons. Failure of investors to hold market portfolio may lead them to be careful about the firm-specific risk and require risk premium for assets with high idiosyncratic risk. In recent years, empirical findings on the existence of idiosyncratic risk premia in stock returns has revisited the interest of idiosyncratic risk in asset pricing studies. In this paper, I investigate the presence of compensation for holding assets with high idiosyncratic risk using 1000 firms traded in NYSE and NASADQ. A distinguishing feature of this study is that it uses a conditional asset pricing models that incorporates idiosyncratic volatility and other time-varying factors. Hence, the conditional relationship between idiosyncratic risk and stock returns can be captured by the association of returns with conditional market. The incremental impact of idiosyncratic risk on asset reruns also assessed by including idiosyncratic volatility extensions to the traditional asset pricing models. The performance of these models evaluated using Fama-MacBeth regressions.

1. THE CROSS-SECTION OF ASSET RETURNS AND DOWNSIDE RISK

1.1 Introduction

Risk has been widely recognized as the driving force of asset returns. Numerous studies proposed distinct theoretical models to elucidate the pricing mechanisms in apparently complex financial markets. The earliest model that gives mathematical explanation what kind of risk systematically explain asset returns was the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966). This model provides idealized portrayal of how asset price can be estimated by quantifying risk, and it is marked as the foundation of modern asset pricing theory. Despite the fundamental and most influential concepts of CAPM in modern finance, the validity and applicability of the model sparks vigorous debate since its conception. A vast amount of debates relies on how risks measured and what kind of factors persistently drives asset returns. This inspired a vast amount of empirical studies to uncover new risk premia and propose alternative risk measures to explain the variation in asset returns.

Merton (1973) introduce a multifactor Intertemporal Capital Asset Pricing Model and Ross (1976) an Arbitrage Pricing Theory, where the expected return of an asset is a linear function of risk factors. The classic studies of Breeden (1979) and Hansen and Singleton (1983) show how a consumption based asset pricing model can capture asset returns. While, Campbell and Cochrane (2000) explain the poor performance of standard consumption based asset pricing model relative to CAPM using a model with external habit formation. Acharya and Pedersen (2005) also suggests a liquidity adjusted CAPM to explain the cross-section of asset returns, where expected return depends on liquidity risk. Prominent study by Fama and French (1992, 1993) provide a three-factor model by extending the basic CAPM to include size and book-to-market value to explain the patterns of average returns. To capture momentum anomaly, Carhart (1997) augmented a four-factor model by extending the Fama and French three-factor model to incorporate momentum effect. More recently, Fama and French (2015) foreword a five-factor model by adding profitability and investment dynamics in their three-factor model. As for the use of different risk measures, several studies employ various risk proxies, such as downside risk using semi-variance or downside beta, to better characterize investor's preference.

One of the best documented positions of CAPM that are seriously questioned by empirical evidence is the price of market risk, which is constant across periods of market upturn and downturns. Extensive studies on asset pricing suggest the necessity of asymmetric treatment of good and bad market returns through distinguishing between downside and upside betas. Ang, Chen, and Xing (2006) argue that investors who are more averse to downside loss compared with upside gain, demand a premium to hold assets with greater downside risk than upside gain. Because, from investors perspective these assets are considered to be unattractive investment as they generate lower return relative to similar assets that are equally sensitive to the upside and downside market movements. Therefore, in a market where investors care much about downside losses than upside gains, assets with higher sensitivities to downward market tend to have higher average returns. Alternative specifications based on this risk perception of investors challenged the dominance of traditional asset pricing models.

The notion that investors' asymmetric response to upside and downside market movement dates back to Roy (1952) and Markowitz (1959), although it was in 1970s asset pricing models with downside risk were introduced. Roy (1952) argues that the main concern of rational investors is 'safety first', and investors should be more sensitive to downside risk relative to upside gains. Hence, assets that tend to do poorly in a decline markets should have an extra premium more than assets that perform in a similar way in a rising market. Markowitz (1959) advocates semi-variance as a measure of risk than variance, since semi-variance provides a good proxy of downside risk instead of upside gains. Accordingly, asset pricing models based on recognizing risk as the deviation below a certain target rate of return has gain momentum, like the mean-lower partial moment framework of Hogan and Warren (1974).

Behavioral based approaches suggest placing more weight on losses compared with gains in the utility function in order to represent investors' aversion to downside risk. In this regard, the loss aversion prospects theory of Kahneman and Tversky (1979) and the disappointment-averse theory of Gul (1991) provide a theoretical explanation of asymmetric attitudes toward upside and downside risk. The central prediction of disappointment-averse utility function is that asymmetric attitudes towards risk cause individuals to overweight the disutility of a potential loss relative to the positive utility from a potential gain. This utility function places higher weights on disappointing outcomes and suggests a greater risk premium in downside risk.

Earlier studies found little evidence on the explanatory power of downside risk asset pricing models on asset returns. For instance, Jahankhani (1976) reports little improvement of Hogan and Warren (1974) mean-lower partial moment asset pricing model relative to the traditional model in explaining expected returns. However, he does not estimate a downside risk premium using a portfolio arranged for downside risk analysis and the market price of risk is not conditional on the aggregate return of the market. Bawa and Lindenberg (1977) propose an extended form of the CAPM by replacing the regular beta with a downside market beta that measures assets co-movements with a declining market. In the Bawa-Lindenberg's model, the downside risk defined as the deviation below the benchmark return of risk-free rate. Harlow and Rao (1989) argue that defining downside risk as the deviation of asset return below the risk-free rate is not successful in explaining the risk premium of risky investment.

While, recent studies provide empirical evidence on the superior performance of downside risk asset pricing models. Ang, Chen, and Xing (2006) provide extensive evidence on the appealing property of downside risk to predict the asset returns. They show the superiority of downside beta asset pricing model to explain the cross-section of stock returns than the regular beta asset pricing model. Lettau, Maggiori, and Weber (2014) extend the downside risk study to the case of several risky assets and report that the price of market risk is highly conditional on downside market returns than on upside market returns. Hence, high yield assets earn higher average returns than low yield assets since their co-movement with the market is strongly conditional on downside market returns than on upside market returns. Moreover, they note that the variations of betas and risk premia in downside risk capital asset pricing model can capture the cross-sectional return of the underline assets. Dobrynskaya (2014) suggests downside risk as a better measure of risk and high explanatory power of downside risk pricing models in the estimation of currency returns.

This study is distinct from other downside risk researches in two major aspects. First, while several downside risk studies examined the performance of downside risk CAPM there are little or no previous studies, to the best of my knowledge, which empirically investigate the ability of extended downside risk models to explain the cross-sectional variation of asset returns. Second, numerous asset pricing studies examine the performance of asset pricing models using a specific asset group. Therefore, this study expands the spectrum of many of earlier downside risk studies in twofold: First, it assesses whether downside risk is an informative measure of risk, and the cross-sectional variation of asset returns can be captured using extended downside risk asset pricing models that include other risk factors. Second, this study investigates a wider range of asset classes such as equities, currencies, bonds, commodities and CDS. Furthermore, it evaluates the performance of asset pricing models using Fama-MacBeth regressions and GMM-SDF approaches. Beside the theoretical contributions, this study may have important implications in financial applications, such portfolio optimization and risk management.

The remainder of the chapter is organized as follows. Section 1.2 presents modeling framework of asset pricing models. Section 1.3 explains the dataset and portfolio formulation. Section 1.4 discusses the main results. Section 1.5 presents the robustness of findings. Section 1.6 concludes.

1.2 Modeling framework

This section presents the methodological approach and estimation strategies of asset pricing models under consideration. In order to assess whether the variation of asset returns can be explained by the association of returns with the market and other risk factors, the market price of risk allowed to be conditional on upside and downside market movements. Finance literature suggests various methods to characterize and examine the precision of risk premium estimation in a particular asset pricing model. The beta and stochastic discount factor (SDF) representations are the two recognized characterizations of asset pricing models. In beta representation, the expected return of an asset is a linear function of its factor betas, whereas in SDF representation the price of an asset is a function of its future payoffs discounted by the stochastic discount factor (SDF). To evaluate the fit of candidate models in beta representation, the most widely cross-sectional test is the two-pass regression approach of Fama and MacBeth (1973). On the other hand, to examine whether the test asset payoffs are correctly prices by the candidate model in SDF representation, the generalized method of moments (GMM) is the most applicable method.

Both beta and SDF methods are theoretically considered equivalent, while the parameters of interest to represent the factor risk premium under the two setups are different. The SDF representation is constructed to estimate the parameters in the imposed SDF; conversely the parameter of interest in beta method is to estimate the factor risk premium. Kan and Zhou (1999) evaluate the efficiency of estimation using beta and SDF approaches in the context of standardized single factor model, and reports the poor performance of SDF relative to the beta approach. However, Jagannathan and Wang (2002) and Cochrane (2005) argue that SDF method provide asymptotically efficient estimate of risk premium as beta methods in a non-standardized single-factor model. Lozano and Rubio (2011) evaluate the performance of these two methods by extending to multi-factor models, and they documented that the beta method dominate the SDF by producing more precise estimates of risk premium. Garrett, Hyde and Lozano (2011) argue that the choice of estimate and evaluation between the Beta and SDF methods is a choice of efficiency versus robustness. If we are interested in making inference, beta method provides more reliable estimates on multifactor model estimators, whereas if we are primarily concerned in estimating pricing errors SDF method is generally more efficient.

Extensive studies in asset pricing evaluate the precision of risk premium and the associated pricing errors by applying either beta or SDF methods. In this study, however, I apply beta and SDF approaches to investigate whether the variation in expected return across assets can be explained by the association of returns with the conditional market risk premia and other price of risk. In this setting, I examine the efficiency of asset pricing models using Fama-MacBeth regression and GMM approaches.

1.2.1 Asset pricing models

1.2.1.1 Linear beta pricing models

Let r_{it} be the vector of n asset returns in excess of risk-free rate and f_t realized value of risk factors in period t. Using the traditional return-generating process, excess return time-series regression can be generated as

$$r_{it} = a_i + \beta_i' f_t + \varepsilon_{it}, \qquad \mathrm{t} = 1,\ 2,\ldots,\mathrm{T}, \qquad \text{for } \forall i = 1, \ldots, N, \tag{1.1}$$

Where ε_t is the residual or idiosyncratic risk of an asset with zero mean and uncorrelated with the factors f_t. $\beta = \mathrm{cov}\left[r_t, f_t\right]/\mathrm{var}\left[f_t\right]$ is the parameters that measures the factor loading of returns with respect to a set of aggregate risk factors. For multifactor model, the linear regression parameters $\beta = (\beta_{1t} + \cdots + \beta_{Kt})$ and the factor loadings $f_t = (f_{1t} + \cdots + f_{Kt})$. N and T are the number of assets and time-series observations, respectively.

Let μ be the mean of the factors f_t. A beta specification pricing model suggests that the excess return of an asset is a function of its beta with respect to factors loading. The standard asset pricing model under the beta representation given by

$$\mathrm{E}\left(r_i\right) = \beta_i' \lambda \qquad i = 1,\ 2,\ldots,\mathrm{N}, \tag{1.2}$$

Where $\mathrm{E}\left(r_i\right)$ is expected excess return of asset i and λ is the vector of factor risk premia.

According to asset pricing theory, investors are assumed to be risk averse and require premium for holding risky assets. The general idea behind this premise is that investors require higher expected return for investment that demonstrates higher risk. The predominant CAPM asserts that the expected return of an asset is a linear function of its market risk computed by beta. A basic representation of this relationship can be exogenously specified in the following cross-sectional regression

$$\mathrm{E}\left(r_i\right) = \beta_i^m \lambda_i^m \tag{1.3}$$

Where $\beta_i^m = \text{cov}(r_{it}, r_{mt})/\text{var}(r_{mt})$ denotes the market beta coefficient and r_{mt} is the market excess return. The assumption of positive risk-return trade-off for risky portfolio holds when the market excess return or beta coefficient is positive. If the market return is less than risk-free rate, a negative risk premium that is proportional to beta can be inferred, although the test uses realized return instead of expected return.

Fama and French (1992, 1993), elucidate the failure of static CAPM to explain asset returns, and incorporate other variables the model that are supposed to capture the variations in returns. The Fama and French (1993) three-factor model defines the expected return of asset as a function of market excess return, size and value factors. These factors are denoted by m for market risk factor, *smb* ('small minus big') for the size factor and *hml* ('high minus low') for the value or book-to-market factor.

Then, the beta representation of expected return under FF three-factor model can be specified as

$$\text{E}\left(r_i\right) = \beta_i^m \lambda_i^m + \beta_i^{smb} \lambda_i^{smb} + \beta_i^{hml} \lambda_i^{hml} \tag{1.4}$$

The sensitivity of asset returns to market risk, size and value factors are denoted by the beta coefficients of β_{it}^m, β_{it}^{smb} and β_{it}^{hml}, respectively. λ_i^m, λ_i^{smb} and λ_i^{hml} indicates the respective risk premium for market, size and value factors.

Alternative specification, which is a reduced form of basic asset pricing models and embeds the aforementioned characteristic factors, is the Carhart factor model. The Carhart model was proposed by Carhart (1997) by adding the momentum factor in the FF three-factor model. The expected mean excess return in Carhart model expressed as

$$\text{E}\left(r_i\right) = \beta_i^m \lambda_i^m + \beta_i^{smb} \lambda_i^{smb} + \beta_i^{hml} \lambda_i^{hml} + \beta_i^{wml} \lambda_i^{wml} \tag{1.5}$$

Where *wml*('winner minus loser') is a momentum factor.

Recent study by Fama and French (2015) argue that a five-factor model, by including profitability and investment dynamics in the three-factor model of Fama and French (FF hereafter), better explain the variation in average returns. This model exogenously express expected average return using the following cross-sectional regression

$$\mathrm{E}\left(r_i\right) = \beta_i^{m}\lambda_i^{m} + \beta_i^{smb}\lambda_i^{smb} + \beta_i^{hml}\lambda_i^{hml} + \beta_i^{rmw}\lambda_i^{rmw} + \beta_i^{cma}\lambda_i^{cma} \tag{1.6}$$

The difference between the returns on robust and week profitability portfolios denoted by *rmw* ('robust minus week') and the difference between the returns on assets of conservative (small) and aggressive (high investment) firms represented by *cma* ('conservative minus aggressive') factor.

The traditional asset pricing models relates the expected excess return of an asset to market risk, which is constant across periods of market upturn and downturns. By relaxing this assumption, Ang, Chen, and Xing (2006) and Lettau, Maggiori, and Weber (2014) augmented the downside risk CAPM that allows a variation in a market factor conditional on upside and downside market movement.

Ang, Chen, and Xing (2006) propose a downside risk CAPM based on conditional association of returns on market returns. The expected average return in this model specified as

$$\mathrm{E}\left(r_i\right) = \beta_i^{m+}\lambda_i^{m+} + \beta_i^{m-}\lambda_i^{m-} \tag{1.7}$$

$$\beta_i^{m+} = \frac{\mathrm{cov}(r_{it}, r_{mt}|r_{mt} \geq \overline{r}_m)}{\mathrm{var}(r_{mt}|r_{mt} \geq \overline{r}_m)}, \qquad \beta_i^{m-} = \frac{\mathrm{cov}(r_{it}, r_{mt}|r_{mt} < \overline{r}_m)}{\mathrm{var}(r_{mt}|r_{mt} < \overline{r}_m)}$$

Where β_i^{m+} and β_i^{m-} are upside and downside betas defined by an exogenous threshold for the market excess return, which measures asset's co-movement with the market conditional on the market excess return being above and below a threshold. λ_i^{m+} and λ_i^{m-} is the upside and downside market prices of risk, respectively. Ang, Chen, and Xing (2006) use the average market return, $\overline{r}_m$, as a threshold and define the downside event when the market rerun fall below its mean.

To assess whether asymmetric treatment of upside and downside component of market return plays an important role in the estimation of asset returns, I propose a new version of downside asset pricing models that incorporates market and other risk factors. The first specification includes size and value factors in Equation (1.7). This specification can be written as

$$\mathrm{E}\left(r_i\right) = \beta_i^{m+}\lambda_i^{m+} + \beta_i^{m-}\lambda_i^{m-} + \beta_i^{smb}\lambda_i^{smb} + \beta_i^{hml}\lambda_i^{hml} \tag{1.8}$$

The second specification is by adding momentum factor in Equation (1.8), or it can be stated as a modified version of Carhart (1997) model that distinguishes between upside and downside market return

$$\mathrm{E}\left(r_i\right) = \beta_i^{m+}\lambda_i^{m+} + \beta_i^{m-}\lambda_i^{m-} + \beta_i^{smb}\lambda_i^{smb} + \beta_i^{hml}\lambda_i^{hml} + \beta_i^{wml}\lambda_i^{wml} \tag{1.9}$$

The third specification is based on FF five-factor model that allows asymmetric treatment of market risk. This model can be specified as

$$\mathrm{E}\left(r_i\right) = \beta_i^{m+}\lambda_i^{m+} + \beta_i^{m-}\lambda_i^{m-} + \beta_i^{smb}\lambda_i^{smb} + \beta_i^{hml}\lambda_i^{hml} + \beta_i^{rmw}\lambda_i^{rmw} + \beta_i^{cma}\lambda_i^{cma} \tag{1.10}$$

Beside the above specifications, I also derive extended versions of Lettau, Maggiori, and Weber (2014) downside risk asset pricing model. These specifications incorporate other factor attributes in the model and distinguish between unconditional and downside components of market.

Lettau, Maggiori, and Weber (2014) propose a downside risk capital asset pricing model (D-CAPM) in a framework that allows a variation in a market return conditional on market movements. This model can be specified as

$$\mathrm{E}\left(r_i\right) = \beta_i^{m}\lambda_i^{m} + \left(\beta_i^{m-} - \beta_i^{m}\right)\lambda_i^{m-} \tag{1.11}$$

$$\beta_i^{m} = \frac{cov(r_i, r_m)}{var(r_m)}, \qquad \beta_i^{m-} = \frac{cov(r_i, r_{mt} | r_{mt} < \mu_{rm} - \sigma_{rm})}{var(r_{mt} | r_{mt} < \mu_{rm} - \sigma_{rm})}$$

Where β_i^{m} and β_i^{m-} are the unconditional and downside beta. The downside beta defined by an exogenous threshold for the market excess return, which measures asset's co-movement with the market conditional on the market excess return being more or less than one standard deviation below its sample mean. Downside market beta captures the notion of asymmetric exposures to market risk across downside market moves. μ_{rm} and σ_{rm} are sample average and standard deviation of market excess return, respectively. λ_i^{m} and λ_i^{m-} are unconditional and downside market price of risks. In the absence of difference between downside and unconditional market risk, $\lambda^{-} = 0$ or if the downside beta is equals to the CAPM beta, $\beta_i^{m-} = \beta_i^{m}$ then the downside risk capital asset pricing model reduces to CAPM. Ang, Chen, and Xing (2006) defines the downside state cut-off, slightly different, as the market return become below its mean.

The forth asset pricing model which I propose includes size and book-to-market ratio in Equation (1.11). This model can be taken as a modified version of FF three-factor model that distinguish between unconditional and downside market risk. The expected average return in this model estimated as

$$\mathrm{E}\left(r_i\right) = \beta_i^m \lambda_i^m + \left(\beta_i^{m-} - \beta_i^m\right) \lambda_i^{m-} + \beta_i^{smb} \lambda_i^{smb} + \beta_i^{hml} \lambda_i^{hml} \tag{1.12}$$

The fifth specification is by adding momentum dynamics in Equation (1.12). It can also be identified as a modified version of the so called Carhart four-factor model that allows asymmetric treatment between unconditional and conditional market risk. The beta representation of this model written as

$$\mathrm{E}\left(r_i\right) = \beta_i^m \lambda_i^m + \left(\beta_i^{m-} - \beta_i^m\right) \lambda_i^{m-} + \beta_i^{smb} \lambda_i^{smb} + \beta_i^{hml} \lambda_i^{hml} + \beta_i^{wml} \lambda_i^{wml} \tag{1.13}$$

The last asset pricing model which I augmented is a modified version of the FF five-factor model. Like the previous specifications, it distinguishes between unconditional and conditional market excess returns. The expected average return of an asset can be represented in this specification as

$$\mathrm{E}\left(r_i\right) = \beta_i^m \lambda_i^m + \left(\beta_i^{m-} - \beta_i^m\right) \lambda_i^{m-} + \beta_i^{smb} \lambda_i^{smb} + \beta_i^{hml} \lambda_i^{hml} + \beta_i^{rmw} \lambda_i^{rmw} + \beta_i^{cma} \lambda_i^{cma} \tag{1.14}$$

These proposed models emphasize the roles of downside market risk exposure in asset pricing. In this setting, I examine whether distinguishing between upside and downside portion of market risk improves estimation performance of asset pricing models.

1.2.1.2 SDF models

The SDF approach provides a general framework for pricing of securities based on conditional expectation of their discounted payoffs. This method has become popular in finance literatures. As discussed by Campbell (2000) and Cochrane (2005), SDF method is adequately general and flexible that can be used to analysis linear and non-linear asset pricing models by introducing explicit assumptions on pricing kernel and on the payoff distributions for various assets. A general framework of asset pricing with

SDF representation can be written as

$$p_t = E_\text{t}\left[m_{t+1}x_{t+1}\right] \tag{1.15}$$

$$m_{t+1} = f(data, parameters)$$

Where p_t is the current price of an asset, E_t is the conditional expectation operator conditioning on information up to current time t, m_{t+1} is the stochastic discount factor (SDF) or the pricing kernel and x_{t+1} is the random payoff on an asset at time $t + 1$ or tomorrow. The payoff includes asset's price, dividend, interest or other payments received at time $t + 1$. This pricing equation illustrates that today's market value of an asset, under a notion of uncertainty, is the expected payoffs tomorrow multiplied by discount factor in light of the probability of each state of nature. In the absences of uncertainty or for risk-neutral investors, the discount factor become constant to covert the expected payoffs into today's value. Campbell (2000) describes the conditional expectation in equation (1.15) as the probability weighted average. Thus, in a discrete-state setting, the price of an asset can be understood as the probability weighted average of the payoffs, multiplied by the ratio of state price to probability of each state.

If p_t is nonzero in equation (1.15), we can divide the payoff x_{t+1} by p_t to obtain a gross return (R). We can divide through by p_t and pass though the conditional expectation operator to make the derivation more convenient and obtain

$$1 = E_\text{t}\left[m_{t+1}R_{i,t+1}\right] \tag{1.16}$$

Where $R_{i,\ t+1} \equiv \frac{x_{t+1}}{p_t}$ is the gross return on asset i. Here, we can think of return as a payoff that has a price equal to one, if we pay one dollar today how much dollar we get tomorrow. If we work with a zero-cost excess return$(r_{i,t+1} \equiv R_{i,t+1} - R_{f,t+1})$, the fundamental pricing equation can be expressed as

$$0 = E_\text{t}\left[m_{t+1}r_{i,t+1}\right] \tag{1.17}$$

We can derive a linear factor model from SDF representation as $m = b'f$. Since we want a connection with a beta representation based on covariance, it is convenient to hold factors mean constant and for simplicity let us remove the subscript and write $m = a - b'f \sim m = a - b'\text{E}[f] + b'(\text{f-E[f]})$. Where b and f

are K-dimensional vectors, with $E[f]$=0 and hence $E[m] = a$. Since we work with excess returns, $0 = E[mr_i]$, that is the mean of m is not identified and we can normalize a aribitrarly. As Cochrane (2005) shown we can normalize by setting $E[m] = 1$, which implies that

$$m = 1 - b(f - E[f])' \tag{1.18}$$

This representation suggests that SDF is a linear function of the demeaned factors, and is supported by Kan and Robotti (2008).

Using the definition of covariance and equation (1.18), the expected excess returns of asset i

$$\begin{aligned} 0 &= E[mr_i] \\ E[r_i] &= -Cov[mr_i] \\ &= Cov[r_i f'] b \\ &= -Cov[r_i f'] \ (Var[f])^{-1} Var[f] b \\ &= \beta_i{}' \lambda \end{aligned} \tag{1.19}$$

Where $\beta_i = (Var[f])^{-1} Cov[fr_i]$ are the regression coefficients of returns on factors that measures quantity of risk for an asset i relative to the factors and $\lambda = Var[f] b$ are factor risk prices.

1.2.2 Evaluation of asset pricing models

There are many finance literatures on the econometric evaluation of beta and SDF asset pricing models. The traditional or beta method of representing linear factor pricing model relies on regression of returns on factor, and assess whether the variation on returns can be captured on the parameters of the regression model. Another approach that becomes common in recent empirical studies is specifying asset pricing models in SDF framework and estimating these models using GMM method. As discussed by Cochrane (2005), these techniques quest to answer how to test asset pricing models. In this subsection, I discuss how I use Fama-MacBeth and GMM approaches to evaluate linear asset pricing models using their beta as well as SDF representation.

1.2.2.1 Fama-MacBeth method

One of the historically important, simple to implement and still widely used methodology to evaluate asset pricing models is the two stage regression approach of Fama and MacBeth (1973). In this approach, the efficiency of the model to predict the cross-section of asset returns examined by using two stages. In the first stage, the beta of each factor with the corresponding time period t are estimated using a time-series regression as shown below

$$r_{it} = a_i + \beta_i' f_t + \varepsilon_{it}, \qquad \text{t = 1, 2,..., T}, \qquad \text{for } \forall i = 1, \ldots, N, \tag{1.20}$$

Where r_{it} is a vector of n asset returns in excess of risk-free rate at time t and f_t is realized value of risk factors in period t. If the exposure to risk factors capture all variations in expected returns, the intercept in the above regression become zero.

The second stage is to estimate the ex-post risk premia and asset returns using ex-ante betas as explanatory variable in the cross-sectional regression.

$$\mathrm{E}\left(r_i\right) = \widehat{\beta}_i' \lambda + \alpha_{it} \tag{1.21}$$

Where β is the right-hand variable, λ the regression coefficient that measures reward for bearing risk and the error term α_{it} is the pricing errors.

The first stage of Ang, Chen, and Xing (2006) downside risk capital asset pricing model includes two regression equations to estimate the market beta factor for each portfolio using realized return for the upstate and downstate observations.

$$r_{it} = a^{+} + \beta_{it}^{+}\, r_{mt} + \varepsilon_{it}^{+}, \qquad \text{Whenever} \quad r_{mt} \geq \overline{r}_m \tag{1.22}$$

$$r_{it} = a^{-} + \beta_{it}^{-}\, r_{mt} + \varepsilon_{it}^{-}, \qquad \text{Whenever} \quad r_{mt} < \overline{r}_m \tag{1.23}$$

Where β_i^{+} and β_i^{-} are upside and downside beta which measures asset's co-movement with the market conditional on the market excess return being above and below zero.

These two regressions provide a proxy for the upside and downside betas, $\widehat{\beta}_{it}^{+}$ and $\widehat{\beta}_{it}^{-}$, which are used as explanatory variable in the second stage for estimating upside and downside risk premia, λ^{+} and λ^{-}. The resulting second stage cross-sectional regression equation is

$$\mathrm{E}\left(r_i\right) = \widehat{\beta}_i^{m+} \lambda_i^{m+} + \quad \widehat{\beta}_i^{m-} \ \lambda_i^{m-} \tag{1.24}$$

Similarly, the first step regression to estimate beta for each factor in Lettau, Maggiori, and Weber (2014) downside risk capital asset pricing model is using the following two time-series regressions.

$$r_{it} = a_i + \beta_i^{m} r_{mt} + \varepsilon_{it} \tag{1.25}$$

$$r_{it} = a^{-} + \beta_{it}^{-} \ r_{mt} \ + \varepsilon_{it}^{-}, \qquad \text{Whenever} \quad r_{mt} \leq \mu_{rm} - \sigma_{rm} \tag{1.26}$$

Then, the second stage regression specified as

$$\mathrm{E}\left(r_i\right) = \widehat{\beta}_i^{m} \lambda_i^{m} + \left(\widehat{\beta}_i^{m-} - \widehat{\beta}_i^{m}\right) \lambda_i^{m-} \tag{1.27}$$

As shown in Equation (1.21) the cross-sectional regression of average asset return on estimated beta can be expressed as

$$\overline{r_i} = \widehat{\beta}_i' \lambda + \alpha_{it}, \qquad \text{for } \forall i = \ 1, \ 2, \ldots, \mathrm{N}, \tag{1.28}$$

Where $\overline{r_i} = \frac{1}{T}\sum_{t=1}^{T} r_i$ is the arithmetic average return of excess returns, $\widehat{\beta}_i'$ is a vector of estimated betas obtained from the first stage regression and are used as explanatory variable in the second stage cross-sectional regression. The error term α_{it} are the pricing errors.

Following Burnside (2011) the model's fit evaluated using R^2 statistics

$$R^2 = 1 - \frac{\left(\overline{r} - \widehat{\beta\lambda}\right)' \left(\overline{r} - \widehat{\beta\lambda}\right)}{\left(\overline{r} - \ddot{r}\right)' \left(\overline{r} - \ddot{r}\right)} \tag{1.29}$$

Where $\ddot{r} = \frac{1}{T}\sum_{t=1}^{T} \overline{r_i}$ is the arithmetic average return of mean excess returns in the data.

Furthermore, models are tested on the basis of pricing errors. According to Cochrane (2005), factor risk premia λ and pricing error α_{it} are estimate using the average value of cross-sectional regression estimates

$$\widehat{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\lambda}_t, \qquad \widehat{\alpha}_i = \frac{1}{T}\sum_{t=1}^{T}\widehat{\alpha}_{it} \tag{1.30}$$

Fama-MacBeth suggests computing the standard errors for these estimates using the standard deviation of the cross-sectional regression estimates

$$\sigma^2\left(\widehat{\lambda}\right) = \frac{1}{T^2}\sum_{t=1}^{T}\left(\widehat{\lambda}_t - \widehat{\lambda}\right)^2, \qquad \sigma^2\left(\widehat{\alpha}_i\right) = \frac{1}{T^2}\sum_{t=1}^{T}\left(\widehat{\alpha}_{it} - \widehat{\alpha}_i\right)^2 \tag{1.31}$$

Let $\widehat{\alpha}$ denotes as a vector of pricing errors across assets, and $\widehat{\alpha}_t$ stacks all $\widehat{\alpha}_{it}$. The covariance matrix of sampling error can be compute as

$$\text{Cov}\left(\widehat{\alpha}\right) = \frac{1}{T^2}\sum_{t=1}^{T}\left(\widehat{\alpha}_t - \widehat{\alpha}\right)\left(\widehat{\alpha}_t - \widehat{\alpha}\right)'; \qquad \text{where} \quad \widehat{\alpha} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\alpha}_t \tag{1.32}$$

Given its theoretical intuitive appeal, we can evaluate asset pricing model by testing whether the pricing errors are jointly zero or not by

$$\widehat{\alpha}'\text{Cov}\left(\widehat{\alpha}\right)^{-1}\widehat{\alpha} \sim \chi^2_{N-K} \tag{1.33}$$

Fama-MacBeth two stage regression suppose that returns are independent and normally distributed over time. In the presence of serial correlation or heteroskedasticity conditional on the factor component of returns, the standard error of estimated parameters and the associated asset pricing test may not be valid. To mitigate these problems, Shanken (1992) explains how to adjust the standard errors if the return exhibits serial correlation in the factors, whereas Jagannathan and Wang (1998) present an asymptotic theory to deal with conditional heteroskedasticity.

1.2.2.2 GMM method

The GMM approach, which was developed by Hansen (1982), become a reliable and more robust method on empirical researches in asset pricing since it allows serial correlation, conditional heteroskedasticity and non-normal distribution in the return residuals and factors. It provides an elegant way to deal with the problems in two stage regression method. Cochrane (2005) and Burnside (2011) describe the econometric techniques how to apply GMM when testing asset pricing models. The sample moment conditions can be expressed as $E[mr_i] = 0$, when suppressing time scripts. The moment restrictions of a model with constant can be written as

$$E\left(r_{it} - a_i - \beta_i' f_t\right) = 0 \tag{1.34}$$

$$E[\left(r_{it} - a_i - \beta_i' f_t\right) f_t'] = 0 \tag{1.35}$$

$$E\left(r_{it} - \delta - \beta_i' \lambda\right) = 0 \tag{1.36}$$

Where a and β are a vector of constants[1] and factor loading for N test assets in the time-series regression that are exactly identified in the top two moment conditions. λ is factor risk prices that is identified by the third group of moment, the asset pricing model, in the GMM procedure.

The last momentum restriction of a model in the absence of constant as

$$E\left(r_{it} - \beta_i' \lambda\right) = 0 \tag{1.37}$$

Estimation of asset pricing model in the GMM method can be done using the following moment conditions:

$$E\left\{r_t\left[1 - (f_t - E[f])' b\right]\right\} = 0 \tag{1.38}$$

$$E\left(f_t - E[f]\right) = 0 \tag{1.39}$$

The moment conditional which allows pricing error across assets can be written as

$$E\left\{r_t\left[1 - (f_t - E[f])' b\right] - \varphi\right\} = 0 \tag{1.40}$$

When identity matrix used to weight the moment, the GMM estimate results the so called first stage estimate, where the pricing errors are identical to the second stage regression in Fama-MacBeth method. The first stage estimate assumes no serial correlation and the regression errors are independent of right-hand explanatory variables. Hence, to produce

[1] The intercept a is not necessarily equal to the pricing error α in the cross-sectional regression.

equivalent result with Fama-MacBeth estimates, I use first-stage estimate of GMM. To mitigate the possibility of serial correlation in errors terms and draw more accurate inference from estimated parameters, the GMM errors are constructed using VAR heteroskedasticity and autocorrelation consistent (HAC) or VARHAC procedure of Haan and Levin (2000). Estimation of asset pricing models are following Burnside (2011).Cochrane (2005) also presents detail procedure on how to apply Fama-MacBeth and GMM methods to evaluate asset pricing models.

1.3 Data

One of the distinguishing features of this study from previous researches is that it investigates multiple asset classes, such as equities, currencies, bonds, commodities and CDS. Furthermore, it examines the robustness of results to a combination of broad range of asset categories.

For equities, I examine the cross section of equity returns using 25 value-weighted equity portfolios formed on size and book-to-market value. These portfolios are constructed as an intersection of five portfolios formed on size and five portfolios formed on the ratio of book-to-market equity. In addition, I test 6 value-weighted equity portfolios formed on size and momentum, which is constructed as an intersection of 2 portfolios formed on size and 3 portfolios formed on prior returns. All these equity portfolios include stocks listed in NYSE, AMEX and NASDAQ. The data are obtained from Fama and French data library[2] and covers the sample period from January 1975 to May 2016.

As for currency, I use spot and one month forward exchange rate against the US dollar to construct bilateral foreign currency excess-returns for a sample of 38 countries: Austria, Belgium, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Israel, Italy, Japan, Kuwait, Mexico, Norway, Philippines, Poland, Portugal, Qatar, Russia, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey and United Arab Emirates. An increase in the foreign exchange rate means a depreciation of the respective currency against the US dollar; the opposite is also true when foreign exchange rate decreases. The data is monthly and cover the period from March 1997 to May 2016. It should be

[2]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

noted that the availability of data for some of these currencies varies over the course of the sample, for instance forward exchange rate are unavailable for some currencies starting from 1997. Thus, I exclude the time period if there is partly exchange rate data and only keep the series both spot and forward exchange rates are available. All data are collected from WM/Reuters and Barclays International Bank (BIB) via Datastream.

Instead of assessing individual currency excess returns, I form different sets of sorted currency portfolios. Following Lustig and Verdelhan (2007) and Burnside (2011) I construct 10 equally weighted portfolios composed of currencies sorted on the basis of their respective forward discount, which is equivalent to sorting on interest rate differentials relative to the US dollar. Currencies are ranked from small to large forward discount and the portfolios re-balance at the end of each month. Portfolio 1 contains those currencies with the smallest forward discounts (the lowest interest rate); the next portfolio 2 composed of the next smallest forward discount basket of currencies, and so on until portfolio 10 which consists of currencies with the largest forward discount (the highest interest rate).

For commodities, I use a set of 24 commodity future portfolios composed of energy products, agricultural crops, live stocks and metals for the period from February 2002 to September 2012. As for the cross-section of US bonds I use ten government bond portfolios sorted by maturity and ten corporate bond portfolios sorted on yield spreads in the same class from January 1975 to December 2012. In order to reduce commonalities and the sensitivity of my findings to the choice of test asset, I also examine 20 credit default swaps (CDS) portfolios sorted by spread using 5-year contracts for the period from February 2001 to December 2012. All commodities, US bonds and CDS portfolios are obtained from He, Kelly, and Manela (2017)[3].

1.4 Empirical results

This section presents the result of asset pricing test for multiple asset categories. Before proceeding to the estimation of asset pricing models, I carry out a simple investigation of candidate factor variables. Table 1.1 reports the descriptive statistics of factor portfolios namely, excess returns on the market (MKT), SML ('small minus big'), HML ('high minus low'), WML

[3]http://apps.olin.wustl.edu/faculty/manela/data.html

(‘winner minus loser’), RMW (‘robust minus week’) and CAM (‘conservative minus aggressive’). These variables represent market, size, value, momentum, profitability and investment factors, respectively. Excess returns on market are computed as the market return minus one month government Treasury bill rate. The result of descriptive statistics shows that market excess return and momentum factors have higher mean return with the corresponding higher standard deviations. Conversely, size and investment factors have lower mean returns. The Sharpe ratio, which measures how much return an asset yields for each unit of volatility, varies between 0.15 and -0.05 on market excess return and investment factor, respectively. Beside the market, momentum factor achieved a positive Sharpe ratio of 0.05 when others have a negative mean return after adjusting for volatility. The Pearson correlation result shows that market factor positively correlated with size, and negatively with value, momentum, profitability and investment factors. High correlation found between value and investment, and low correlation between momentum and investment factors.

Table 1.1: *Descriptive statistics of factor portfolios*

				Correlation					
Variable	**Mean**	**Std.dev**	**Sharpe**	**MKT**	**SML**	**HML**	**WML**	**RMW**	**CMA**
MKT	1.06	4.47	0.15	1					
SML	0.27	2.97	-0.04	0.24	1				
HML	0.32	2.89	-0.02	-0.25	-0.10	1			
WML	0.62	4.42	0.05	-0.11	0.04	-0.22	1		
RMW	0.31	2.36	-0.03	-0.30	-0.41	0.20	0.11	1	
CMA	0.29	1.95	-0.05	-0.37	-0.06	0.68	0.00	0.10	1

Asset pricing model need to correctly capture the variation in betas and risk premia to explain the cross-section of returns. The CAPM argues the existence of interdependence between mean return and market beta. It claims that assets which strongly covary with the market tend to have high average returns. Hence, a systematic pattern should be demonstrated between the return and market beta. Figure 1.1 depicts the relationship between risk and return using the mean excess return and estimated betas from equity and bond portfolios. Beside the regular beta β, I compute upside and downside betas, β^{+}, β^{-}, following Ang, Chen, and Xing (2006) to explore the linkage between average return and market risk conditional on market rise and decline. A relative downside beta ($\beta^{-} - \beta$) also computed to examine the difference between downstate and unconditional beta.

The left top panel of Figure 1.1 shows asset's mean excess return against regular beta. There is no consistent pattern between regular beta and mean excess returns across assets. This implies that a change in mean excess return is less associated with regular beta, in contrast with the CAPM premise.

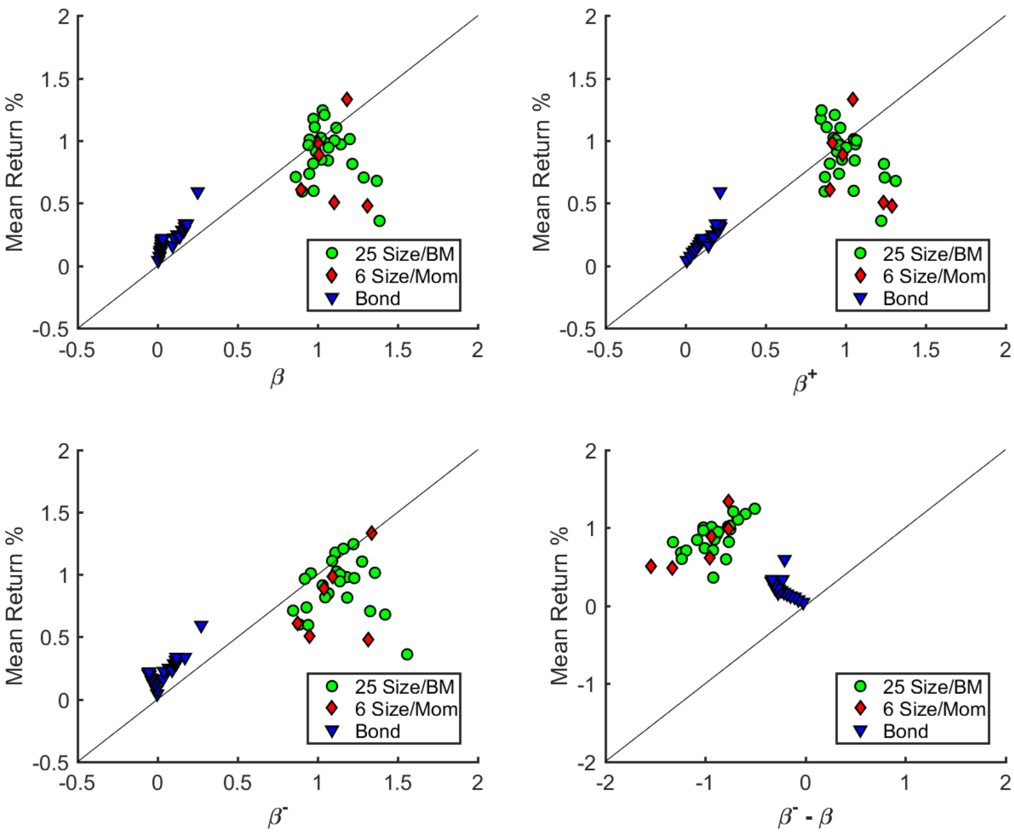

Figure 1.1: *Risk versus returns: equities and bonds*

The figure shows OLS estimate of realized mean excess returns versus betas to illustrate the risk-return relationship for equity and bond portfolios. β denotes the CAPM beta, β^{+} upside betas, β^{-} downside betas and $(\beta^{-} - \beta)$ are relative downside betas.

To examine whether distinguishing beta between market upturn and downturn better explain asset returns, I compute upside and downside betas for each portfolio. The top right panel of Figure 1.1 plots mean excess return of each portfolio against upside beta. It is evident that using upside beta as a measure of risk does not improve the relationship between market risk and average returns. I plot the relationship between mean excess return and downside beta in the bottom left panel of Figure 1.1. The result exhibits a slight improvement in the risk and return relationship of equity portfolios. The bottom right panels of Figure 1.1 illustrate the risk-return pattern by depicting the mean excess return against relative downside beta$(\beta^{-} - \beta)$, which measures additional impact of downside beta over regular beta. The plot prevails that the link between average return and relative downside beta is negative. This implies an increase in average return is associated with a contemporaneous decrease in relative downside beta.

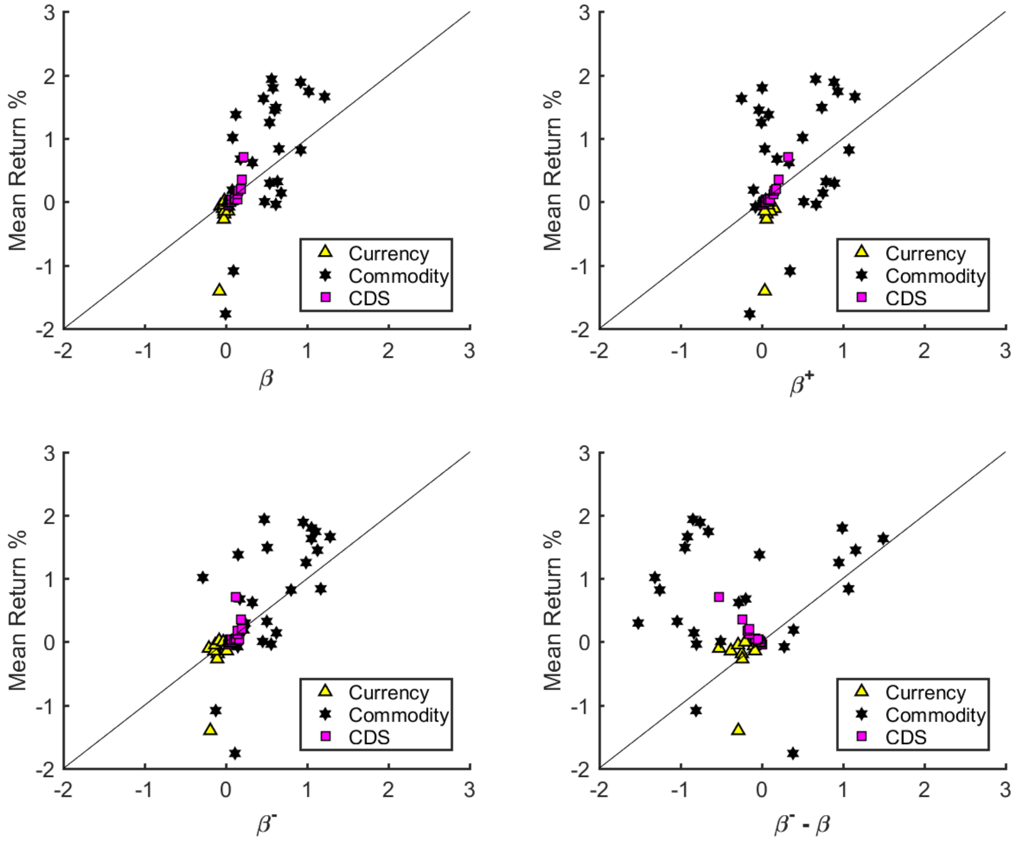

Figure 1.2: *Risk versus returns: currencies, commodities and CDS*

The figure shows OLS estimate of realized mean excess returns versus betas to illustrate the risk-return relationship for currency, commodity and CDS portfolios. β denotes the CAPM beta, β^+ upside betas and β^- downside betas and $\beta^- - \beta$ are relative downside betas.

Additionally, I investigate the relationship between mean excess return and market beta using currency, commodity and CDS portfolios, and the results are shown in Figure 1.2. The top left panel of Figure 1.2 shows the absence of clear relationship between average returns and regular beta. This confirms the failure of CAPM to explain asset returns as shown in Figure 1.1. Similarly, the top right panel of Figure 1.2, which depicts the relationship between average return and upside beta, reveals that average excess returns are not meaningfully related with upside beta. While, this finding infers the irrelevance of upside beta to explain asset returns, it cannot support the evidence of failure of CAPM beta to price asset reruns. Because, portfolios that have higher regular beta also prevails higher upside beta.

I plot asset's average return against downside beta in the bottom left panel of Figure 1.2. A slight positive relation is visible between downside beta and average commodity reruns, which implies that portfolios with higher exposure to downside beta tend to have higher average returns. As for currency and CDS portfolios, association of returns with the market conditional on downstate does not alter the dynamics. The right panel in the bottom row of Figure 1.2 depicts mean excess returns versus relative downside beta. It shows that relative downside beta decreases with the increase in average returns of most portfolios. The results in Figure 1.1 and 1.2 demonstrate that downside beta better capture average return of assets than regular or upside betas.

Next, empirical estimation of asset pricing models are performed for several test assets namely, equity, currency, bond, commodity and CDS portfolios.

1.4.1 Equity portfolios

My investigation of risk premia begins with presenting the estimation result of asset pricing models. Table 1.2 reports the test results of asset pricing models based on 25 equity portfolios sorted on size and book-to-market ratio. To make model comparisons easy, I present all models under consideration in one table. The statistical significance of coefficients and pricing errors are evaluated using standard errors computed by applying VARHAC procedure. As a rule of thumb, if the absolute value of a coefficient or pricing errors that is twice as large as standard error considered as statistically significant at 5% level.

In evaluating model fit, it becomes more meaningful comparing asset pricing models that have the same information in addition to comparing asset pricing models in a similar category. For instance, comparing among CAPM, downside risk CAPM of Ang, Chen, and Xing (2006) and the downside risk CAPM of Lettau, Maggiori, and Weber (2014). Even though, both Ang, Chen, and Xing (2006) and Lettau, Maggiori, and Weber (2014) downside risk CAPM have two factors, the only information require to create these factors is market return. Moreover, in the absence of agent's disappointment or risk aversion, the CAPM become a restrictive version of the downside risk capital asset

Table 1.2: *Estimation of linear factor models: 25 equity portfolios*

	CAPM	**FF3F**	**CHRT**	**FF5F**	**ACX**	**SpecI**	**SpecII**	**SpecIII**	**LMW**	**SpecIV**	**SpecV**	**SpecVI**
$\widehat{\boldsymbol{\lambda}}^{m}$	0.82	0.64	0.76	0.61					1.87	-0.75	0.70	0.01
	(0.21)	(0.20)	(0.27)	(0.23)					(0.96)	(0.76)	(0.22)	(0.66)
$\widehat{\boldsymbol{\lambda}}^{m-}$									1.09	-1.31	-0.48	-0.58
									(0.83)	(0.65)	(1.27)	(0.53)
$\widehat{\boldsymbol{\lambda}}^{m+}$					-0.19	1.78	1.28	1.17				
					(0.44)	(0.56)	(0.87)	(0.38)				
$\widehat{\boldsymbol{\lambda}}^{m-}$					0.94	-1.20	-0.56	-0.59				
					(0.46)	(0.58)	(0.88)	(0.38)				
$\widehat{\boldsymbol{\lambda}}^{smb}$		0.28	0.26	0.35		0.34	0.31	0.36		0.34	0.29	0.37
		(0.13)	(0.17)	(0.13)		(0.15)	(0.16)	(0.13)		(0.16)	(0.16)	(0.15)
$\widehat{\boldsymbol{\lambda}}^{hml}$		0.39	0.39	0.29		0.37	0.38	0.31		0.39	0.40	0.31
		(0.14)	(0.28)	(0.17)		(0.18)	(0.28)	(0.19)		(0.14)	(0.14)	(0.14)
$\widehat{\boldsymbol{\lambda}}^{mom}$			3.54				2.70				3.01	
			(0.91)				(1.06)				(1.05)	
$\widehat{\boldsymbol{\lambda}}^{rmw}$				0.32				0.25				0.30
				(0.23)				(0.25)				(0.25)
$\widehat{\boldsymbol{\lambda}}^{cma}$				0.26				0.30				0.30
				(0.23)				(0.24)				(0.22)
$\mathbf{R}^2$	-0.60	0.39	0.70	0.59	-0.47	0.56	0.78	0.63	-0.51	0.49	0.74	0.61
MAE	0.19	0.12	0.08	0.10	0.17	0.11	0.07	0.10	0.18	0.12	0.08	0.10
χ^2**-test**	101.70	90.13	34.46	75.79	79.75	46.29	29.73	61.90	73.09	55.30	27.11	56.62
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)

The table reports risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model(CHRT) and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications(Spec). Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 25 Fama-French equity portfolios sorted by size and book-to-market value. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

pricing models. Likewise, FF three-factor model has to be compared with specification I and specification IV, and Carhart model with Specification II and Specification V, beside overall model's comparison.

The left section of Table 1.2 shows the estimation results of conventional asset pricing models. The first model is the CAPM. While, the market risk premia is statistically significant, the R^2 statistics of the model is negative (-60%) and the mean absolute pricing error is quite substantial, that is 0.19% per month. Moreover, the χ^2-test rejects the null hypothesis that the pricing errors are jointly zero. This result illustrates the failure of CAPM to capture the returns of 25 equity portfolios sorted by size and book-to-market ratio, which is in line with the previous studies. The FF three-factor model performs relatively well with significant factor price of risks, albeit the R^2 value is small and the pricing error is still large.

The Carhar model which includes momentum factor better explains the return of 25 equity portfolios. The R^2 value increase to 70%, the MAE fall to 0.08%. Moreover, the performance of FF five-factor model is relatively good compared to CAPM and FF three-factor models. It provides modest fit with R^2 value of 60% and the mean absolute pricing error of 0.1%. However, The χ^2-test rejects the null of all four models at 5% level of significance, which indicates that the pricing errors of these models are statistically different from zero.

The next section of Table 1.2 shows estimation result of Ang, Chen, and Xing (2006, ACX) downside risk asset pricing model and extended specifications. ACX downside risk model shows a negative R^2 estimate of -46%, hence the model has no explanatory power of equity returns. Asymmetric treatment of upside and downside market risk does not bring significant improvement to the CAPM. The model is also rejected by the χ^2-test.

As can be seen from the table, the first specification constructed by including size and value factors in ACX downside risk model. This model amends the FF three-factor model to allow for asymmetries across upside and downside markets. Even though, Each factor prices of risk are statistically significant and the R^2 increase to 55%, the mean absolute pricing error barely decreases and the test of pricing errors rejects the null hypothesis. The second specification, which incorporates momentum factor, explains around 78% of the cross-sectional variation of returns. The MAE is 0.07%, which is fairly low. Moreover, the χ^2-test of this model fails to reject the null hypothesis that pricing errors are jointly zero. The third specification in this category can be interpreted as the modified version of FF five-factor model that splits market factor into upside and downside components. This model improves the explanatory power of FF five-factor model, while the pricing error test rejects the model.

The result of Lettau, Maggiori, and Weber (2014, LMW) downside risk model and extended specifications are displayed in the right section of Table 1.2. The LMW model basically does not explain the variation in equity returns, as indicated by a negative R^2(-51%), large MAE and statistically

Table 1.3: *Estimation of linear factor models: 6 equity portfolios*

	CAPM	FF3F	CHRT	FF5F	ACX	SpecI	SpecII	SpecIII	LMW	SpecIV	SpecV	SpecVI
$\widehat{\lambda}^{m}$	0.73	0.79	0.71	0.50					3.48	5.17	0.97	27.42
	(0.21)	(0.21)	(0.21)	(0.41)					(1.76)	(3.50)	(0.42)	(143.90)
$\widehat{\lambda}^{m-}$									2.74	4.24	4.84	25.75
									(1.70)	(3.34)	(6.86)	(137.73)
$\widehat{\lambda}^{m+}$					-1.02	-1.62	2.40	11.49				
					(0.82)	(1.52)	(1.46)	(39.99)				
$\widehat{\lambda}^{m-}$					1.70	2.45	-1.79	-10.90				
					(0.79)	(1.59)	(1.49)	(39.79)				
$\widehat{\lambda}^{smb}$		0.29	0.27	0.60		0.17	0.39	1.13		0.11	0.08	-1.06
		(0.17)	(0.14)	(0.79)		(0.17)	(0.18)	(2.19)		(0.21)	(0.37)	(9.13)
$\widehat{\lambda}^{hml}$		-1.10	0.54	-2.00		0.10	0.81	0.82		0.11	0.04	-1.44
		(0.42)	(0.29)	(2.38)		(0.58)	(0.44)	(12.53)		(0.68)	(0.93)	(13.13)
$\widehat{\lambda}^{mom}$			0.60				0.60				0.60	
			(0.20)				(0.34)				(0.23)	
$\widehat{\lambda}^{rmw}$				2.99				-2.35				1.55
				(2.48)				(19.80)				(17.36)
$\widehat{\lambda}^{cma}$				-3.13				10.82				-12.16
				(3.01)				(49.37)				(59.13)
$\mathbf{R}^2$	-0.13	0.30	0.83	0.92	0.54	0.73	0.87	1.00	0.61	0.86	0.86	1.00
MAE	0.28	0.20	0.11	0.08	0.16	0.15	0.10	0.00	0.15	0.11	0.11	0.00
χ^2**-test**	49.16	35.14	18.10	1.15	16.43	9.31	6.05	899.46	10.36	2.70	1.72	5215.79
	(0.00)	(0.00)	(0.00)	(0.28)	(0.00)	(0.01)	(0.01)	(0.00)	(0.04)	(0.26)	(0.19)	(0.00)

The table reports risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model(CHRT) and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications(Spec). Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 6 Fama-French equity portfolios sorted by size and momentum. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

insignificant factor prices of risk. The next augmented model that include size and value factors, provides a substantial improvement to the LMW downside risk CAPM and FF three-factor model. The goodness-of-fit is relatively modest (49%). The result in the fifth specification is substantially better when momentum factor included. The R^2 value increase to 74% and the MAE fall to 0.08%, moreover the model passes the χ^2-test, that the pricing errors are not statistically different from zero. The last pricing model in Table 1.2 transforms the FF five-factor model to treat market upturn and downturn separately. The estimation result reveals that this specification has a similar fit with the FF five-factor model.

Table 1.3 presents estimation result of asset pricing models for 6 equity portfolios sorted on size and momentum. The CAPM performs badly to explain the cross-section of equity returns. FF three-factor model also provide a relatively small fit to explain the variation in returns. The R^2 value is small and the MAE is large. As for Carhart model, the result substantially improves the previous two models. The R^2 estimate raises to 83% and the MAE fall to 0.11%. The χ^2-test of these models shows that the pricing errors are different from zero. The momentum factor is the key reason behind Carhart model's high goodness-of-fit. The FF five-factor model do a good job in explain the variation in equity returns. It provides a considerable improvement in the model fit (92%) relative to other conventional asset pricing models. The MAE is quite low and the p-value of χ^2-test confirms that these pricing errors are jointly zero.

The risk premia estimate of Ang, Chen, and Xing (2006, ACX) downside risk capital asset pricing model shows that asymmetric treatment of market return better price the cross-section of equity returns relative to CAPM. Similarly, the first and second specifications which treats upside and downside market return separately substantially improves the explanatory power. The R^2 on these models are 73% and 87%, as compared to 30% and 83% for FF three-factor and Carhart models, respectively, while the pricing error test rejects the null hypothesis. The result of the third specification seems surprising as the R^2 is 100%. However, most likely such very high value of R^2 occurs due to sampling error. The pricing errors test also rejects the null hypothesis.

The downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) is much more successful that the CAPM and the downside risk CAPM of Ang, Chen, and Xing (2006). The MAE is 0.15% and the R^2 estimate is 61%. The prices of conditional and unconditional market risks are positive but not statistically significant. The χ^2-test rejects the model at 5% significance level. The fourth specification better explains the cross-section of equity return than FF three-factor model and the first specification. The fifth specification has very similar fit with the forth specification, with the mean absolute pricing error of 0.11% and R^2 estimate of 86%. The pricing errors of these models are not different from zero. The last column of Table 1.3 reports an estimate of a modified version of FF five-factor model which treat unconditional and downside market risk asymmetrically. Similar to the third specification the mean absolute pricing error is 0% and R^2 value is 100%. However, the pricing error test strongly rejects the model.

The result of asset pricing tests using 25 equity portfolios sorted by size and book-to-market show that the second specification better explains the cross-section of equity returns. As for 6 equity portfolios sorted by size and momentum, specification four and five do a good job based on model's fit combined with pricing error test. Asymmetric treatment of upside and downside market risk improves the explanatory power of conventional asset pricing models. The result is consistent across all proposed asset pricing specifications. I investigate further whether this finding is appealing in other asset classes too.

1.4.2 Bond portfolios

Table 1.4 presents assets pricing model estimations using 20 bond portfolios. The CAPM shows a slight improvement, with explanatory power of 44%. The market risk premia remains positive and statistically significant. However, the MAE is relatively high as compared to other models and the χ^2-test strongly rejects the model. The FF three-factor and Carhart models explain a significant portion of the variation in risk prmia. They have similar mean absolute pricing error of 0.04% and R^2 estimate of 78%. The χ^2-test illustrates that the pricing errors of these models are not statistically different from zero. The FF five-factor model has the highest coefficient of determination, 84%, relative other conventional models, although the pricing error test rejects the model.

The estimation result of Ang, Chen, and Xing (2006, ACH) downside risk model reveals that the model explains 70% of the variation in average returns, which is 26% more than that of CAPM. The mean absolute pricing error is 0.05% and the χ^2-test indicates that these pricing errors are jointly different from zero. The first and second specification of asset pricing models adds more light on the explanation of the cross-section of bond returns compared with FF three-factor and Carhart models. The mean absolute pricing error on these model drops to 0.02% and R^2 value rises to 93%. While, the pricing error test strongly rejects the null of both specifications. The third asset pricing specification offer the biggest fit than other asset pricing models, with R^2 estimate of 96%. The mean absolute pricing error is 0.02%, but the model does not pass the χ^2-test.

Table 1.4: *Estimation of linear factor models: 20 bond portfolios*

	CAPM	FF3F	CHRT	FF5F	ACX	SpecI	SpecII	SpecIII	LMW	SpecIV	SpecV	SpecVI
$\widehat{\lambda}^{m}$	2.09	-0.69	-0.50	1.46					1.67	-2.25	-0.12	-0.99
	(0.62)	(1.59)	(1.74)	(1.32)					(0.85)	(2.17)	(1.89)	(2.31)
$\widehat{\lambda}^{m-}$									-0.08	-2.08	-2.04	-2.02
									(0.69)	(1.07)	(1.25)	(1.34)
$\widehat{\lambda}^{m+}$					1.57	1.42	1.45	2.29				
					(0.58)	(0.83)	(0.86)	(1.08)				
$\widehat{\lambda}^{m-}$					0.22	-1.38	-1.27	-1.00				
					(0.40)	(0.81)	(0.79)	(0.80)				
$\widehat{\lambda}^{smb}$		-1.44	-1.06	-0.30		0.89	1.13	0.86		1.02	1.12	0.83
		(1.61)	(2.17)	(1.35)		(1.21)	(1.74)	(1.32)		(1.36)	(2.56)	(1.62)
$\widehat{\lambda}^{hml}$		4.71	4.62	1.07		1.97	1.92	0.02		2.31	2.29	0.28
		(2.38)	(2.41)	(2.07)		(2.12)	(2.18)	(2.27)		(2.24)	(2.83)	(2.54)
$\widehat{\lambda}^{mom}$			-0.67				-0.47				-0.72	
			(3.09)				(2.21)				(3.98)	
$\widehat{\lambda}^{rmw}$				2.55				0.50				0.12
				(1.48)				(1.40)				(1.67)
$\widehat{\lambda}^{cma}$				1.34				1.59				2.15
				(1.46)				(1.25)				(1.58)
$\mathbf{R}^2$	0.44	0.78	0.78	0.84	0.70	0.93	0.93	0.96	0.68	0.91	0.91	0.95
MAE	0.07	0.04	0.04	0.04	0.05	0.02	0.02	0.02	0.06	0.03	0.03	0.02
χ^2-**test**	72.35	25.06	26.27	34.80	68.79	41.34	41.35	27.84	43.05	36.15	26.24	19.14
	(0.00)	(0.09)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.04)	(0.16)

The table reports risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model(CHRT) and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications(Spec). Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 20 bond portfolios. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

The last section of Table 1.4 presents the Lettau, Maggiori, and Weber (2014, LMW) downside risk capital asset pricing model and other augmented specifications. In the test with bond portfolios LMW model performs well relative to the CAPM. It has a goodness-of-fit of 68%. While, the fourth and fifth specifications have R^2 value of 91%, and the mean absolute pricing error of 0.03% per month. However, the pricing errors test rejects the null of both models. The last column reports an estimate of a modified version of FF five-factor model which treat unconditional and downside market risk asymmetrically. The model is much more successful than other asset pricing models. The mean absolute pricing error is low, 0.02%, and the R^2 is 95%. The χ^2-test also fails to reject the null hypothesis that the pricing errors are jointly zero.

Figure 1.3 displays a visual summary of CAPM, FF three-factor model, Carhart model and FF five-factor model fit. It plots realized versus predicted average excess returns of equity and bond portfolios using these models. In a perfect model, all points which represents the test assets would lie in the 45-degree diagonal line. While, a vertical distance from the diagonal line characterizes the corresponding pricing error. The figure shows that the FF five-factor model pricing error is much smaller than the pricing errors of CAPM and FF three-factor model in all portfolios. It also outperforms Carhart model in bond and 6 equity portfolios sorted on size and momentum. The plot illustrates the failure of CAPM explain the cross-section of mean returns, as shown in Table 1.2, 1.3 and 1.4.

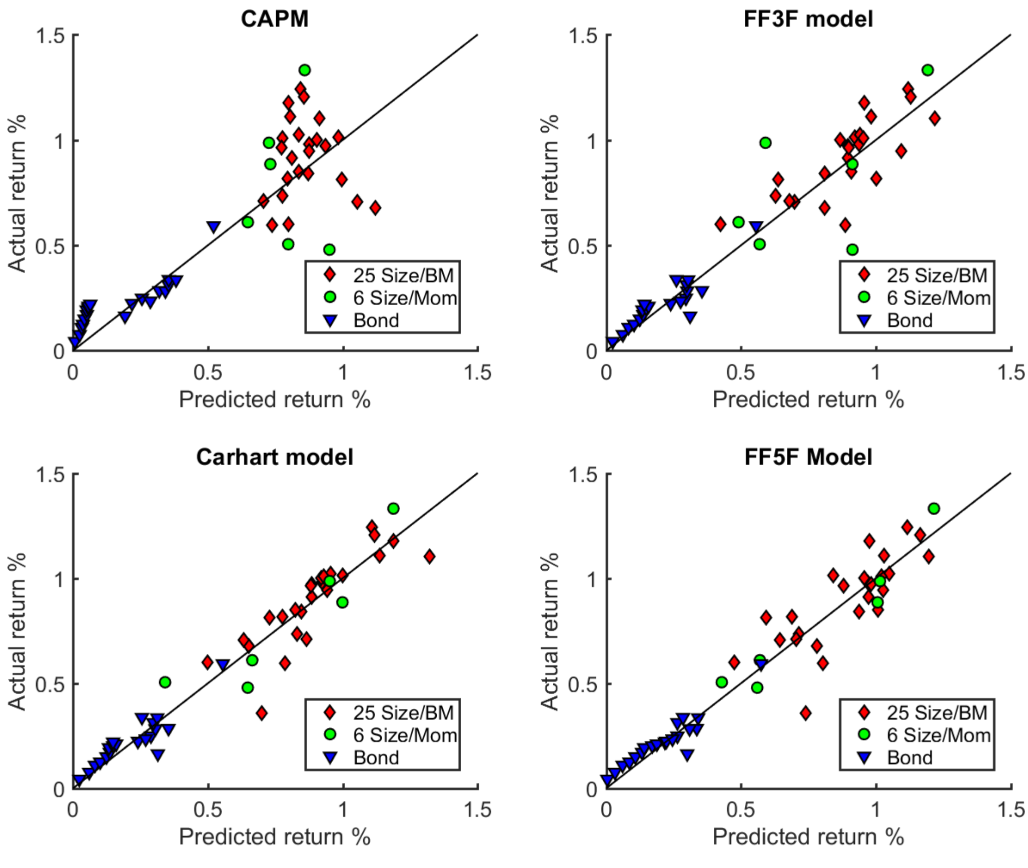

Figure 1.3: *Realized versus predicted returns: equities and bonds*

The figure shows the realized mean excess returns against the predicted excess returns for CAPM, the Fama–French three-factor model, the Carhart model and the FF five-factor model using equity and bond portfolios. The predictions are made from the first four set models reported in Table 1.2, 1.3 and 1.4.

Figure 1.4 plots realized against predicted mean excess returns of equity and bond portfolios using Ang, Chen, and Xing (2006) downside risk asset pricing model and extended specifications. These models distinguish market risk between upside and downside components. As clearly shown in the picture, all specifications substantially improve the fit of corresponding traditional asset pricing models. The mean return of 25 equity portfolios better explained by the first specification, while the third specification performs well for 6 equity and bond portfolio.

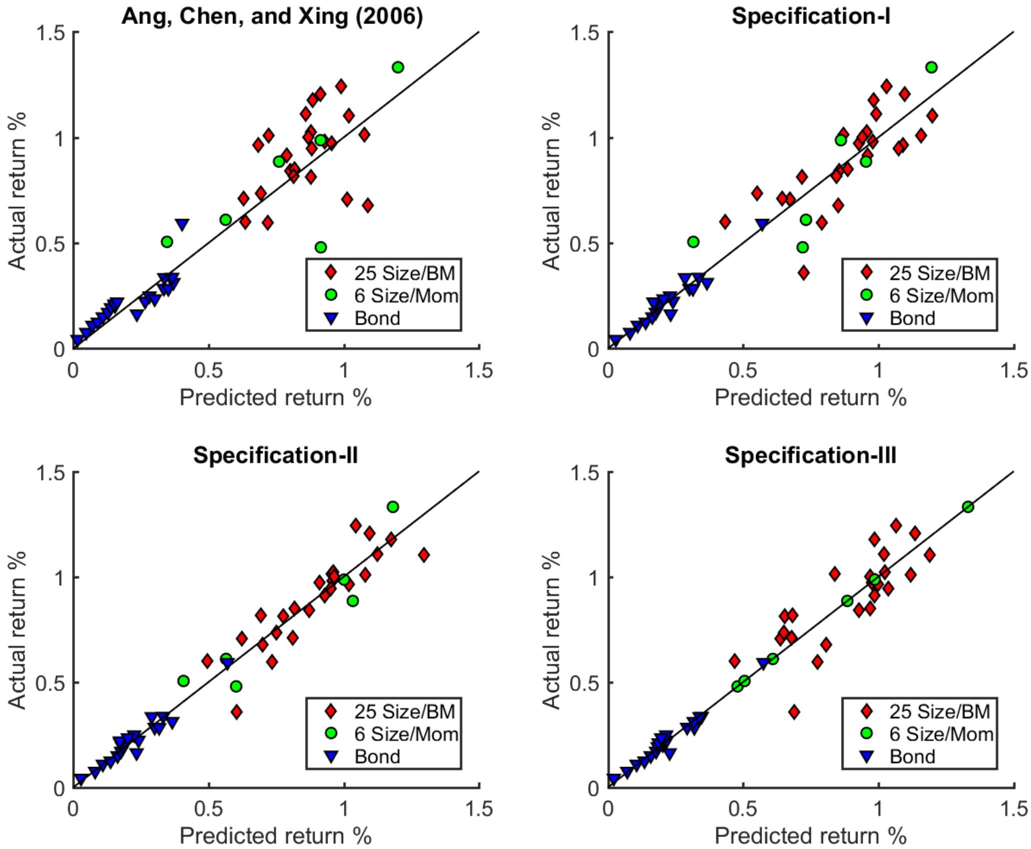

Figure 1.4: *Realized versus predicted returns using ACX and Spec.I-III: equities and bonds*

The figure shows the realized mean excess returns against the predicted excess returns of equity and bond portfolios using Ang, Chen, and Xing (2006, ACX) and extended specifications. The predictions are made from the second four set models reported in Table 1.2, 1.3 and 1.4.

In order to portray the performance of Lettau, Maggiori, and Weber (2014, LMW) downside risk capital asset pricing model and other augmented specifications, Figure 1.5 depicts the scatter plot of actual against predicted return. When we look at the pricing errors of these models it becomes apparent that making distinction between unconditional and downside component of market considerably enhances the explanatory power of asset pricing models. In this regard, the fifth specification excel in explaining the mean return of 25 equity portfolios. While, the cross-section of 6 equity and bond returns better explained by the sixth specification.

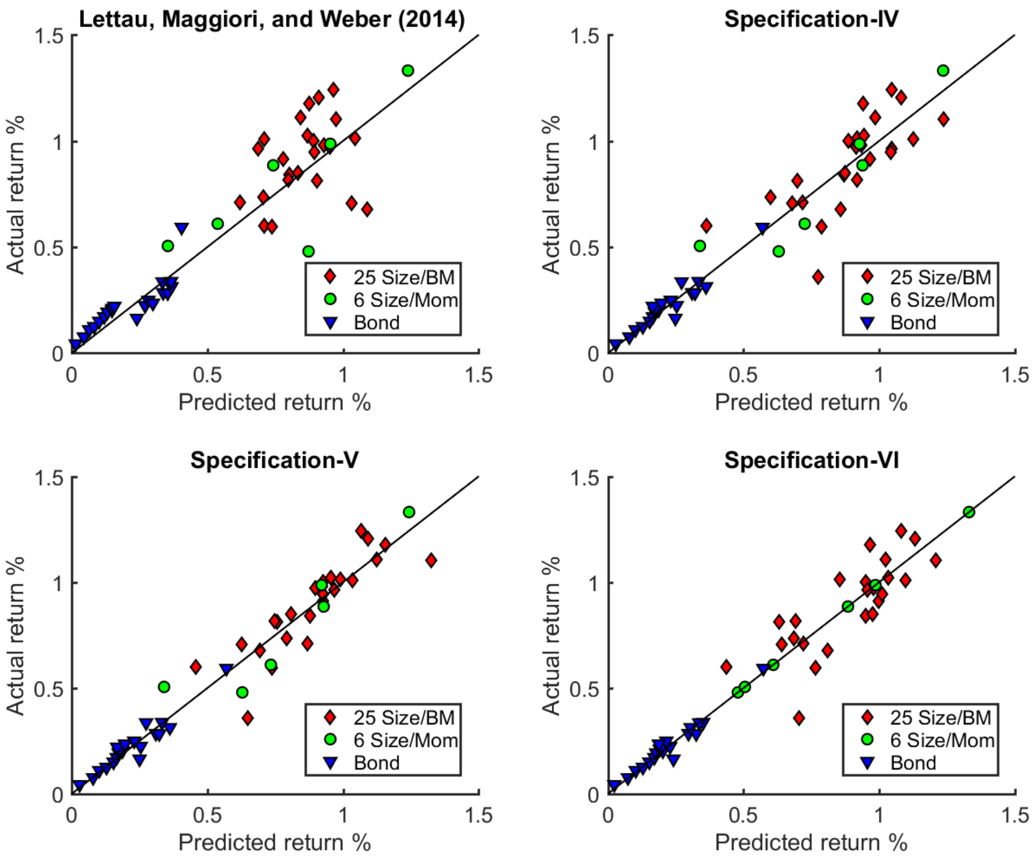

Figure 1.5: *Realized versus predicted returns using LMW and Spec.IV-VI: equities and bonds*

The figure shows the realized mean excess returns against the predicted excess returns of equity and bond portfolios from Lettau, Maggiori, and Weber (2014, LMW) and an extended specification. The predictions are made from the third four set models reported in Table 1.2, 1.3 and 1.4.

The results in Figure 1.4 and 1.5 provide intuitive evidence that asymmetric treatment of upside and downside market risk improves the explanatory power of conventional asset pricing models.

1.4.3 Currency portfolios

Next, I investigate whether the cross-section of currency returns better explained by factor pricing models that allows the market risk to change on the market condition.

Table 1.5 presents the estimation result of asset pricing models for 10

Table 1.5: *Estimation of linear factor models: 10 currency portfolios*

	CAPM	FF3F	CHRT	FF5F	ACX	SpecI	SpecII	SpecIII	LMW	SpecIV	SpecV	SpecVI
$\widehat{\lambda}^{m}$	7.91	-4.00	-8.54	-3.27					10.11	-5.71	-8.66	-9.11
	(7.03)	(18.24)	(15.86)	(10.25)					(8.38)	(24.87)	(17.01)	(22.01)
$\widehat{\lambda}^{m-}$									3.66	-1.76	-4.13	-4.69
									(3.89)	(10.39)	(10.53)	(8.83)
$\widehat{\lambda}^{m+}$					3.51	-1.86	-3.29	0.40				
					(2.10)	(4.47)	(6.95)	(5.45)				
$\widehat{\lambda}^{m-}$					4.07	-1.35	-3.18	-3.01				
					(2.59)	(7.31)	(8.21)	(6.73)				
$\widehat{\lambda}^{smb}$		7.54	8.36	2.45		7.38	8.16	5.26		7.60	8.70	5.54
		(6.18)	(8.64)	(5.40)		(7.32)	(8.75)	(7.14)		(9.19)	(10.78)	(8.68)
$\widehat{\lambda}^{hml}$		7.70	9.70	4.78		7.26	8.80	4.21		7.71	9.94	5.70
		(9.39)	(11.56)	(9.25)		(7.96)	(10.68)	(9.67)		(10.87)	(13.33)	(11.95)
$\widehat{\lambda}^{mom}$			-2.57				-2.47				-2.86	
			(15.89)				(9.95)				(12.37)	
$\widehat{\lambda}^{rmw}$				5.13				-0.71				1.21
				(10.65)				(7.17)				(7.90)
$\widehat{\lambda}^{cma}$				5.05				6.88				7.57
				(3.89)				(6.26)				(7.89)
R^2	0.32	0.64	0.66	0.89	0.33	0.63	0.64	0.98	0.34	0.64	0.66	0.97
MAE	0.24	0.19	0.19	0.11	0.24	0.20	0.21	0.04	0.25	0.20	0.20	0.05
χ^2**-test**	12.83	2.39	1.39	0.45	13.23	2.66	1.70	0.21	7.45	2.46	1.47	0.19
	(0.17)	(0.94)	(0.97)	(0.99)	(0.10)	(0.85)	(0.89)	(1.00)	(0.49)	(0.87)	(0.92)	(1.00)

The table reports risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model(CHRT) and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications(Spec). Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 10 currency portfolios. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

currency portfolios sorted on forward discount. The result shows that the CAPM have similar performance with the downside risk CAPM of Ang, Chen, and Xing (2006) and Lettau, Maggiori, and Weber (2014). They have very close R^2 and mean absolute pricing error. Moreover, the χ^2-test cannot reject the null hypothesis of pricing errors.

The FF three-factor model has done relatively well and has similar explanatory power with the first and forth specifications. The R^2 and the mean absolute pricing error on these models are around 64% and 0.2%, respectively. Moreover, the χ^2-test fail to reject null hypothesis of these models. The second and fifth specifications, which separate market returns, fails to improve the fit of Carhart model, while specification three and six provides considerable improvement to the FF five-factor model. The mean absolute pricing errors on the third and sixth specifications are 0.04% and 0.05% respectively. The χ^2-test shows that the pricing errors of these models are not statistically different from zero. Surprisingly, in the estimation of factor risk premia using currency portfolios, the χ^2-test indicates that all asset pricing model under consideration cannot reject the null hypothesis that pricing errors are jointly zero.

1.4.4 Commodity portfolios

The estimation result of model's fit for 24 commodity portfolios are shown in Table 1.6. The first model is the CAPM. It has a positive but insignificant market risk premia and the goodness-of-fit is only 31%, which is similar to the result in currency returns. The mean absolute pricing error of CAPM is very high, 0.65% per month and the χ^2-test rejects the model at 5% significant level. The downside risk CAPM of Ang, Chen, and Xing (2006) and Lettau, Maggiori, and Weber (2014) slightly increase the model fit, the R^2 rise to 37% and 36% respectively. Moreover, the mean absolute pricing errors on these models decrease to 0.59%, but still high. The widely-known FF three-factor model unable to improve much the explanatory power of CAPM. It increases the R^2 value just to 35% and barely decreases the mean absolute pricing errors. Similarly, the first and forth specifications provide a small improvement the FF three-factor model. These models have a positive but insignificant downside market risk premia, low R^2 values and a mean absolute pricing error of 0.59%. However, they do not reject the null hypothesis of χ^2-test at 5% significant level.

The Carhart model has a similar goodness-of-fit with FF three-factor model. Alternatively, the second and fifth specifications provide a relatively well fit in explaining the cross-section of commodity returns. The χ^2-test of the second specification indicates that the pricing errors are jointly zero, but the null hypothesis of the fifth specification rejected at 5% significance level. The next model is FF five-factor model. It explains around 47% of commodity average returns, which is similar to the estimation result of third specification. These two models have the same mean absolute pricing error of 0.51% and the pricing errors are not statistically different from zero.

The sixth specification, has better fit relative to other models under

Table 1.6: *Estimation of linear factor models: 24 commodity portfolios*

	CAPM	FF3F	CHRT	FF5F	ACX	SpecI	SpecII	SpecIII	LMW	SpecIV	SpecV	SpecVI
$\widehat{\lambda}^{m}$	1.55	1.65	1.70	1.16					2.41	2.44	1.56	1.61
	(0.86)	(0.95)	(0.77)	(0.75)					(1.51)	(1.58)	(0.88)	(1.27)
$\widehat{\lambda}^{m-}$									1.08	1.03	1.41	0.42
									(0.85)	(0.92)	(0.85)	(0.79)
$\widehat{\lambda}^{m+}$					0.24	0.33	0.20	0.40				
					(0.64)	(0.64)	(0.73)	(0.69)				
$\widehat{\lambda}^{m-}$					1.20	1.19	1.62	0.76				
					(0.77)	(0.83)	(0.71)	(0.67)				
$\widehat{\lambda}^{smb}$		0.92	0.96	0.24		0.59	0.59	0.22		0.49	0.38	0.36
		(0.98)	(0.85)	(0.81)		(0.80)	(0.82)	(0.80)		(0.89)	(0.89)	(0.93)
$\widehat{\lambda}^{hml}$		-0.01	-0.01	0.16		-0.14	-0.23	0.13		-0.19	-0.34	0.32
		(0.66)	(0.67)	(0.67)		(0.67)	(0.69)	(0.66)		(0.72)	(0.69)	(0.79)
$\widehat{\lambda}^{mom}$			-0.82				-1.46				-1.49	
			(1.75)				(1.96)				(1.90)	
$\widehat{\lambda}^{rmw}$				-0.51				-0.52				-0.55
				(0.44)				(0.44)				(0.47)
$\widehat{\lambda}^{cma}$				-0.52				-0.51				-0.59
				(0.44)				(0.45)				(0.44)
R^2	0.31	0.35	0.35	0.47	0.37	0.39	0.45	0.47	0.36	0.39	0.43	0.48
MAE	0.65	0.63	0.64	0.51	0.59	0.58	0.57	0.51	0.59	0.59	0.58	0.49
χ^2**-test**	35.88	34.48	33.78	23.40	31.05	31.11	28.98	23.02	30.35	30.94	30.70	22.19
	(0.04)	(0.03)	(0.03)	(0.22)	(0.10)	(0.05)	(0.07)	(0.19)	(0.11)	(0.06)	(0.04)	(0.22)

The table reports risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model(CHRT) and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications(Spec). Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 24 commodity portfolios. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

consideration. The goodness-of-fit is 48% and the mean absolute pricing errors is 0.49%, yet still large. The χ^2-test also fails to reject the null hypothesis of pricing errors. Similar to previous test assets, asset pricing models that asymmetrically treat market movements provide empirical improvement relative to the conventional asset pricing models for commodity returns.

1.4.5 Credit Default Swaps(CDS) portfolios

Finally, I examine the performance of asset pricing models using the cross-section of CDS. Table 1.7 presents estimation result of linear factor models for 20 CDS portfolios sorted by spread using 5-year contracts. The CAPM

Table 1.7: *Estimation of linear factor models: 20 CDS portfolios*

	CAPM	**FF3F**	**CHRT**	**FF5F**	**ACX**	**SpecI**	**SpecII**	**SpecIII**	**LMW**	**SpecIV**	**SpecV**	**SpecVI**
$\widehat{\lambda}^{m}$	1.42	-0.97	-2.21	1.97					-0.68	-1.13	1.18	0.81
	(0.64)	(1.37)	(1.82)	(1.65)					(1.69)	(1.94)	(1.33)	(2.61)
$\widehat{\lambda}^{m-}$									-2.03	-2.12	-2.10	-0.88
									(1.00)	(1.04)	(1.31)	(1.37)
$\widehat{\lambda}^{m+}$					2.83	2.41	2.53	2.02				
					(0.71)	(0.55)	(0.66)	(0.64)				
$\widehat{\lambda}^{m-}$					-1.69	-1.82	-1.75	-0.60				
					(0.91)	(0.92)	(0.84)	(1.21)				
$\widehat{\lambda}^{smb}$		3.04	0.87	0.87		1.01	1.14	0.76		1.15	1.28	0.84
		(2.62)	(2.12)	(1.95)		(0.98)	(1.08)	(1.25)		(0.95)	(1.40)	(1.37)
$\widehat{\lambda}^{hml}$		4.59	4.83	1.24		0.68	0.50	0.82		0.21	0.03	0.59
		(3.03)	(2.92)	(2.73)		(1.73)	(1.54)	(1.89)		(1.70)	(1.84)	(1.93)
$\widehat{\lambda}^{mom}$			-7.23				-0.96				-0.55	
			(3.60)				(2.39)				(2.84)	
$\widehat{\lambda}^{rmw}$				-3.89				-2.31				-2.62
				(2.10)				(2.05)				(2.35)
$\widehat{\lambda}^{cma}$				3.20				1.90				1.99
				(1.76)				(1.34)				(1.57)
$\mathbf{R}^2$	0.53	0.67	0.79	0.97	0.97	0.97	0.97	0.99	0.96	0.97	0.97	0.99
MAE	0.08	0.08	0.06	0.02	0.02	0.02	0.02	0.01	0.03	0.03	0.03	0.02
χ^2**-test**	44.40	13.63	9.50	5.46	12.12	12.49	12.08	4.77	14.72	12.74	7.24	4.64
	(0.00)	(0.69)	(0.89)	(0.99)	(0.84)	(0.71)	(0.67)	(0.99)	(0.68)	(0.69)	(0.95)	(0.99)

The table reports risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model(CHRT) and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications(Spec). Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 20 CDS portfolios. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

captures 53% of the variation in mean returns. The market risk premia are positive as expected and statistically significant at 5% level. However, it is the only model χ^2-test strongly rejects at 5% significance level.

The downside risk asset pricing model of Ang, Chen, and Xing (2006, ACX) and Lettau, Maggiori, and Weber (2014, LMW) considerably improve the explanatory power of CAPM. The R^2 statistics rise to 97% and 96%, and the mean absolute pricing error decline to 0.02% and 0.03% for ACX and LMW models, respectively. Similarly, the first and forth specifications do better job in explaining CDS returns relative to the corresponding FF three-factor model. They provide considerable improvement in the goodness-of-fit, that is 30% more than FF three-factor model. Furthermore, the MAE is very small. The

χ^2-test reveals that the pricing errors of these models are not different from zero.

The Carhart model captures a significant portion of the variation in risk premia. The R^2 estimate is 79% and the mean absolute pricing error is 0.06%. The augmented models, specification two and five, enhances the explanatory power of the cross-section of CDS returns. In the test with CDS portfolio, the fit of FF five-factor model increases remarkably, as shown by R^2 value of 97% and the mean absolute pricing error of 0.02% per month. The corresponding specification three and six add more light in the model fit by explaining a remarkable fraction of the cross-section of returns, with is close to 99%. Most likely such very high value of R^2 occurs due to sampling error. The mean absolute pricing errors of these two models fall to 0.01% and 0.02% per month, respectively. Moreover, the χ^2-test fails to reject the null hypothesis of these models at 5% significant level.

The improvement in model's fit is prevalent as we move from left to right, that is from CAPM to FF five-factor model, from ACX to the third specification and from LMW to specification six. The results in Table 1.6 demonstrates the superior performance of asset pricing models with downside market risk factor.

To illustrate the empirical fit of models, Figure 1.6 plots actual versus predicted mean excess return of currency, commodity and CDS portfolios using conventional asset pricing models.

The top left panel shows the poor performance of CAPM to capture the returns of currency and commodity portfolios. The CAPM model predicts similar returns while the actual return change significantly. The FF three-factor and Carhart models, improves the fit of CAPM especially for currency and CDS portfolios. The points, which represents asset returns, lie close to the 45-degree diagonal line. The right bottom panel of the figure indicates the performance of FF five-factors model. This model provide improvement in explaining the returns of currency and CDS relative to other conventional asset pricing models.

Figure 1.7 depicts the scatter plot of actual against predicted returns of currency, commodity and CDS portfolios using the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications. The top panel shows that ACX model and first specification considerably improve the

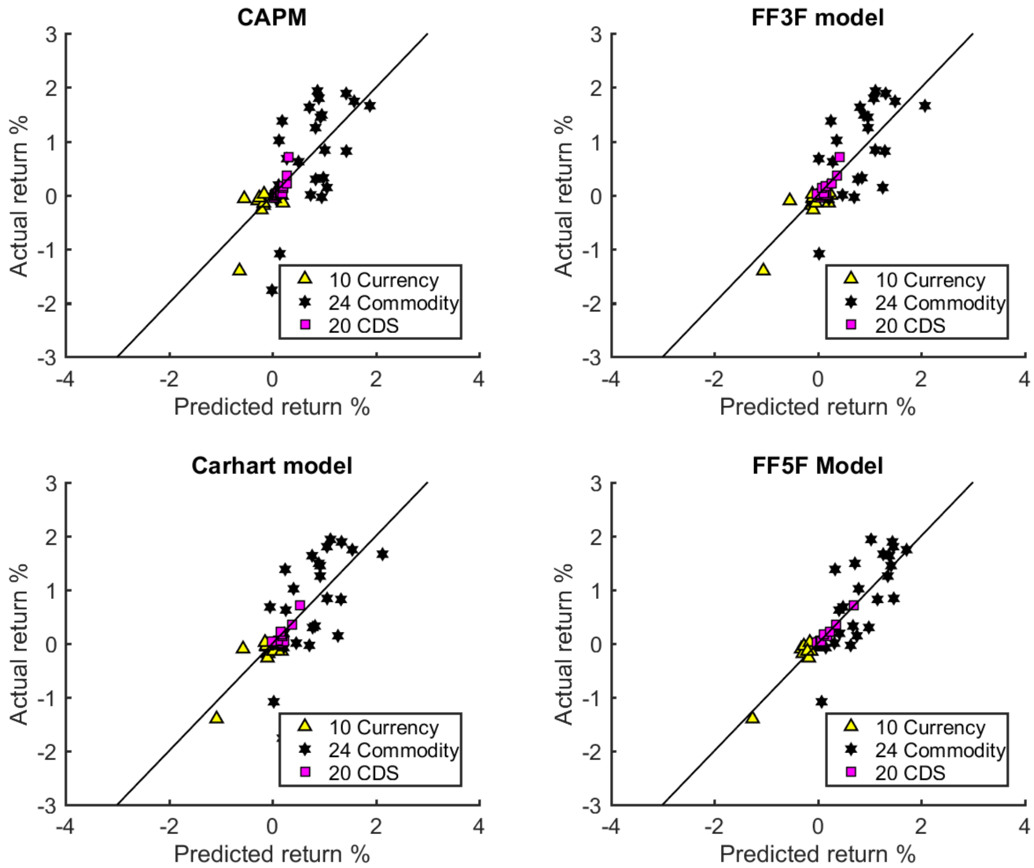

Figure 1.6: *Realized versus predicted returns: currencies, commodities and CDS*

The figure shows the realized mean excess returns against the predicted excess returns of currency, commodity and CDS portfolios using CAPM, the FF three-factor model, the Carhart model and the FF five-factor model. The predictions are made from the first four set models reported in Table 1.5, 1.6 and 1.7.

fit of CAPM and FF three-factor model for CDS portfolios. Looking at the second specification, in the left bottom panel, it becomes clear that allowing the market returns to change conditional on market movement improves the fit of Carhart model in commodity and CDS portfolios. In the third specification, the points which represents the test assets are close to the diagonal line. The pricing error of this model is much smaller and provide better fit than other pricing specifications.

To assess the fit of Lettau, Maggiori, and Weber (2014, LMW) and subsequent specifications visually, Figure 1.8 plots the actual versus predicted mean returns of currency, commodity and CDS portfolios. Comparing the performance of LMW with the standard CAPM and ACX model in Figure 1.6 and 1.7, it become apparent that LMW downside risk model provide a

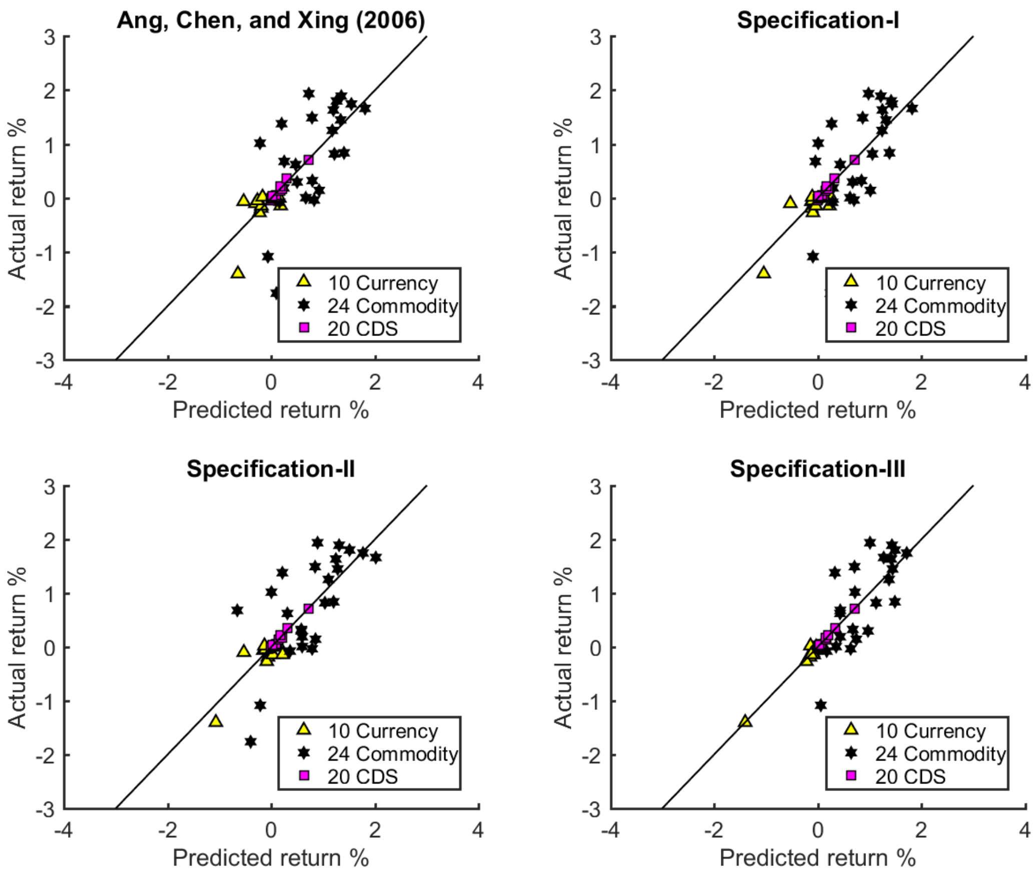

Figure 1.7: *Realized versus predicted returns using ACX and Spec.I-III: currencies, commodities and CDS*

The figure shows the realized mean excess returns against the predicted excess return of currency, commodity and CDS portfolios using Ang, Chen, and Xing (2006, ACX) and extended specifications. The predictions are made from the second four set models reported in Table 1.5, 1.6 and 1.7.

good job in currency and CDS portfolios. In the right top panel of the figure, the forth specification improves the fit of the corresponding FF three-factor model in commodity and CDS portfolios. Moreover, it provides very close fit with the first specification. In left bottom panel, the fifth specification considerably enhances the explanatory power of Carhat model in commodity and CDS portfolios. The sixth specification also provide even superior improvement relative to the fit of other models in all three portfolios. The points, which indicates portfolio returns, line up close to the diagonal line.

The visual test of asset pricing models confirms the superiority of asset pricing specifications that distinguish market return between upside and downside movements as compared to the unconditional asset pricing

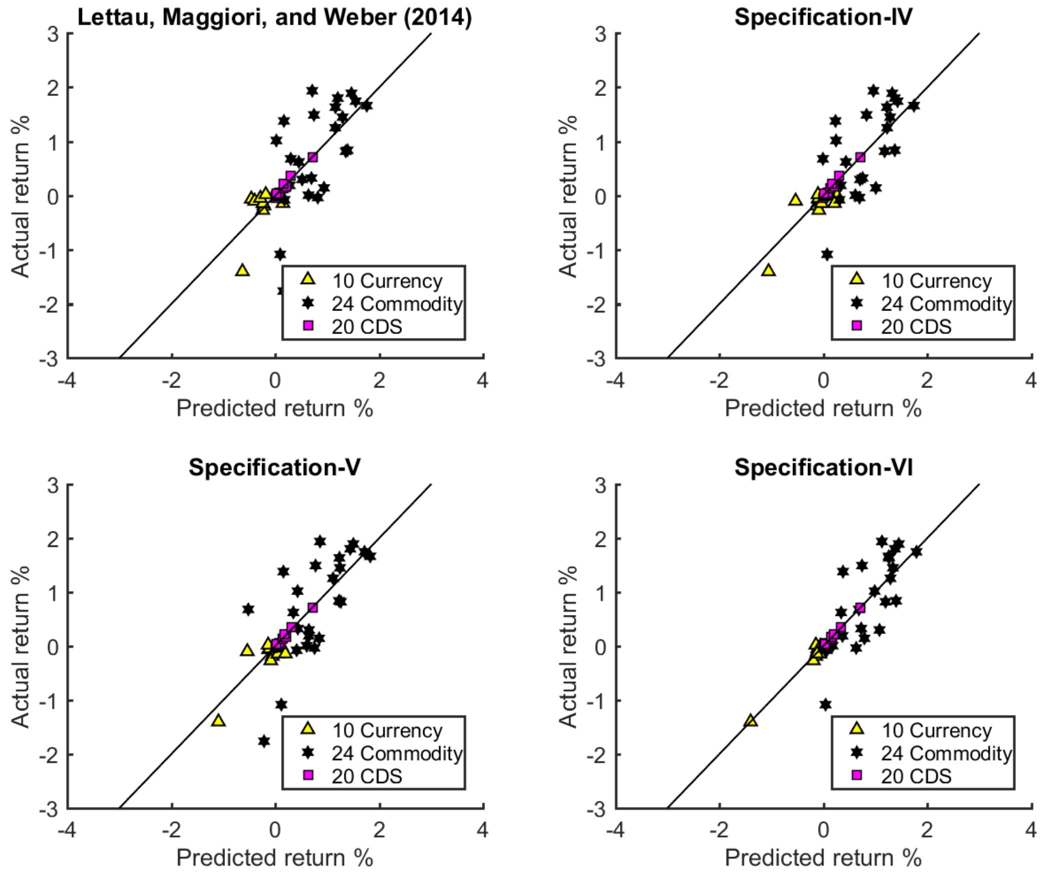

Figure 1.8: *Realized versus predicted returns using LMW and Spec.IV-VI: currencies, commodities and CDS*

The figure shows the realized mean excess returns against the predicted excess returns of currency, commodity and CDS portfolios from Lettau, Maggiori, and Weber (2014, LMW) and extended specifications. The predictions are made from the third four set models reported in Table 1.5, 1.6 and 1.7.

specifications. Moreover, it become evident that the model fit increases as we move from left to right panels and from top to bottom panels in the figures.

1.4.6 Robustness check

Next, I examine the robustness of results based on jointly using the cross-section of multiple asset classes. Table 1.8 reports estimation result of asset pricing models when the test assets are a combination of 25 equity portfolios sorted by size and book-to-market value, 6 equity portfolios sorted by size and momentum and 10 currency portfolios. In the first column, the market risk premia for CAPM is statistically significant and has a positive sign as

Table 1.8: *Models robustness: equities and currencies*

	CAPM	FF3F	CHRT	FF5F	ACX	SpecI	SpecII	SpecIII	LMW	SpecIV	SpecV	SpecVI
$\widehat{\lambda}^{m}$	0.81	0.63	0.71	0.68					1.31	1.01	0.70	0.49
	(0.32)	(0.30)	(0.31)	(0.38)					(0.87)	(0.83)	(0.31)	(0.78)
$\widehat{\lambda}^{m-}$									0.50	0.38	0.20	-0.19
									(0.67)	(0.66)	(0.66)	(0.58)
$\widehat{\lambda}^{m+}$					-0.04	0.10	0.41	0.66				
					(0.50)	(0.48)	(0.48)	(0.44)				
$\widehat{\lambda}^{m-}$					0.83	0.54	0.29	0.01				
					(0.53)	(0.50)	(0.51)	(0.44)				
$\widehat{\lambda}^{smb}$		0.30	0.25	0.31		0.29	0.25	0.32		0.30	0.25	0.32
		(0.22)	(0.22)	(0.29)		(0.22)	(0.22)	(0.31)		(0.23)	(0.23)	(0.23)
$\widehat{\lambda}^{hml}$		0.35	0.36	0.12		0.35	0.36	0.12		0.35	0.36	0.12
		(0.23)	(0.25)	(0.31)		(0.24)	(0.26)	(0.37)		(0.22)	(0.22)	(0.23)
$\widehat{\lambda}^{mom}$			0.48				0.47				0.48	
			(0.37)				(0.37)				(0.41)	
$\widehat{\lambda}^{rmw}$				0.10				0.05				0.04
				(0.44)				(0.46)				(0.33)
$\widehat{\lambda}^{cma}$				0.74				0.89				0.88
				(0.43)				(0.38)				(0.33)
$\mathbf{R}^2$	0.60	0.68	0.77	0.81	0.61	0.69	0.77	0.81	0.60	0.68	0.77	0.81
MAE	0.22	0.20	0.15	0.15	0.22	0.20	0.14	0.15	0.22	0.20	0.14	0.15
χ^2**-test**	94.26	94.16	93.47	77.72	91.50	92.59	91.17	70.35	82.08	80.06	75.00	57.72
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

The table presents risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications. Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 25 equity portfolios sorted by size and book-to-market value, 6 equity portfolios sorted by size and momentum and 10 currency portfolios. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

expected. The downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and Lettau, Maggiori, and Weber (2014, LMW) slightly improve the fit of CAPM. Additionally, the three-factor model of FF enhances the explanatory power of CAPM and provide similar fit with specification one and four.

The result for Carhart model shows that the model captures a significant part of the variation in risk premia. The R^2 statistics is 77% and the mean absolute pricing error is 0.15% per month. Augmented specification two and five, offer a minor improvement in explaining the cross-section of returns. Likewise, the third and sixth specifications provide further improvement relative to FF five-factor model, the goodness-of-fit rises to 81%. However, the χ^2-test significantly rejects the null hypothesis that the

Table 1.9: *Models robustness: commodities, bonds and CDS*

	CAPM	FF3F	CHRT	FF5F	ACX	SpecI	SpecII	SpecIII	LMW	SpecIV	SpecV	SpecVI
$\widehat{\boldsymbol{\lambda}}^{m}$	1.81	1.87	1.91	1.42					2.83	2.85	1.75	2.14
	(0.91)	(0.97)	(0.75)	(0.74)					(1.64)	(1.72)	(0.88)	(1.32)
$\widehat{\boldsymbol{\lambda}}^{m-}$									1.26	1.22	1.57	0.70
									(0.93)	(1.03)	(0.95)	(0.78)
$\widehat{\boldsymbol{\lambda}}^{m+}$					0.29	0.38	0.26	0.46				
					(0.65)	(0.61)	(0.67)	(0.66)				
$\widehat{\boldsymbol{\lambda}}^{m-}$					1.38	1.36	1.69	0.97				
					(0.85)	(0.90)	(0.73)	(0.68)				
$\widehat{\boldsymbol{\lambda}}^{smb}$		0.96	0.99	0.30		0.58	0.55	0.26		0.48	0.35	0.78
		(0.98)	(0.85)	(0.80)		(0.77)	(0.79)	(0.78)		(0.89)	(0.88)	(0.89)
$\widehat{\boldsymbol{\lambda}}^{hml}$		0.23	0.24	0.33		0.08	0.09	0.29		0.00	-0.07	0.42
		(0.65)	(0.69)	(0.66)		(0.66)	(0.71)	(0.65)		(0.74)	(0.76)	(0.77)
$\widehat{\boldsymbol{\lambda}}^{mom}$			-0.90				-1.27				-1.46	
			(1.62)				(1.68)				(1.72)	
$\widehat{\boldsymbol{\lambda}}^{rmw}$				-0.50				-0.52				-0.52
				(0.45)				(0.45)				(0.46)
$\widehat{\boldsymbol{\lambda}}^{cma}$				-0.50				-0.49				-0.53
				(0.50)				(0.51)				(0.49)
$\mathbf{R}^2$	0.30	0.33	0.33	0.43	0.36	0.37	0.40	0.43	0.36	0.37	0.40	0.43
MAE	0.40	0.40	0.39	0.34	0.37	0.37	0.36	0.34	0.38	0.37	0.36	0.34
χ^2**-test**	97.33	95.96	94.53	94.72	91.73	90.36	82.16	93.59	95.04	89.34	88.11	86.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)

The table presents risk premia estimate of asset pricing models. Column 1 to 4 presents the result of CAPM, the FF three-factor model, the Carhart model and the FF five-factor model. Column 5 to 8 shows the downside risk CAPM of Ang, Chen, and Xing (2006, ACX) and extended specifications. Columns 9 to 12 presents estimation results for the downside risk CAPM of Lettau, Maggiori, and Weber (2014, LMW) and extended asset pricing models that incorporate other risk factors. The test assets are 24 commodities, 20 bonds and 20 CDS portfolios. Asset pricing models from CAPM to specification three are estimated using GMM approach with identity weighting matrix. Following Lettau, Maggiori, and Weber (2014) I use Fama-MacBeth approach to estimate LMW and extended specifications. The table also reports R^2 statistics along with the mean absolute pricing error (MAE). In terms of asset pricing error, second stage Fama-MacBeth and first stage GMM approaches produce equivalent results. VARHAC standard errors are in parentheses at 5 percent significance level. The χ^2-test statistics are with the null hypothesis that the pricing errors are jointly zero. The p-values for χ^2-test are in parenthesis.

pricing errors are indistinguishable from zero.

The results in Table 1.8 shows that the superior performance of downside risk asset pricing models is robust across many asset classes.

Finally, I investigate whether asymmetric treatment of market return plays a key role in the performance of asset pricing models using a different combination of asset returns. Table 1.9 reports the estimation result of linear factor models using a joint cross-section of 24 commodity, 20 bond and 20 CDS portfolios.

Moving from left to right in each section of the table, that is from CAPM to FF five-factor model, from Ang, Chen, and Xing (2006, ACX) model to specification three and from Lettau, Maggiori, and Weber (2014, LMW) model to the sixth specification, it is evident that the R^2 statistics increases and the mean absolute pricing error decreases. This implies that the variation in asset returns can be better captured by extended factor pricing models.

The first column in Table 1.9 shows the estimate of CAPM. This model has lower fit as prevailed by small goodness-of-fit and high mean absolute mean error. ACX and LMW downside risk CAPM improve the fit of CAPM by increasing $R^2$and decreasing the mean absolute pricing error estimates. Similarly, the second and forth specifications, which take into account market asymmetries enhances the explanatory power of FF three-factor model. Another customary asset pricing model is the Carhart four-factor models. It has similar fit with FF three-factor model. However, the second and fifth specifications that have similar information with Carhart model associated with high R^2 and low pricing errors. Furthermore, the third and sixth specifications improve the explanatory power of FF five-factor model across asset returns. Overall, the empirical estimate of models clearly shows that the cross-section of asset returns better explained by asset pricing models that asymmetrically treat market movements.

1.5 Conclusions

Conventional asset pricing models relates asset returns to market risk, which is constant across periods of market upturn and downturns. However, these models do not characterize the risk aversion of representative investors. In order to examine whether asymmetric treatment of market movement plays a vital role in the estimation of asset returns, I propose alternative asset pricing specification that distinguish market factor between upside and downside components. The central idea of these models is that investors care differently between downside loss and upside gain, and asset pricing models that distinguish downward market from upward trend tend to characterize investors' risk perception.

The finding of this study suggests that asset pricing models based on risk perception of investors better explains the cross-section of equity, currency, bond, commodity and CDS portfolio returns. It gives an integrated view the presence of downside risk premium in asset returns and empirical content in the theoretical paradigm of downside risk. The success of these models is measured based on the cross-sectional price of risk, R^2 statistics, mean absolute pricing error statistics and χ^2-test that evaluate pricing errors across asset pricing models. The empirical results are consistent with other downside risk studies that suggests conditional association of market factor with asset returns. A close examination of the findings shows some negative relationship between downside market risk and asset returns, which remains a puzzle in this study, suggestive of further empirical and theoretical works.

2. MOMENTUM IN EQUITY AND CURRENCY MARKETS

2.1 Introduction

Momentum is an asset pricing anomaly that has attracted a great deal of attention in asset pricing studies and market efficiency debates. It refers to the tendency of asset's return to stay on its recent relative performance. Momentum strategy implemented simply by buying recent winner and selling recent loser assets. The possibility of making abnormal return based on the historical pattern of asset returns, which is contrary to the market efficiency theory that predicts the future returns do not follow any trend, has been documented in the finance literatures. A prominent study of Jegadeesh and Titman (1993) examine the historical pattern of US stock returns and show that recent winner stocks continue to outperform recent losers over the next few months, and buying stocks with high recent returns and selling stocks with low recent returns generates abnormal returns in the short-run. In subsequent studies, momentum effect has been detected in currency, bond, commodity and other asset classes. Menkhoff et al. (2012) investigate the cross-section of 48 currencies and show that buying past winner currencies and selling past losers yields annual excess return of 10%. Momentum return in corporate bonds and commodities has also been reported by Jostova et al. (2013) and Gorton, Hayashi, and Rouwenhorst (2008), respectively. Asness, Moskowitz, and Pederson (2013) report the existence significant momentum return premia across numerous markets and asset classes.

Despite the persistence of momentum has been extensively reported in many markets, the literature do not have yet conclusively explain the underlying mechanism that causes this effect. Several explanations have been given by researchers about the source of momentum returns. The major approaches to explain the cause of this anomaly can be broadly classified into three distinct categories. The first approach is using risk-based models based on the idea that the returns of this strategy as a compensation of risk. Grundy and Martin (2001) derive models to detects the dynamic factor risk exposure of momentum returns and find that factor models can explain a significant portion of the variability in momentum profits. Liu and Zhang (2008) examine whether momentum is a risk driven phenomenon and show that macroeconomic risk plays an important in explaining more than half of momentum returns. Asness, Moskowitz, and Pederson (2013) also report that liquidity risk partly explains momentum returns in many markets and asset classes. Wang and Xu (2015) investigate the role of market volatility in characterizing momentum profit and find that market volatility has a significant explanatory power of momentum payoffs after controlling for business cycle and market conditions. Recently, Min and Kim (2016) show the payoffs to momentum strategy is conditional on economic conditions. They argue that momentum strategy provides positive returns in good economic states when market risk premium is low, whereas it delivers a great negative payoffs in bad economic conditions when expected market risk premium is high. Moreover, they state that momentum strategy is fundamentally risky as it exposes investors to huge downside risk.

The second sets of approach to explain momentum is based on transaction costs and other asset characteristics. Lesmond, Schill, and Zhou (2004) argue that stocks that generate high returns associated with momentum are those stocks with high transition costs. Therefore, abnormal returns of momentum strategy is an illusion profit and nonexistent. Using currency data, Menkhoff et al. (2012) investigate the sensitivity of momentum returns to transaction costs by making bid–ask spread adjustments. They show that the transaction cost accounts half of the momentum returns. In a similar sprit, Barroso and Santa-Clara (2015) assess whether managing the risk of momentum will lead to low transaction costs so that it enables to exploit momentum strategy. Despite, the transaction costs of risk-managed momentum roughly 40% higher than plain momentum, managing the risk of momentum greatly improves the Sharpe ratio and reduce high-order risk of excess kurtosis and negative skewness.

The third approach presents behavioral-based models to provide explanations of momentum effects. It is based on the premise that the profitability of momentum strategies arises because of investors inherent bias in the way they interpret or react to information, investor's sentiment and confidence. Jegadeesh and Titman (2001) argue that investors are slow to adjust to new information and their delayed overreaction to recent information push the price of recent winners (losers) above (below) their fundamental values, this results short-term momentum. Earlier studies such as DeBondt and Thaler (1985) provide evidence of long-term overreaction of investors; Chan, Jegadeesh, and Lakonishok (1996) on how investors under-react to information such as past earnings, and Daniel, Hirshleifer, and Subrahmanyam (1998) on investor overconfidence to discount new information that conflicts with their prior knowledge. A study by Stambaugh, Yu, and Yuan (2012) show that the profitability of momentum strategy is stronger when investor's sentiment is high. Similarly, Antoniou, Doukas and Subrahmanyam (2013) examine whether investors sentiment affects the momentum return based on the notion that investors feel unduly optimistic or pessimistic based on the spread of good or bad news which causes cognitive dissonance. They indicate that momentum profits are more pronounced only when investors are optimistic as they expect price continuations during optimistic periods, which is similar to the result shown by Hong and Stein (1999). Chui, Titman and Wei (2010) investigate the influence of cultural difference on the profitability of momentum returns. They show that investors from different cultural backgrounds interpret information in different ways, which significantly impact the pattern of stock return and momentum strategies.

Given the pervasive and outstanding performance of momentum across diverse markets and asset classes, it exposes to sporadic crashes. Barroso and Santa-Clara (2015) show that momentum provide investors the highest Sharpe ratio as compared with the market, value or size factors with huge crash risk. They illustrated this with the fact that in July and August of 1932 momentum resulted a cumulative return of -91.59%, and from March to May 2009 it delivers another huge loss of -73.42%. These two periods marked as market reversal after stock market collapsed associated with great depression and Global financial crisis. Similarly, Daniel and Moskowitz (2016) argue that despite the highest positive return momentum strategy can offer across diverse assets, it suffers from great crash as the market starts to rebound after experiencing large decline. Using US equity data, they find momentum reversal following market drawdowns that losers outperforms winner by 200% and 155% in 1932 and 2009, respectively. Therefore, it results a strong momentum crash as momentum strategy long winners and short losers.

Previous researches attempt to explain what eventually drives momentum crash. One explanation of this phenomenon is the time-varying beta of momentum portfolios. Grundy and Martin (2001) argue that when the market falls dramatically, the stocks that fall tremendously with the market are high beta stocks and those who performed well are low beta stocks. Consequently, following market drawdown, the momentum strategy likely to short past loser or high beta stocks and long past winners or low beta stocks, which results a significant negative momentum beta. When the market rebound, momentum strategy interrupted with strong reversal or crash. They suggest that hedging the dynamic time-varying market exposure dramatically improve the performance of momentum strategy. Martens and Oord (2014) analyze whether hedging the time-varying exposures improve momentum returns, and they show that hedged momentum provide more stable returns over different market conditions than raw momentum that experience losses following bear market.

Barroso and Santa-Clara (2015) propose managing the risk of momentum using realized variance instead of time-varying beta. They argue that specific risk is more persistent and predictable component of momentum risk than market risk, thus hedging time-varying betas does not avoid momentum crash. Their risk managed momentum strategy not only improves the Sharpe ratio but also avoids momentum crash. Furthermore, Daniel and Moskowitz (2016) suggest a dynamic momentum strategy based on ex-ante expected return and variance of momentum portfolio. They show that this strategy offers positive and statistically significant alpha relative to the constant volatility strategy of Barroso and Santa-Clara (2015). Moreover, alpha and Sharpe ratio of dynamic momentum strategy using bear market indicators and forecasted mean and variance of momentum is approximately twofold of the static momentum strategy.

This study extends previous researches in several ways. First, beside examining momentum strategies in equity markets, it investigates currency momentum using extended time span and larger cross-section of currencies in foreign exchange markets. Thus, it allows to capture the variation in momentum returns across time and markets. Second, it proposes a different approach to mitigate the risk of momentum, which is based on hedging the time-varying risk exposure of momentum then by scaling the hedged long-short portfolio using its forecasted semi-variance. This approach is more closely related to the method suggested by Grundy and Martin (2001) and Barroso and Santa-Clara (2015). But the optimal momentum strategy designed in this paper is distinct from their work in the way it defines upside and downside risk exposure and estimate the risk of momentum using forecasted semi-variances instead of variance. Finally, this study examines the risk exposure of currency momentum by decomposing the risk factors into systematic and idiosyncratic components.

The reminder of the chapter organized as follows. Section 2.2 provides detail description of the data and portfolio construction. Section 2.3 discusses the main findings of equity momentum strategy and its exposure to crash risk. Section 2.4 examine the performance of optimal momentum strategy. Section 2.5 discusses currency momentum and decomposing momentum risk. Section 2.6 presents the conclusions.

2.2 Data and portfolio constructions

2.2.1 Equity momentum

The equity data used in this study are daily and monthly decile portfolios constructed using NYSE, AMEX and NASDAQ stocks prior returns. The winner portfolio contains a group of stocks in the top decile portfolio based on their cumulative return in the ranking period (from month t-12 to t -2). While, the loser portfolio is a set of stocks in the bottom decile of portfolio over the past 11 months. Hence, the momentum return is the return of past winner minus the return of past loser portfolio. One month gap between the ranking and holding period is to avoid short term reversal. The sample period covers between January 1927 to February 2017. The data for momentum decile portfolios, including market return, size and value factor are obtained from Kenneth French's data library[1].

2.2.2 Currency momentum

I use spot and one month forward exchange rates against the US dollar to construct bilateral foreign currency excess-returns then momentum portfolios. The currencies included in the sample are from 56 different counties: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India,

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Indonesia, Israel, Italy, Japan, Jordan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Arab Emirates, Ukraine and United Kingdom. The sample period is from January 1985 to March 2017, while the availability of data for some of these currencies varies over time. Figure 2.1 shows the number of currencies available over the course of the sample. The daily and monthly currency data are collected from WM/Reuters and Barclays International Bank (BIB) via Datastream.

Currency excess returns: I define the log excess return of currencies from US investor perspective. The log excess return rx from buying a foreign currency k in the forward market and selling it later in spot market after one month is given by

$$rx_{t+1}^{k} = f_t^k - s_{t+1}^k \tag{2.1}$$

Where s_t^k and f_t^k denotes log one month spot and forward exchange rate of foreign currency per US dollar at time t, respectively. It can also be represented as the difference between the log forward discount and the change in spot exchange

$$rx_{t+1}^{k} = (f_t^k - s_{t+1}^k) - \Delta s_{t+1}^k \tag{2.2}$$

If the investor covers the investment with a forward contract, covered interest rate parity (CIP) holds, interest rate differential is equal to the forward discount i.e. $i_t^k - i_t \approx f_t^k - s_{t+1}^k$. Where i_t^k and i_t denotes one month interest rates in foreign and domestic country. Hence, the monthly excess return for investing in foreign currency k equals the interest rate differential less exchange rate depreciation[2]

$$rx_{t+1}^{k} = (f_t^k - s_{t+1}^k) - \Delta s_{t+1}^k \approx f_t^k - s_{t+1}^k \tag{2.3}$$

Momentum portfolios: Currency momentum portfolios are formed by ranking currencies into octile based on their past performance during the ranking period (months t-12 to t-2). The procedure for constructing 8 currency portfolios are similar to the method applied by Menkhoff et al. (2012) to

[2] Lustig, Roussanov and Verdelhan (2011) sort currencies based on their respective interest rates to build currency portfolios for analyzing carry trade.

analyze the cross-section of currency momentum. The first portfolio contains currencies with the worst past performance (losers), the next basket composed of currencies with the next better prior returns and so no, and the last portfolio consists of currencies with the best prior performance (winners). Momentum profit is computed by deducting the returns of loser portfolio from the return of winner portfolio.

2.3 Equity momentum returns

In this section, I investigate the performance of equity momentum strategy using different sample periods. Furthermore, the dark side of momentum strategy, momentum crash, are examined in detail.

2.3.1 Performance of equity momentum

Table 2.1 shows the characteristics of momentum decile, winner minus loser (WML) and market portfolio over the sample period from January 1927 to February 2017. The average payoffs increase when moving from loser portfolio to winner portfolio. Conversely, the returns of winner portfolios are more negatively skewed than the returns of loser portfolios. The WML strategy has an average annual excess return of 14.14%, which is almost twofold of the market returns, with the corresponding volatility of 27.10%. The Sharpe ratio of this strategy is higher than the Sharpe ratio of the market. However, looking at the distribution of returns, momentum strategy characterized by fat left tails as indicated by high excess kurtosis of 17.40 coupled with considerable negative skewness of -2.34. This reflects high exposure of momentum to crash risk, as shown by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).

The next section of Table 2.1 shows ordinary least square (OLS) regression result of momentum portfolios on the market, size and value factors to examine whether high excess return of momentum related with high risk exposure. The CAPM regression result shows that after controlling significant negative exposure to market, the WML portfolio yields abnormal annual return of 18.33%. Moreover, zero-investment WML portfolio generates abnormal return of 21.15% after controlling significant negative loading on the market (-0.38), size (-0.26) and value (-0.74) factors.

Table 2.1: *Equity momentum portfolios and market*

	Decile Momentum Portfolios											
Statistics	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**WML**	**RMRF**
Mean	0.57	5.12	5.77	7.26	7.33	7.95	8.89	10.13	11.04	14.70	14.14	7.83
Std.	33.93	27.91	24.21	22.03	20.64	20.12	19.06	18.52	19.49	22.47	27.10	18.63
SR	0.02	0.18	0.24	0.33	0.36	0.40	0.47	0.55	0.57	0.65	0.52	0.42
Sk.	1.78	1.81	1.51	1.53	1.31	0.86	0.09	0.02	-0.31	-0.50	-2.34	0.19
Ku.	16.03	20.50	19.02	18.00	17.67	12.99	7.37	4.71	3.63	2.19	17.40	7.76
α^{CAPM}	-11.64	-5.28	-3.44	-1.30	-0.80	-0.13	1.29	2.81	3.49	6.69	18.33	0.00
t(α)	-6.24	-3.86	-3.15	-1.47	-1.05	-0.20	2.00	4.18	4.33	5.30	6.85	3.58
β^{RMRF}	1.56	1.33	1.18	1.09	1.04	1.03	0.97	0.93	0.96	1.02	-0.53	1.00
t(β)	54.32	63.03	69.83	79.86	88.31	105.20	97.60	90.29	77.84	52.70	-13.00	∞
α^{FF3F}	-13.69	-6.79	-4.61	-2.15	-1.58	-0.65	1.17	2.89	3.71	7.46	21.15	0.00
t(α)	-8.06	-5.33	-4.53	-2.57	-2.24	-1.07	1.84	4.31	4.60	6.38	8.43	3.56

This table presents descriptive statistics of equity momentum portfolios and market. The first decile portfolio(loser) contains stocks with the worst past performance and the tenth decile portfolio(winner) consists of stocks with the best prior performance. The Winner-Minus-Loser (WML) portfolio is the difference between the return of top decile (winner) portfolio and the return of bottom decile(loser) portfolio. The table presents annualized average excess return, annualized standard deviation, annualized Sharpe ratio, skewness and kurtosis. The CAPM alpha and Fama and French alpha along with their t-statistics are also shown from ordinary least square(OLS) regression of WML portfolio on market and Fama and French (1992) three factor. All statistics are computed using monthly data from January 1927 to February 2017.

Figure 2.1 shows the cumulative returns from investing in the market portfolio, risk-free asset, loser portfolio, winner portfolio and winner-minus-loser (WML) portfolio from January 1927 to February 2017. The left side of the figure shows the dollar value of each portfolios at the end of the period by investing $1 in January 1927, without adjusting the transaction costs. The payoffs to the winner and WML portfolios are remarkably higher than other portfolios in the sample period. This reflects the impressive performance of momentum strategy over the sample period.

However, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) documented the long-term dramatic under performance of momentum strategy following market drawdown. They illustrate their points by taking two sample periods that include market turbulence, Great depression and Global financial crisis. In a similar way, I examined the presence of momentum crash after the market experiencing heavy loss using two sample periods, from 1930 to 1939 and from 2007 to 2017.

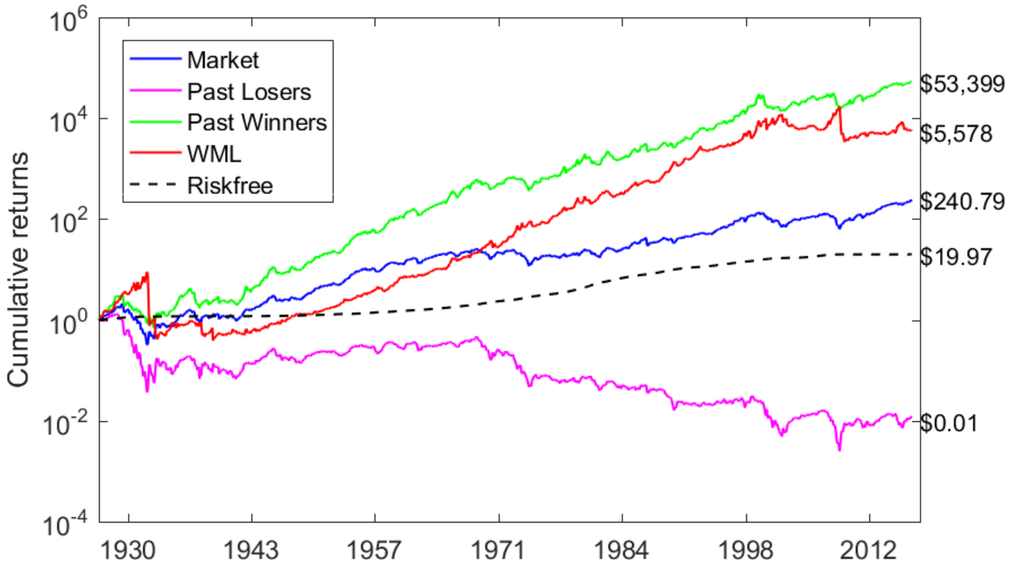

Figure 2.1: *Cumulative returns of equity portfolios from 1927 to 2017*

The figure plots cumulative returns of market portfolio, risk-free asset, loser portfolio, winner portfolio and winner-minus-loser(WML) portfolio over the full sample period from January 1927 to February 2017. The dollar value in the left side of the figure shows the worth of each portfolios at the end of the period by investing $1 in January 1927, without adjusting the transaction costs.

Figure 2.2 displays the performance of momentum during and after Great depression from January 1930 to December 1939. In July and August 1932, momentum strategy results a negative return of -60.17% and -77.02%, respectively. While, the loser and market portfolio yields 93.95% and 74.27%, and 37.06% and 33.84% returns during the same months. The figure shows that momentum strategy experienced server crash as the market reverse after stock market collapsed associated with Great depression. Moreover, it takes a long time to recover the initial investment.

Figure 2.3 shows the cumulative returns of portfolios between January 2007 and February 2017. In a similar way, WML portfolio crashes when the market rebound from major losses in the Global financial crisis. In March 2009, momentum strategy provides a negative return of -45.79%. Conversely, the loser and market portfolios yields 45.66% and 10.19% returns, respectively, during the same month. Furthermore, it takes more than 10 years to recover initial investment after experiencing momentum crash.

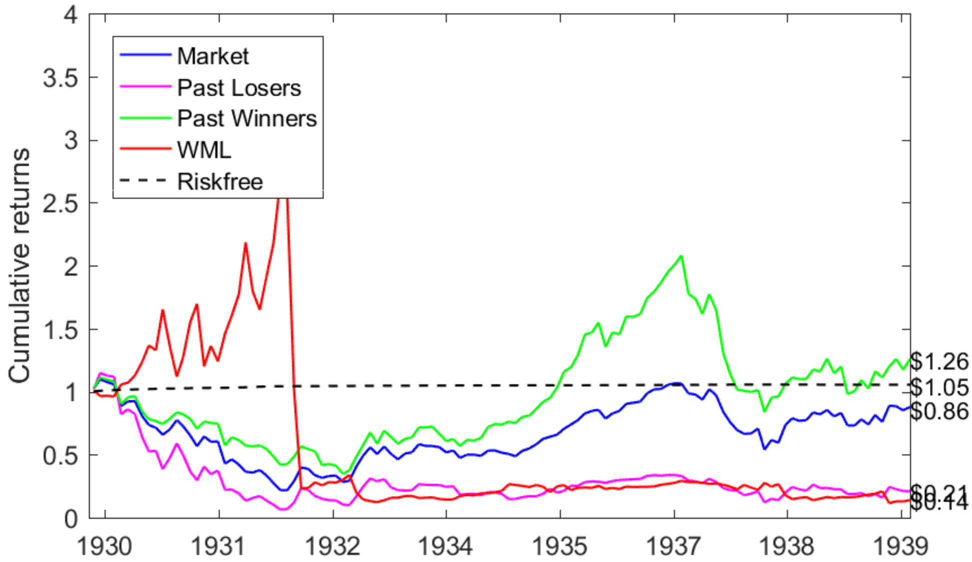

Figure 2.2: *Cumulative returns of equity portfolios from 1930 to 1939*

The figure plots cumulative returns of market portfolio, risk-free asset, loser portfolio, winner portfolio and winner-minus-loser(WML) portfolio from January 1930 to December 1939. The dollar value in the left side of the figure shows the worth of each portfolios in December 1939 by investing $1 in January 1930, without adjusting the transaction costs.

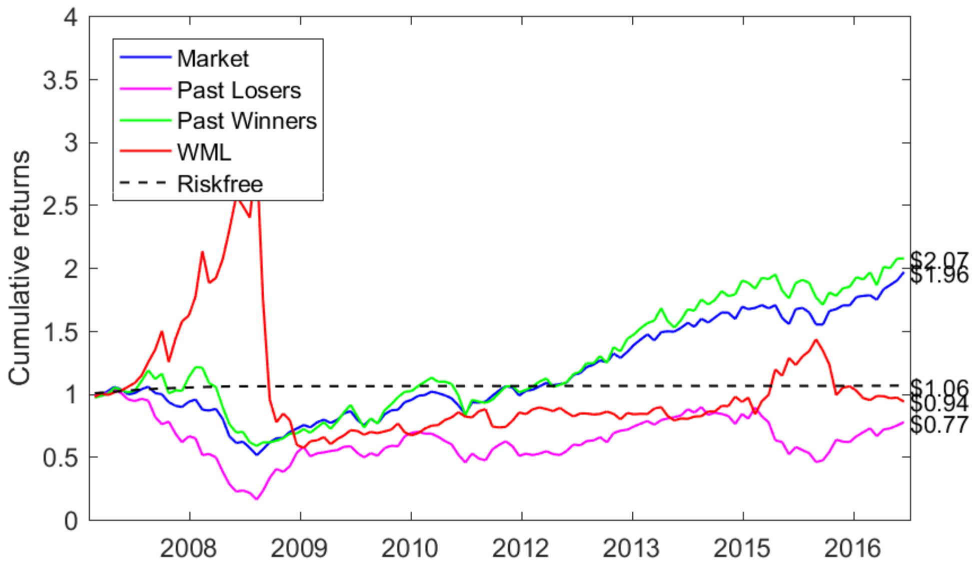

Figure 2.3: *Cumulative returns of equity portfolios from 2007 to 2017*

The figure depicts cumulative returns from January 2007 to February 2017. The dollar value in the left side of the figure shows the value of portfolios in February 2017 by investing $1 in January 2007, without adjusting the transaction costs.

2.3.2 Time-varying risk exposure of momentum

Grundy and Martin (2001) find a significant time-varying risk exposure of momentum strategy. They argue that, in a simple scenario where stock returns are governed by their co-movement with the market, during bear market ranking period winner stocks are those stocks with low market beta and loser stocks are with high market beta. Alternatively, during bull market ranking period winner stocks are those with high market beta and loser stocks are low market beta stocks. Therefore, the momentum portfolio, which long past winners and short past losers, tends to have a significant negative beta after bear market and a significant positive beta following bull market. When the market rebound after market drawdown, momentum strategy experience huge losses. I investigate the time-varying risk exposure of momentum by analyzing the beta of winner and loser portfolio. Figure 2.4 and 2.5 plots the market beta of winner and loser decile portfolios from August 1930 to January 1940 and from January 2007 to February 2017, respectively. These two periods marked as market reversal after stock market collapsed associated with Great depression and Global financial crisis, and include a time periods momentum strategy experienced worst returns. The winner and loser beta are estimated by running 6 months rolling regression of market model using monthly data.

As shown in Figure 2.4, the market beta of loser portfolio before momentum crash (before July 1932) ranges between 1.35 and 2.70, while the market beta for winner portfolios during the same period is between 0.50 and 1.09. This indicates that during bear market, Great depression, stock that fell with the market (losers) are high beta stocks, conversely stocks that performs well(winner) are low market beta stocks, which results a negative market beta of momentum strategy. During the crash period, in July 1932, loser portfolio has a market beta of 1.92 and winner 0.56. Similarly, in August 1932, losers and winners have a market beta of 1.97 and 0.49, respectively. After momentum crash, which is characterized by market recovery, the variability of beta between winner and loser portfolios widened sharply. The beta of loser portfolio reached as high as 3.58 and a minimum value of 0.38 and the beta of winner portfolio varies between 1.97 and 0.29. This reflects the time-varying risk exposure of momentum strategy.

To examine the time-varying exposure of momentum before and after

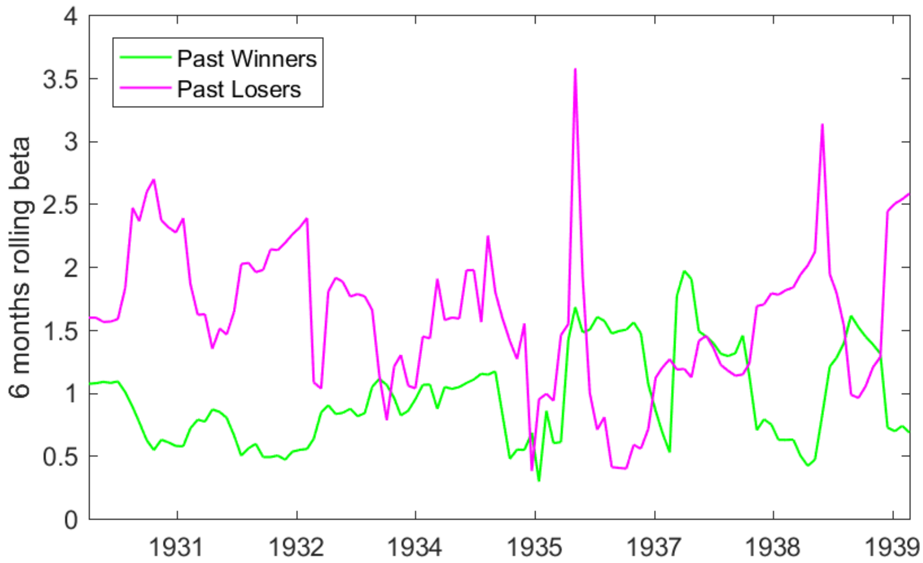

Figure 2.4: *Market beta of winner and loser decile portfolios from 1930 to 1940*

The winner and loser beta are estimated by running 6 months rolling regression of market model using monthly data.

Global financial crisis, Figure 2.5 depicts the market beta of winner and loser portfolios between August 2007 and February 2017. The upward and downward trend of winner and loser portfolio's market beta reversed after they reached 2.36 and -0.02 on March 2008, respectively. In this month, the financial market panicked when JP Morgan acquire Bear Sterns. Following this bear market phenomenon, the dynamics of loser and winner market betas changed dramatically. The beta of loser portfolio, a group of stocks that fell with the market, gradually increase until it reaches 4.37 on September 2009. While, the market beta of winner portfolio steadily decreases until it reaches its minimum value of -0.10 on October 2009. This indicates that following bear market winner portfolio tend to have low market beta and loser portfolio high market beta, consequently a negative momentum beta.

Similar tends are also observed when Lehman Brothers collapsed on September 2008, which brought down the financial system. Following this incident, there was a wide difference between the beta of loser and winner portfolios. When momentum strategy experience huge crash on March 2009 following market upswing from Global financial crisis, momentum portfolio has a market beta of -0.89, which is the differences between market beta of

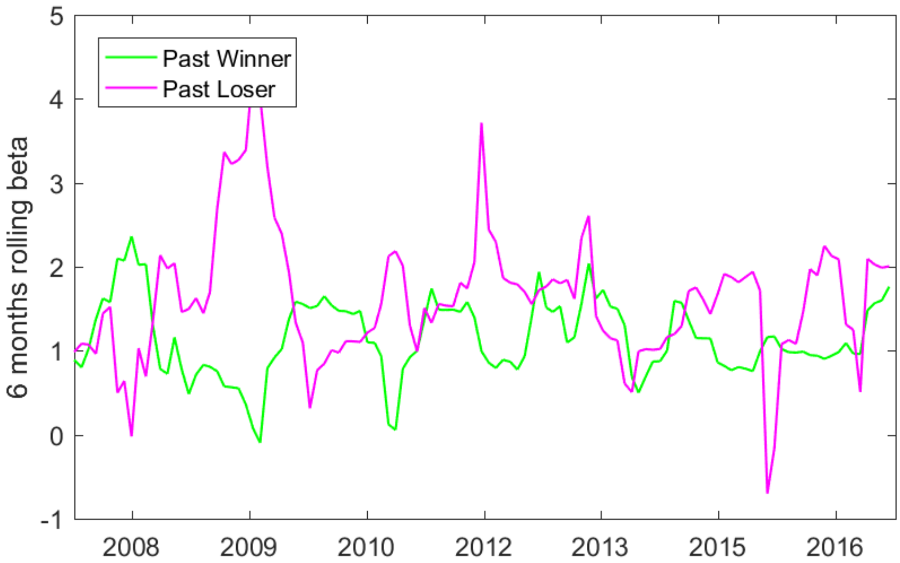

Figure 2.5: *Market beta of winner and loser decile portfolios from 2007 to 2017*

The winner and loser beta are estimated by running 6 months rolling regression of market model using monthly data.

loser and winner portfolios. Following bull market the momentum portfolio has positive market beta. This illustrates the time-varying beta of momentum strategy.

2.3.3 Hedging risk exposure of momentum

Grundy and Martin (2001) and Martens and Oord (2014) suggests that hedging the time-varying exposure improves the performance of momentum and provide more stable returns than unhedged momentum portfolio. I assess whether hedging market exposure of momentum avoids momentum crash and provide stable return using two most turbulent decades of the strategy. Momentum hedging are performed in two ways. The first approach is by taking opposite positions of unconditional market factor from CAPM regression

$$r_{WML,\ t} = \alpha + \beta_t * r_{M,t} + e_t \tag{2.4}$$

Then Hedged momentum portfolio computed as

$$r^{hedged}_{WML,\ t+1} = r_{WML,\ t+1} - \widehat{\beta}^{hedged}_{WML,\ t+1} * r_{M,t+1} \tag{2.5}$$

The second version of hedging momentum portfolio is by taking opposite position of upside and downside market risk factors using downside risk CAPM of Ang, Chen and Xing (2006) regression, which is based on association of momentum returns on market risk factor conditional on upside and downside market movements.

$$r^{c}_{WML,\ t} = \alpha + \beta_t^{+} \beta_t * r^{+}_{M,t} + \beta_t^{-} \beta_t * r^{-}_{M,t} + e_t \quad (2.6)$$

Then conditionally hedged momentum portfolio generated as

$$r^{c\_hedged}_{WML,\ t+1} = r^{c}_{WML,\ t+1} - \widehat{\beta}^{+\ c\_hedged}_{WML,\ t+1} * r^{+}_{M,t+1} - \widehat{\beta}^{-\ c\_hedged}_{WML,\ t+1} * r^{-}_{M,t+1} \quad (2.7)$$

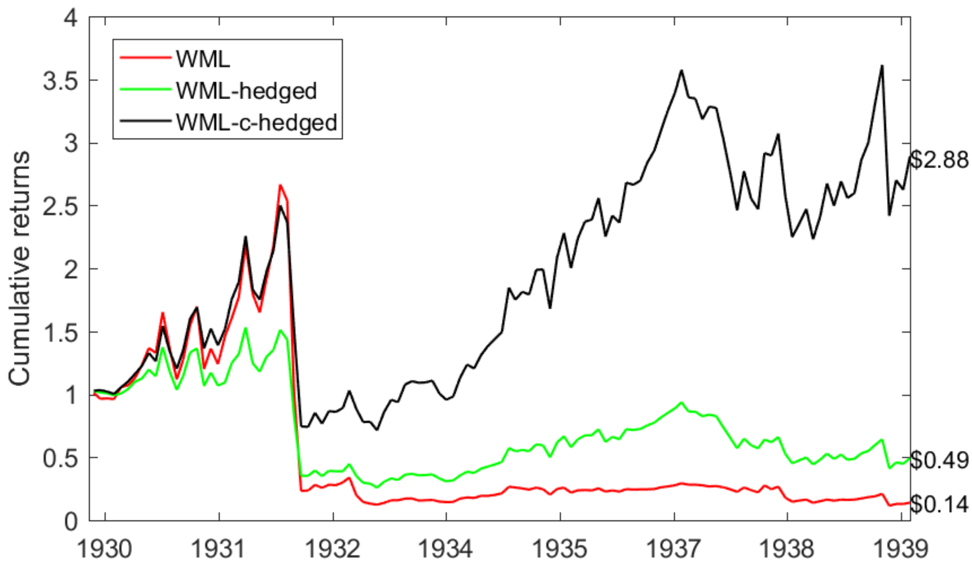

Figure 2.6: *Hedging time-varying exposure of momentum from 1930 to 1939*

The figure shows cumulative returns of unhedged winner-minus-loser(WML), hedged WML and conditionally hedged WML portfolios from January 1930 to December 1939. The dollar value in the left side of the figure shows the worth of each portfolios in December 1939 by investing $1 in January 1930, without adjusting the transaction costs.

Figure 2.6 shows the performance of unhedged momentum portfolio and two hedged momentum portfolios between January 1930 and December 1939. The cumulative returns of hedged momentum portfolios are higher than raw (unhedged) momentum portfolio. Furthermore, asymmetric treatment of upside and downside market risk exposure improves the profitability of unconditional hedged momentum. However, both version of hedging

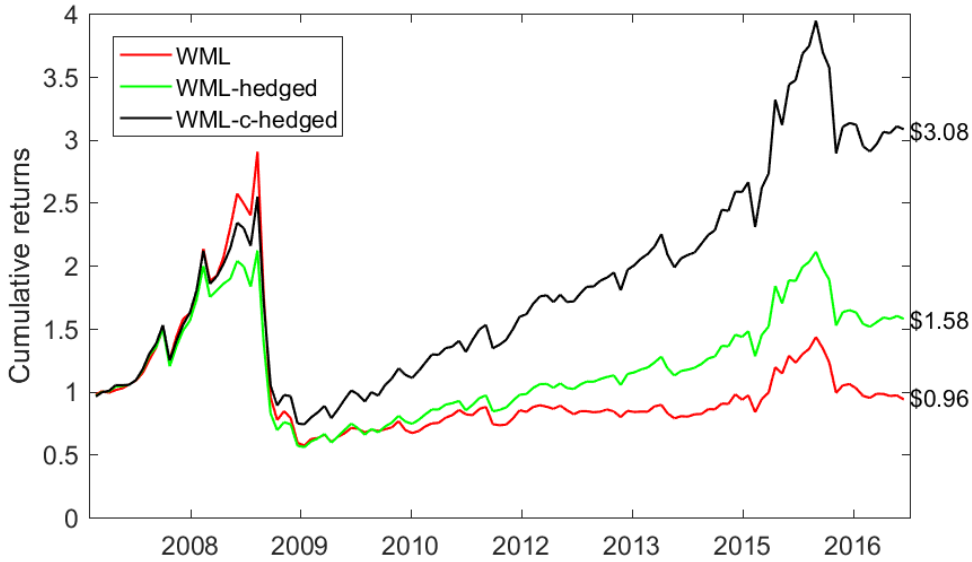

Figure 2.7: *Hedging time-varying exposure of momentum from 2007 to 2017*

The figure plots cumulative returns of unhedged winner-minus-loser(WML), hedged WML and conditionally hedged WML portfolios from January 2007 to February 2017. The dollar value in the left side of the figure shows the value of each portfolios in February 2017 by investing $1 in January 2007, without adjusting the transaction costs.

strategies cannot not avoid the risk of momentum crash. The returns of momentum strategies suffer huge loss following dramatic upswing of market after severe drawdown. Figure 2.7 depicts the cumulative returns of hedged and unhedged momentum portfolios from January 2007 to February 2017. The figure shows that while hedging the exposure of market risk improve the returns momentum strategy, it cannot alleviate the risk of momentum crash.

2.4 Optimal momentum strategy

The previous section gives important insights that merely hedging the time-varying risk exposure of momentum can not prevent this strategy from enormous losses. Therefore, it requires to design more efficient risk management technique that increase the payoff and mitigate crash risk. In this study, I propose a risk management strategy that scale zero-investment momentum strategy by its forecasted semi-variance. This approach involves two major steps. First, the time-varying risk exposure of plain momentum portfolio are conditionally hedge out by taking opposite positions of upside and downside market risk factors, as shown in equation (2.7). Second, the conditionally hedged momentum portfolios are scaled using its forecasted semi-variances. Barndor-Nielsen, Kinnebrock, and Shephard (2010) show the construction of upside and downside semi-variances. For each month, upside and downside volatilities (semi-variances) are forecasted using previous 126-day (≈ six months) momentum returns. Let $\left\{r^{c\text{-}hedged}_{WML,\ t}\right\}^{T}_{t=1}$ and $\left\{r^{c\text{-}hedged}_{WML,\ d}\right\}^{D}_{d=1}$ be the monthly and daily returns of conditionally hedged momentum portfolio. The upside and downside semi-variances forecasts are

$$\widehat{sv}^{U\ \ c\_hedged}_{WML,t} = 21 \sum_{j=0}^{125} r^{2\ \ c\_hedged}_{WML,\ d_{t-1-j}} / 126 * \phi_{[r^{c\text{-}hedged}_{WML,\ dt-1} \geq 0]} \tag{2.8}$$

$$\widehat{sv}^{D\ \ c\_hedged}_{WML,t} = 21 \sum_{j=0}^{125} r^{2\ \ c\_hedged}_{WML,\ d_{t-1-j}} / 126 * \phi_{[r^{c\text{-}hedged}_{WML,\ dt-1} < 0]} \tag{2.9}$$

Where, ϕ is a dummy variable that take a value 1 if the argument is true, otherwise zero.

Then I use the forecasted semi-variances to scale the conditionally hedged momentum portfolio returns. Risk adjusted optimal momentum portfolio computed as

$$r^{\ddagger}_{WML,t} = \frac{sv^{U}_{target}}{\widehat{sv}^{U}_{t}}\ r^{U\ c\text{-}hedged}_{WML,\ t} + \frac{sv^{D}_{target}}{\widehat{sv}^{D}_{t}}\ r^{D\ c\text{-}hedged}_{WML,\ t} \tag{2.10}$$

Where, $r^{\ddagger}_{WML,t}$ is optimal momentum portfolio, $r^{U\ c\text{-}hedged}_{WML,\ t}$ is upside (positive) conditionally hedged momentum, $r^{D\ c\text{-}hedged}_{WML,\ t}$ is downside (negative) conditionally hedged momentum. sv^{U}_{target} and sv^{D}_{target} denotes the corresponding target level of upside and downside semi-variance. Barroso and Santa-Clara (2015) picked 12% annual target volatility to scale momentum return. For easy comparison, the returns of optimal strategy scaled to 6% upside and 6% downside annualized target semi-variances.

Figure 2.8 shows the performance of plain (unscaled) momentum, risk managed momentum of Barroso and Santa-Clara (2015) and optimal momentum strategy over the 90-year full sample period from January 1927 to February 2017. The optimal WML strategy immensely outperform the constant variance risk managed momentum strategy and plain momentum. The dollar value shown in the left side of the graph is without adjusting the

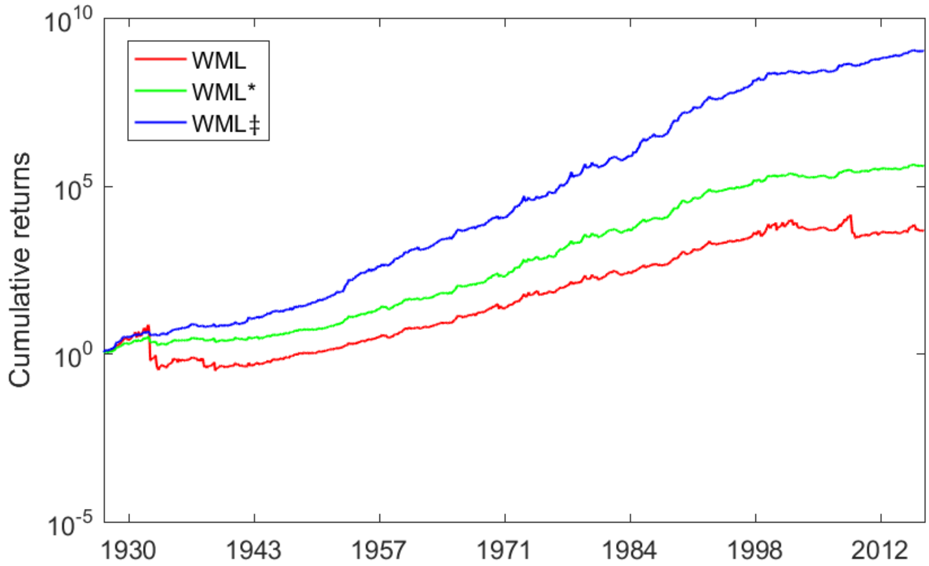

Figure 2.8: *Cumulative returns of plain and risk-managed momentums from 1927 to 2017*

The figure reports cumulative returns of plain momentum(WML), Barroso and Santa-Clara (2015)'s risk managed momentum(WML*) and optimal momentum(WML‡) over the 90-year full sample period from January 1927 to February 2017. Optimal portfolio uses the semi-variance of previous 126-day (≈ six months) to scale conditionally hedged momentum portfolio. The left side of the figure shows the dollar value of each portfolios at the end of the period by investing $1 in January 1927, without adjusting for transaction costs.

transaction cost. Practical implementation of optimal WML strategy may incur high transaction costs than other two strategies and reduce exaggerated payoff.

The robustness of optimal momentum portfolio checked using two turbulence decades, Great depression and Global financial crisis: 1930 to 1939 and 2007 to 2017. Figure 2.9 plots the cumulative reruns of raw momentum, Barroso and Santa-Clara (2015)'s risk managed momentum and optimal momentum between January 1930 and December 1939. Optimal portfolio uses the semi-variance of previous 126-day (≈ six months) to scale conditionally hedged momentum portfolio. Interestingly, beside mitigating momentum crash, optimal strategy yields higher payoff than other two strategies.

Figure 2.10 also illustrates the performance of momentum strategies for the subsample period from January 2007 to February 2017. Consistent with

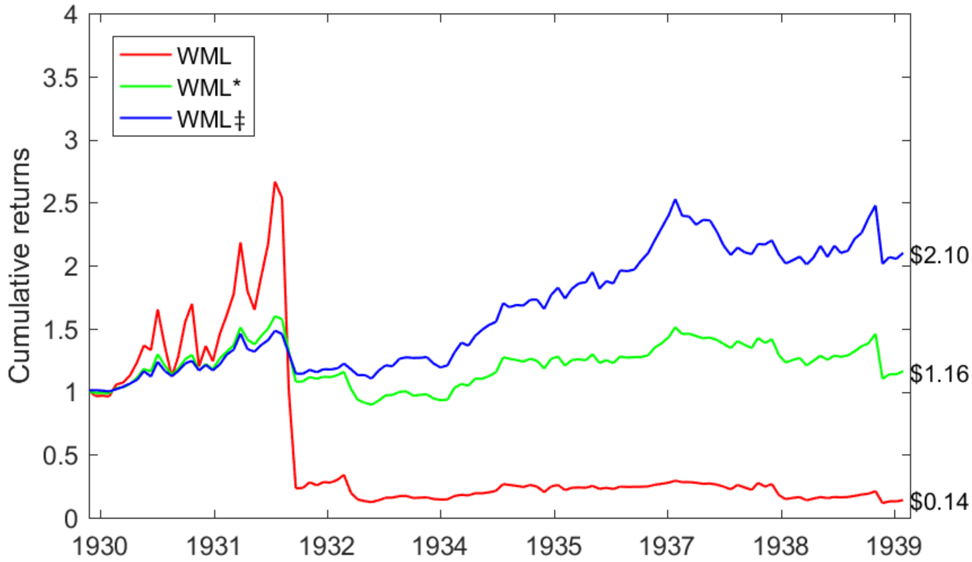

Figure 2.9: *Cumulative returns of plain and risk-managed momentums from 1930 to 1939*

The figure plots cumulative returns of plain momentum(WML), Barroso and Santa-Clara (2015)'s risk managed momentum(WML*) and optimal momentum(WML‡) from January 1930 to December 1939.

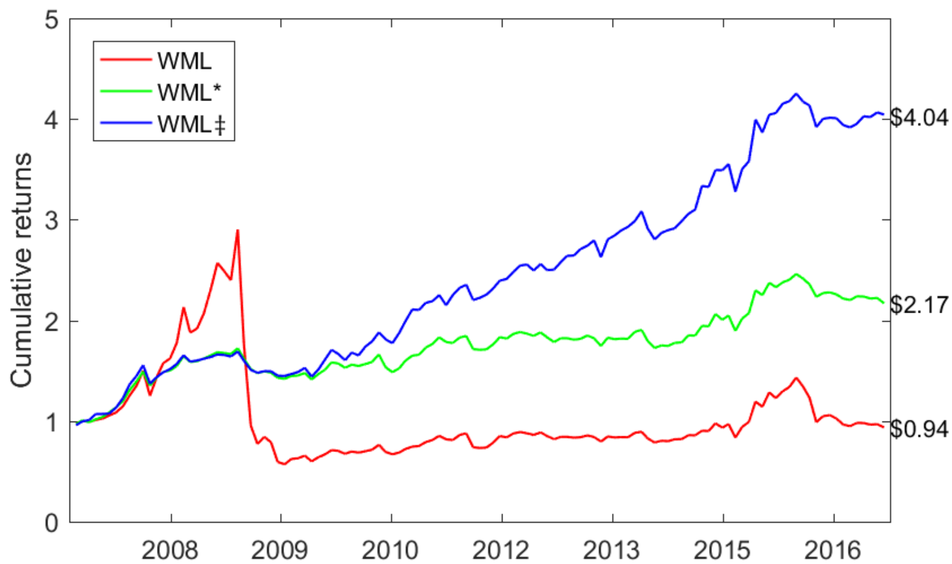

Figure 2.10: *Cumulative returns of plain and risk-managed momentums from 2007 to 2017*

The figure shows cumulative returns of plain momentum(WML), Barroso and Santa-Clara (2015)'s risk managed momentum(WML*) and optimal momentum(WML‡) from January 2007 to February 2017.

the previous results, optimal strategy remarkably outperforms the plain momentum and Barroso and Santa-Clara (2015)'s risk managed strategies by providing better returns and mitigating crash risk. These result indicates the outstanding performance of optimal momentum strategy. However, transaction cost should be taken into account for practical implementation of this strategy.

Table 2.2: *Twelve worst plain WML losses together with risk managed momentum strategies*

Rank	Month	$\mathbf{WML}_t$	$\mathbf{WML}_t$*	$\mathbf{WML}_t$‡	$\mathbf{Market}_t$
1	1932:08	-77.02	-18.26	-12.22	37.06
2	1932:07	-60.17	-16.28	-10.65	33.84
3	2009:04	-45.79	-6.44	-5.58	10.19
4	1939:09	-45.16	-24.57	-18.75	16.88
5	2001:01	-41.97	-13.65	-15.64	3.13
6	1933:04	-41.92	-11.79	-3.70	38.85
7	2009:03	-39.39	-6.07	-5.51	8.95
8	1938:06	-33.20	-8.97	-5.09	23.87
9	1931:06	-29.26	-9.85	-6.22	13.90
10	1933:05	-26.87	-8.41	-4.00	21.43
11	2009:08	-24.85	-3.51	-2.96	3.33
12	2002:11	-20.40	-7.79	-7.08	5.96
Mean (1:12)		-40.50	-11.30	-8.12	18.12

This table reports twelve worst plain WML losses together with the monthly reruns of Barroso and Santa-Clara (2015)'s constant volatility risk managed momentum(WML*), optimal momentum strategy (WML‡) and the contemporaneous market return.

In order to compare the performance of risk management strategies in more detail, Table 2.2 shows twelve worst WML losses together with the monthly reruns of Barroso and Santa-Clara (2015)'s constant volatility risk managed momentum, optimal momentum strategy and the market. Optimal strategy better reduces WML losses relative to Barroso and Santa-Clara (2015)'s risk managed momentum strategy. The average monthly returns of constant volatility and optimal momentum strategies over twelve worst returns of WML portfolio are -11.30% and -8.12%, respectively. This result illustrates that optimal strategy reduces momentum crash quite substantial.

Furthermore, Table 2.3 presents the characteristics of plain momentum, risk managed momentum of Barroso and Santa-Clara (2015), optimal momentum and the market returns over full sample period from January 1927 to February 2017. The optimal momentum strategy has average annual excess return of 25.26%, with the corresponding volatility of 19.60%. While, the plain momentum and Barroso and Santa-Clara (2015)'s risk managed momentum strategy have average excess returns of 14.12% and 15.77%, with annualized volatility of 27.11% and 16.45%, respectively. Excess kurtosis dropped from 17.38% in plain momentum to 2.90% of optimal momentum strategy. Higher Sharpe ratio coupled with positively skewed return of optimal momentum make this strategy more attractive.

Table 2.3: *Descriptive statistics of plain WML and risk managed momentum strategies*

Statistics	$\mathbf{WML}_t$	$\mathbf{WML}_t$*	$\mathbf{WML}_t$‡	$\mathbf{Market}_t$
Mean	14.12	15.77	25.26	7.84
Std.	27.11	16.45	19.60	18.64
SR	0.52	0.96	1.29	0.42
Sk.	-2.34	-0.33	0.12	0.19
Ku.	17.38	2.11	2.90	7.75

This table reports descriptive statistics of plain WML portfolio, constant volatility risk managed momentum(WML*) of Barroso and Santa-Clara (2015), optimal momentum strategy (WML‡) and the contemporaneous market return over the 90-year full sample period from January 1927 to February 2017. The table presents annualized average excess return, annualized standard deviation, annualized Sharpe ratio, skewness and kurtosis.

2.5 Currency momentum returns

In this section I examined the characteristics of currency momentum returns. Moreover, I assess whether momentum crash that observed in equity momentum are also prevalent in currency market.

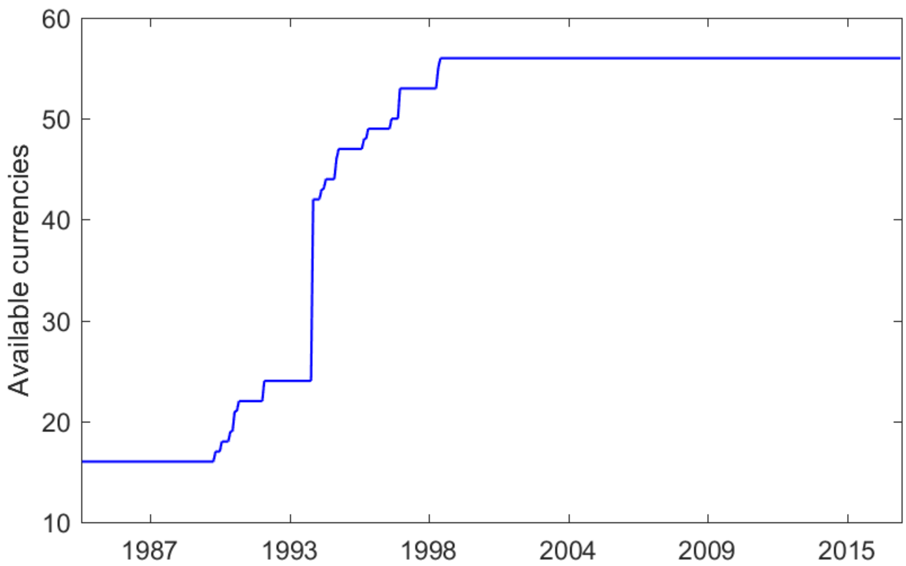

Figure 2.11: *Number of available currencies from 1985 to 2017.*

As explained before, currency portfolios are formed by ranking currencies based on their prior performance. The availability of currency data, spot and forward exchange rate, varies over time. Figure 2.11 depicts the number of available currencies from January 1985 to March 2017. The plot shows that the number of currencies in the sample period ranges from 16 to 56.

Table 2.4 presents the characteristics of octile (8) currency momentum, the winner minus loser(WML) and market portfolios over the full sample period from January 1985 to March 2017. Consistent with finance literatures, the average excess return of currency momentum rises when moving from loser to winner portfolio. While looking at annualized volatility, winner tend to have higher volatility than loser portfolio. Moreover, the return distribution of winner portfolio are more positively skewed and fat-tail as indicated by high excess kurtosis.

Zero-investment WML currency portfolio has an average excess return of 14.62 % per year, almost twofold of market returns, coupled with high Sharpe

Table 2.4: *Currency momentum portfolios and market*

Statistics	Octile Momentum Portfolios 1	2	3	4	5	6	7	8	WML	RMRF
Mean	-4.71	-1.84	-0.01	0.07	1.41	0.55	0.39	9.91	14.62	7.93
Std.	8.05	5.62	5.63	5.95	6.16	6.47	6.93	17.12	18.21	15.38
SR	-0.58	-0.33	0.00	0.01	0.23	0.09	0.06	0.58	0.80	0.52
Sk.	0.91	0.03	0.13	0.12	0.23	0.30	0.29	3.87	3.63	-0.91
Ku.	4.78	3.48	2.11	4.07	1.88	4.47	3.69	20.62	19.56	2.75
α^{CAPM}	-4.40	-1.39	0.47	0.43	1.86	0.93	0.88	10.96	15.36	0.00
t(α)	-3.02	-1.38	0.47	0.40	1.68	0.79	0.71	3.55	4.66	nan
β^{RMRF}	-0.04	-0.06	-0.06	-0.05	-0.06	-0.05	-0.06	-0.13	-0.09	1.00
t(β)	-1.45	-3.08	-3.24	-2.27	-2.78	-2.17	-2.68	-2.30	-1.52	∞

The table reports descriptive statistics of currency momentum portfolios and market returns. The first portfolio(loser) contains currencies with the worst past performance and the eighth portfolio(winner) consists of currencies with the best prior performance. The Winner-Minus-Loser (WML) portfolio is the difference between the return of top octile (winner) portfolio and the return of bottom octile (loser) currency portfolio. The table presents annualized average excess return, annualized standard deviation, annualized Sharpe ratio, skewness and kurtosis. The CAPM alpha along with their t-statistics are also shown from ordinary least square(OLS) regression of WML portfolio on market. All statistics are computed using monthly data from January 1985 to March 2017.

ratio and positively skewed return distribution. However, its large payoff come at the cost of high excess kurtosis. To identify whether high excess return of currency momentum related with high market risk exposure, the last four rows present ordinary least square(OLS) regression result of currency momentum portfolios on the market factor. The result shows that currency WML portfolio has no significant exposure to market, and it offers abnormal annual return of 15.36%.

Figure 2.12 plots the cumulative returns of market portfolio, risk-free asset, currency loser portfolio, winner portfolio and WML portfolio from February 1986 to March 2017. Comparing the overall performance of these portfolios, the return of currency WML portfolio outperform others in the sample period. In the early part of the sample, zero-investment momentum strategy provides lower return than market portfolio and risk-free asset. However, the momentum strategy experience huge return upswing after January 2001. One possible explanation of this result is availability of fewer currencies in the early years of the sample. Menkhoff et al. (2012) explain this phenomenon that, while it is possible to implement momentum strategy using closely linked currencies, the expected momentum return should be relatively lower in the early years of the sample. Interestingly, the figure also shows that there is no huge drop-down in currency momentum returns.

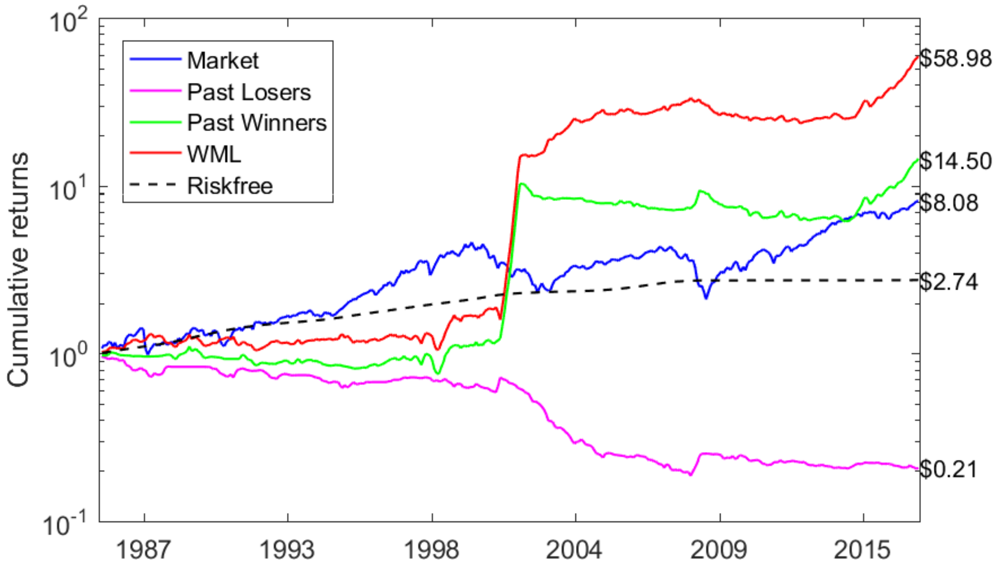

Figure 2.12: *Cumulative returns of currency portfolios from 1986 to 2017*

The figure presents cumulative returns of market portfolio, risk-free asset, currency loser portfolio, winner portfolio and winner-minus-loser(WML) portfolio from February 1986 to March 2017. The dollar value in left side of the figure shows the worth of each portfolios in March 2017 by investing $1 in February 1986, without adjusting the transaction costs.

To examine further whether momentum crash are also prevalent in currency market, I sort twelve worst monthly returns of currency momentum. These returns ranges from -10.88% in October 1998 to -5.34% in October 2010. This reflects the absence of huge crash in currency momentum. Interestingly, the performance of currency momentum do not interrupted even following Global financial crisis. It seems that large disconnection of currency momentum from US business cycle.

Table 2.5 presents the risk exposure of currency momentum to the systematic risk factors using univariate and multivariate regressions. I decompose market risk to upside and downside market factor to consider asymmetric response of momentum strategy to upward and downward market movement. Panel A of the Table shows univariate regression of WML on each risk factors. The first row is the result of OLS regression of WML on market(CAPM). Currency momentum portfolio have no significant exposure

Table 2.5: *Risk exposure of currency momentum strategy*

	Panel A: Univariate regression			Panel B: Multivariate regression			
Variable	α t(α)	β t(β)	R^2	Variable	α t(α)	β t(β)	R^2
RMRF	15.36 (4.66)	-0.09 (-1.52)	0.61	$RMRF^U$	17.73 (4.46)	-0.17 (-1.80)	0.92
HML	14.53 (4.46)	0.11 (1.29)	0.45	$RMRF^D$		-0.01 (-0.10)	
SMB	14.38 (4.39)	0.09 (0.93)	0.23	RMRF	15.01 (4.54)	-0.10 (-1.64)	1.65
$RMRF^U$	17.88 (4.84)	-0.17 (-1.85)	0.91	HML		0.17 (1.87)	
$RMRF^D$	14.13 (4.10)	-0.04 (-0.44)	0.05	SMB		0.10 (1.07)	

The table presents ordinary least square(OLS) regression of currency momentum returns on market(RMRF), size(SMB), value(HML), upside market ($RMRF^U$) and downside market($RMRF^D$) risk factors along with their t-statistics. Panel A of the Table shows univariate regression of WML on each risk factors. Panel B shows the multivariate regression of WML portfolio using downside CAPM of Ang, Chen and Xing (2006) and Fama and French (1992) three-factor model. Alpha and R^2values are in percent, and t-statistics are in parentheses. All statistics are computed using monthly data from February 1986 to March 2017.

to market risk factor. This result reinforces the findings in Figure 2.12, that great disconnection of currency markets form US stock market. The result of second and third row implies that currency momentum exposure to size and value factors are minimal. Asymmetric treatment of upside and downside market risk exposure cannot change the dynamics of relationship.

Panel B presents multivariate regression of WML portfolio using downside CAPM of Ang, Chen and Xing (2006) and Fama and French (1992) three-factor model. The result shows that strategy's exposure to the upside and downside market risk factor is insignificant. Moreover, the exposure to the Fama and French (1992) three factor are also negligible. Hence, it can be infer that systematic risk factors do not help to understand currency momentum return.

2.5.1 Decomposing currency momentum risk

In this sub-section I provide an in-depth analysis of currency momentum by decomposing the risk factor into systematic and specific(idiosyncratic) components. I propose realized semi-variance to decompose the risk of currency momentum into systematic and specific risks. This approach helps to investigate the source of momentum risk by further decomposing the systematic risk component into upside and downside market risk factors. The construction of upside and downside realized semi-variance are detailed by Barndor-Nielsen, Kinnebrock, and Shephard (2010).

For momentum portfolio or market risk factor, upside and downside semi-variances computed as

$$\mathrm{RS}_t^{+} = \sum_{j=1}^{n_t} r_{j,t}^2 * \phi_{[r \geq 0]} \tag{2.11}$$

$$\mathrm{RS}_t^{-} = \sum_{j=1}^{n_t} r_{j,t}^2 * \phi_{[r < 0]} \tag{2.12}$$

Where, ϕ is a dummy variable that take a value 1 if the argument is true, otherwise zero. I set zero threshold to decompose upside and downside portfolio returns. Subsequently, I use the conditional market model to decompose momentum risk into upside(downside) market and specific risk:

$$\mathrm{RS}_{WML,\ t}^{+} = \beta_t^{2^+} RS_{RMRF,t}^{+} + \mathrm{RS}_{\varepsilon}^{+} \tag{2.13}$$

$$\mathrm{RS}_{WML,\ t}^{-} = \beta_t^{2^-} RS_{RMRF,t}^{-} + \mathrm{RS}_{\varepsilon}^{-} \tag{2.14}$$

Upside(downside) semi-variance and betas are estimated using previous 126-day ($\approx$ six months) return.

I test in-sample and out-of-sample(OOS) predictability of risk. The main idea of this approach is to run regression on 240 months training sample and use the estimated coefficients and recent month realized variance to forecast the realized variance of next month. To evaluate the forecasting fit using realized variance, the OOS R^2 calculated as

$$R_{i,OOS}^2 = 1 - \frac{\sum_{t=S}^{T-1} \left(\widehat{\alpha}_t + \widehat{\rho}_t RV_{i,t} - RV_{i,t+1}\right)^2}{\sum_{t=S}^{T-1} \left(\overline{RV}_{i,t} - RV_{i,t+1}\right)^2} \tag{2.15}$$

Where, $\widehat{\alpha}_t$ and $\widehat{\rho}_t$ are estimated coefficients from AR (1). S denotes training sample. The OOS goodness-of-fit or R^2 using semi-variance estimated

Table 2.6: *Decomposing the risk of currency momentum*

Panel A: Upside realized semi-variance					**Panel B: Downside realized semi-variance**				
Variable	α t(α)	ρ t(ρ)	R^2	R^2_{oos}	Variable	α t(α)	ρ t(ρ)	R^2	R^2_{oos}
RS^+_{WML}	0.04 (1.16)	0.21 (1.63)	4.30	36.3	RS^-_{WML}	0.00 (1.35)	-0.02 (-0.17)	0.05	-6.07
RS^+_{RMRF}	0.01 (1.92)	0.77 (9.18)	58.80	82.88	RS^-_{RMRF}	0.00 (0.64)	0.78 (10.39)	64.70	97.84
β^{2+}	9.98 (2.25)	0.05 (0.38)	0.24	2.35	β^{2-}	0.00 (1.02)	0.25 (1.98)	6.27	42.80
$\beta^{2+}RS^+_{RMRF}$	0.24 (1.54)	0.00 (-0.00)	0.00	-2.64	β^{2-} RS^-_{RMRF}	0.00 (0.99)	0.28 (2.24)	7.84	47.21
RS^+_{ε}	-0.22 (-1.51)	-0.16 (-1.22)	2.49	-36.15	RS^-_{ε}	0.00 (1.17)	-0.01 (-0.09)	0.01	-3.44

The table shows AR (1) for each component of risk. α and ρ are estimated coefficients from AR(1). Panel A of the Table shows upside realized semi-variance for each component of risk, and Panel B the corresponding downside realized semi-variance. The first row shows the upside(downside) realized semi-variance of currency WML portfolio. The second row is upside(downside) realized semi-variance of market(RMRF) portfolio. The third one is upside(downside) squared beta, which is estimated by regression of upside(downside) WML portfolio on upside(downside) market using six months' daily return. The forth row presents the systematic component of upside(downside) market risk. The last row presents the specific component of risk. R^2 and ${R^2}_{oos}$denotes in-sample and out-of-sample coefficient of determination. All statistics are computed using currency data from February 1986 to March 2017.

by employing upside realized semi-variance ($RS^+_{i,t}$) and downside semi-variance ($RS^-_{i,t}$).

Table 2.6 reports AR (1) result of each components of risk. Panel A of the table shows the upside realized semi-variance for each component of risk, while Panel B presents the result of downside semi-variance. Moreover, in-sample and out-of-sample(OOS) predictability of each component of risk are also reported in the table. The result shows that, while realized upside and downside market semi-variances are the most predictable component of momentum risk either in sample or OOS, upside and downside market betas remain the least predictable. When combined, upside market risk, $\beta^{2+}{RS^+}_{RMRF,}$ has no contribution to the upside momentum risk. Furthermore, the downside component of market risk, $\beta^{2-}{RS^-}_{RMRF,}$ accounts only 7.8% of downside momentum risk with an OOS R-square of 47.21%. This illustrates that the systematic (market) risk component of momentum strategy is very less. Upside momentum risk found to be the more

Table 2.7: *Currency momentum volatility on upside and downside realized semi-variance of market*

	Realized Variance: $RV_{WML,t} = \beta_t^{+} RS_{RMRF,t}^{+} + \beta_t^{-} RS_{RMRF,t}^{-} + RV_{\varepsilon}$			
	α t(α)	ρ^{+} t(ρ^{+})	ρ^{-} t(ρ^{-})	R^2
RV_{WML}	0.034 (1.08)	0.05 (2.08)	-6.91 (-0.18)	6.98

The table shows AR (1) of currency momentum volatility on upside and downside realized semi-variance of market. α, ρ^{+} and ρ^{-} are estimated coefficients from AR(1). All statistics are computed using currency data from February 1986 to March 2017.

predictable risk with an OOS R-square of 36.30% relative to the downside risk. Either in-sample or OOS, specific risk is the least predictable component of upside and downside momentum risk.

To investigate the volatility of currency momentum, I compute realized variance, which is a sum of upside and downside semi-variance:

$$RV_{WML,t} = \beta_t^{2-} RS_{RMRF,t}^{-} + \beta_t^{2-} RS_{RMRF,t}^{-} + RV_{\varepsilon} \tag{2.16}$$

Table 2.7 presents the result of equation (2.16). Consistent with the previous finding, on average market component of momentum volatility accounts only 7%, another 93% is specific to the momentum strategy.

I also investigate the composition of currency momentum risk by decomposing the total risk into market and specific component using market model. The results are available in the Appendix (Table A1). The market component of risk, β^2 $RV_{RMRF,}$is the least predictable component of total momentum risk. This implies that hedging the market risk of currency momentum do not improve the performance of strategy, as most risk remain unhedged.

2.6 Conclusions

In this chapter, I investigate momentum strategies in equity and currency markets. In a stable economic condition buying recent winner and selling recent loser assets provide higher positive returns. However, the impressive performance of equity momentum interrupts following market draw-down and results huge momentum crash, which wiped out amassed returns and takes a long time to recover. In July and August 1932, momentum strategy results a negative stock return of -60.17% and -77.02%, respectively. In March 2009, equity momentum provides a negative return of -45.79%. I propose an optimal momentum strategy to manage the risk of crash and keep momentum performance consistent. This strategy remarkably mitigates momentum crash and provide higher payoff than plain momentum and risk managed momentum strategy suggested by Barroso and Santa-Clara (2015). In July and August 1932, this strategy reduces momentum crash to -10.65% and -12.22%, respectively. It also provides higher positive return in the tranquil and crisis periods.

Momentum strategy provide higher Sharpe ratio in currency market. Unlike equity momentum, huge crash risk is not pronounced in currency momentum. The strategy do not have significant risk exposure to the standard risk factors. Further decomposing the risk of currency momentum shows that systematic market risk is the least component of total risk, which implies that specific risk accounts the main source of currency momentum risk. In general, managing the risk of momentum mitigate crash risk and provide consistent higher positive returns.

3. CONDITIONAL ASSET PRICING, IDIOSYNCRATIC RISK AND THE CROSS-SECTION OF RETURNS

3.1 Introduction

Most empirical studies on asset pricing have focused on testing whether asset pricing models can explain the cross-section of returns when one or more systematic risk factors are incorporated in the model and assume risk premium. However, the possibility of asset pricing model that could price idiosyncratic risk to compensate investors' under-diversification has given less emphasis. This is partly due to the views of modern portfolio theory that suggest only systematic risk of assets should be priced in equilibrium, but the exposure to idiosyncratic risk should not be compensated as it can be eliminated in a well-diversified portfolio. This assumption holds if investors optimally diversify their portfolios. As a rule of thumb, Campbell, Lettau et al. (2001) suggests a portfolio of 50 stocks to achieving a large fraction of diversification benefits. In reality, however, investors may not hold diversified portfolio for various reasons. Barber and Odean (2000) report that a typical US individual investor holds a portfolio contains only four stocks. Huberman (2001) and Polkovnichenko (2005) provide additional evidence that investors ignore to diversify their portfolios in practice. Goetzmann and Kumar (2008) examine the portfolio choice of 62,387 US individual investors from 1991 to 1996. They show that more than 50% of investors' portfolio hold one to three stocks, 70% of portfolios contains less than five stocks and 90-95% of portfolios comprise of less than ten stocks.

Some prior studies propose asset pricing models that incorporate idiosyncratic risk to account for holding imperfectly diversified portfolio. Mayers (1976), Levy (1978) and Merton (1987) advance a model by extending the CAPM to include investors' under-diversification effect in asset prices. Merton argues that if investors unable to hold diversified market portfolio because of incomplete information or deliberately structure their portfolios to accept considerable firm-specific risk, they require higher returns for assets with high idiosyncratic risk. Malkiel and Xu (2006) show that in the absence of fully diversified portfolio, investors demand compensation for holding securities with idiosyncratic risk. Boehme et al. (2009) find strong support of Merton's suggestion that investors price idiosyncratic risk when they hold under-diversified portfolios, and the relationship between idiosyncratic risk and expected returns is positive.

Empirical evidences on the existence of idiosyncratic risk premia in expected returns revisited the interest of idiosyncratic risk in asset pricing studies, while the findings are mixed. The seminal work of Campbell, Lettau et al. (2001) find that idiosyncratic risk is the main component of total risk and varies over time. They develop an equilibrium model that consider an idiosyncratic risk premium in the cross-section of asset returns, and report the existence of significant positive linkage between expected returns and idiosyncratic risk. Goyal and Santa-Clara (2003) observe a significant positive interdependence between idiosyncratic volatility and subsequent stock returns. Fu (2009), Bali and Cakici (2008) and Chua, Goh, and Zhang (2010) also show a positive linkage between returns and idiosyncratic volatility. While, Ang, Hodrick, Xing, and Zhang (2006, 2009, hereafter AHXZ) find a significant negative relationship between average returns and lagged idiosyncratic risk, they call it a "substantive puzzle". The conflicting results in the existing literatures may be due to lack of consistency in the choice of variable used to proxy idiosyncratic risk and asset returns. Some studies use lagged or realized idiosyncratic volatility as a measure of idiosyncratic risk, while others employ conditional or expected idiosyncratic volatility. Additionally, there is also disparity in using realized and future returns.

AHXZ (2006) sort the return of stocks by their idiosyncratic volatility and find low average returns for stocks with high idiosyncratic volatility in the subsequent month. More specifically, the quantile of stock portfolio with the highest idiosyncratic volatility earns average monthly return of 1.06 % less than the quantile of stocks with the lowest idiosyncratic volatility. They also show a negative linkage between average returns and idiosyncratic volatility after controlling firm specific characteristics. In their subsequent study, AHXZ (2009) provide evidence of significant negative relationship between future average returns and past idiosyncratic volatility in other G7 countries. Moreover, they report a -1.31% difference of average monthly returns between high and low quantiles sorted on idiosyncratic volatility after considering for the exposure to the world market, size and value factors across 23 developed markets.

Jiang and Lee (2006) argue that lagged idiosyncratic volatility is not a proper proxy of idiosyncratic risk as it may not capture the time-varying property, rather they suggest using conditional expected idiosyncratic volatility instead. They show a positive relationship between idiosyncratic volatility and returns. Fu (2009) point out that the theoretically correct factor to explain expected returns should be the same period expected idiosyncratic volatilities, since the time-varying nature of idiosyncratic volatility may not make the one-month lagged idiosyncratic volatilities a good proxy of current month expected idiosyncratic volatility. Therefore, the negative relationship between lagged idiosyncratic volatilities and average returns reported by AHXZ (2006, 2009) could not be used to infer the relationship between expected returns and idiosyncratic risk. To explain the time-variation in the idiosyncratic volatility process, Fu (2009) estimate the expected idiosyncratic volatility using the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model and uncover a strong positive relationship between expected returns and conditional idiosyncratic volatility.

Fu (2009) argues that AHXZ's results are driven by return reversal over the next month. Stocks with the highest idiosyncratic volatility tend to have high expected return, but the trend reverse in the following month and yield abnormally low average returns. Huang, et al. (2010) suggest that AHXZ's results of negative relations are as a result of biased portfolio weighting and biased estimate of cross-sectional relation brought by return reversal. They find a significant positive relation between conditional idiosyncratic volatility and aveage returns after controlling for return reversal. Bali, Cakici, and Whitelaw (2011) investigate the existence of idiosyncratic risk puzzle by including additional control variable, past month daily returns, and find the reverse of negative relationship between returns and idiosyncratic volatility report by AHXZ.

The purpose of this study is to investigate whether idiosyncratic risk priced in the cross-section of stock returns. Assessing the existence of idiosyncratic risk premia is important to determine the presence of compensation for under-diversified investors as they are exposed to specific risk for various reasons. The main contribution of this study to the existing literature is two folds. The first one related to the methodological approach for examining the role of idiosyncratic risk in the asset pricing process. In order to assess idiosyncratic risk in a different way, I employ a parsimonious conditional asset pricing models in the analysis. This approach enables to model risk–return relation by correcting the time-variation in market factor and incorporating idiosyncratic risk in the asset pricing models. Hence, the conditional relations of idiosyncratic risk and stock returns can be explained by the association of returns with the conditional market return. It is close to the method used by Cotter, Sullivan and Rossi (2015) to analyze the conditional relation between idiosyncratic risk and returns of UK equity markets. They provide evidence of significant negative linkage between idiosyncratic risk and returns in the downside market.

The second contribution related to the estimation of idiosyncratic volatility. Lack of consistency in the variable used to proxy idiosyncratic risk induced conflicting results in the literature. For instance, AHXZ (2006, 2009) used one-month lagged idiosyncratic volatility as a proxy of specific risk and find a negative relation between stock returns and idiosyncratic volatility. While, Fu (2009) suggests using expected idiosyncratic volatility and shows a significant positive relationship between idiosyncratic volatility and average returns. For better comparison, I compute idiosyncratic risk using the approaches suggested by both authors and assess whether idiosyncratic risk component is compensated in the financial markets.

The rest of the chapter organized as follows. Section 3.2 describes the data set and how I construct idiosyncratic volatility and other cross-sectional variables. Section 3.3 explains the methodology employed to examine the cross-sectional relationship between idiosyncratic volatility and stock returns. Section 3.4 discusses the main results. Section 3.5 concludes.

3.2 Data and variable construction

The data set includes 1000 firms traded in NYSE and NASADQ. I obtained daily and monthly stock prices, book values, and shares outstanding from DataStream. All stocks have equal sample period ranges from March 2000 to December 2016. I use share prices and shares outstanding to compute firm's market values, and book values to calculate the book-to-market ratio of each stock. Furthermore, I obtained the daily and monthly risk-free rate and Fama and French three-factor returns from Kenneth French's data library. These factors are used in the time-series regression of Fama and French (1993) three-factor model for computing idiosyncratic volatility.

3.2.1 Idiosyncratic volatility

Earlier studies that investigate the interdependence between idiosyncratic risk and average returns use idiosyncratic volatility as a proxy of specific risk. To be consistent and for better comparison with these studies, I use the same proxy to define idiosyncratic risk. While, finance literatures suggest several ways of measuring idiosyncratic volatility, I estimate idiosyncratic volatilities using the following two distinct approaches. The first approach is using prior realized or lagged idiosyncratic volatility. AHXZ suggests using one-month lagged idiosyncratic volatility as a proxy of idiosyncratic risk. They define idiosyncratic volatility as the standard deviation of regression residuals. Following AHXZ, I estimate monthly individual stock residuals by regressing daily excess returns on the daily Fama and French (1993) three factors: market excess return(MKT), size (SMB) and book-to-market (HML).

$$r_{it} = \alpha_i + \beta_i MKT + s_i SMB + h_i HML + \varepsilon_{it} \quad (3.1)$$

Where r_{it} is the daily excess return of stock i in month t, that is daily raw stock return minus T-bill rate. β_i, s_i and h_i are factor loadings. Stock i idiosyncratic volatility calculated as the standard deviation of regression residuals ε_{it}. The daily standard deviation of residuals transforms to monthly by multiplying the daily standard deviation of residuals by the square root of the number of trading days in that month.

To examine whether idiosyncratic volatility follows a random walk process or not, I conduct a test by regressing the change in idiosyncratic volatility(IVOL) against the past month idiosyncratic volatility.

$$\mathrm{IVOL}_{i,t+1} - \mathrm{IVOL}_{i,t} = \alpha_i + \beta_i \mathrm{IVOL}_{i,t} + \varepsilon_i \quad (3.2)$$

with the associated hypothesis

$$H_0\colon \beta_i = 0; H_1\colon \beta_i \neq 0$$

Where α_i is an arbitrary drift parameter and ε_i is the random disturbance

Table 3.1: *Random walk tests of idiosyncratic volatility*

	Panel A : $IVOL_{i,t+1}-IVOL_{i,t}=\alpha_i+\beta_i IVOL_{i,t}+\varepsilon_i$					Panel B : $\ln(IVOL_{i,t+1})-\ln(IVOL_{i,t})=\alpha_i+\beta_i\ln(IVOL_{i,t})+\varepsilon_i$				
Variables	**Mean**	**Std.dev.**	**Q1**	**Median**	**Q3**	**Mean**	**Std.dev.**	**Q1**	**Median**	**Q3**
β	-0.45	0.14	-0.54	-0.43	-0.34	-1.42	0.06	-1.47	-1.43	-1.38
t(β)	(-7.59)	(1.60)	(-8.64)	(-7.45)	(-6.48)	(-22.09)	(1.61)	(-23.15)	(-22.07)	(-20.97)

The table presents the time-series regression statistics of the change in idiosyncratic volatility with the past month idiosyncratic volatility to test whether the individual stock idiosyncratic volatility follows random walk process. The sample period is from March 2000 to December 2016. Idiosyncratic volatilities(IVOL) calculated as the standard deviation of regression residuals of the Fama and French (1993) three-factor model estimated using the daily stock returns with in a month. The logarithm of idiosyncratic volatilities ln(IVOL) computed as $\ln(IVOL_t/IVOL_{t-1})$. The table reports the cross-firm mean, standard deviation, lower quantile, median and upper quantality estimation coefficients of β_i with the corresponding t-statistics. The critical values of Dickey-Fuller unit-root t-statistics to reject the random walk null hypothesis at 1% is -3.43.

term with $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$. If the time-series of idiosyncratic volatility follows a random process the coefficient of β_i should be equal to zero.

Table 3.1 presents the test statistics of random walk in idiosyncratic volatility. Panel A reports the mean, standard deviation, lower quantile, median and upper quantile of β_i coefficient and the t-statistics for the changes in idiosyncratic volatility(IVOL) across 1000 firms in the sample. The critical values of Dickey-Fuller unit-root t-statistics at 1% for a sample of greater than 500 is -3.43. The mean β_i among these firms is -0.45 with the corresponding t-statistics of -7.59. Comparing the t-statistics with the Dickey-Fuller critical value, I reject the random walk null hypothesis. In Panel B, I estimate the β_i and the associated t-statistics of changes in the natural logarithm of idiosyncratic volatility (ln(IVOL)). The mean β_i is -1.42 and the t-statistics is -22.09, which significantly rejects the random walk null hypothesis. Overall, the findings in Table 3.1 suggest that idiosyncratic volatility of stock returns do not follow a random walk process. This is consistent with the findings of Fu (2009) that argues against using the value of past month idiosyncratic volatility to proxy this month idiosyncratic volatility, as it could induce estimation error.

The second method of idiosyncratic risk measure is using conditional idiosyncratic volatility. Fu (2009) argues that the theoretically correct factor to capture the variation in stock returns should be the same period idiosyncratic volatilities instead of lagged idiosyncratic volatility. In order to characterize the time-varying property of firm-specific risk, I estimate the conditional expected idiosyncratic volatility using the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model. The exponential GARCH (EGARCH) was proposed by Nelson (1991) as an extension of the GARCH model that capture the asymmetric effects of volatility. It has been widely advocated to model the conditional volatility of asset returns. Spiegel and Wang (2005), Fu (2009), Peterson and Smedema (2011) and Guo, Kassa and Ferguson (2014) apply EGARCH model to estimate the conditional idiosyncratic volatility. Using the monthly return, I estimate the conditional expected idiosyncratic volatility from the Fama and French (1993) three-factor model with an error term that follows an EGARCH (p, q) process.

$$r_{it} = \alpha_i + \beta_i MKT + s_i SMB + h_i HML + \varepsilon_{it} \tag{3.3}$$

The conditional error term, ε_{it}, is assumed to have a normal distribution with mean of zero and the variance of σ_{it}^2, that is $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$.

and the conditional variance, σ_{it}^2, as a function of the past p-periods residual variance and q-periods of return shocks

$$\ln\sigma_{it}^2 = \alpha_i + \sum_{l=1}^{p} b_{i,l} \ln\sigma_{i,t-1}^2 + \sum_{k=1}^{q} c_{i,k} \left\{ \theta \left(\frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right) + \gamma \left[\left| \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right| - \left(\frac{2}{\pi} \right)^{1/2} \right] \right\} \tag{3.4}$$

I estimate the conditional idiosyncratic volatility of each stock using the full sample and EGARCH (1,1) specification.[1] The full sample is from March 2000 to December 2016, and all stocks have 200 monthly observations in the estimation.

3.2.2 Other cross-sectional factors

Empirical studies show that variables such as beta, size and book-to-market ratio have an effect in the cross-section of returns, I use these factors in the cross-sectional regression. The market beta is constructed following the procedures of Fama and French (1992). I estimate monthly firm pre-ranking betas (β) from the first stage regression of a market model using the previous

[1] Cao and Han (2016) and Guo, Kassa and Ferguson (2014) also estimate idiosyncratic volatility with EGARCH (1, 1) model.

60 months of returns. Next, stocks are assigned to 10x10 two-way sort portfolios based on size and pre-ranking beta. I then calculate equal-weighted portfolio monthly returns for 100 portfolios. Finally, I estimate the betas as the sum of coefficients in the full sample regression of size-β portfolio returns on the current and prior month's market returns, then the beta of size-β portfolio are allocated to stocks in the portfolio. I employ these betas in the cross-sectional regression of each stock returns. Table A2 shows the average monthly returns and beta for stock portfolios formed on size and pre-ranking betas in the appendix.

I use the firm's market value of equity (ME), the number of outstanding shares multiplied by closing price, as a measure of size. Moreover, the book-to-market ratio (BE/ME) is book value of equity for the fiscal year end divided by the market value of equity at the end of calendar year. These variables transformed into natural logarithm to mitigate high skewness.

3.3 Methodology

I examine the relationship between idiosyncratic volatility and stock returns using two-stage Fama and MacBeth (1973) regression approach. In the first stage, monthly excess reruns of firms regress on the idiosyncratic volatility and other firm specific characteristics to estimate the regression coefficient of each factors with the corresponding time period. In the second stage, I use the ex-ante regression coefficients as explanatory variables to estimate the ex-post risk premia, and test whether the coefficient of idiosyncratic volatility is different from zero. For each month, I run the following cross-sectional regression

$$R_{it} = \gamma_{0t} + \gamma_{Xt} X_{it} + \gamma_{IVt} IV_{it} + \varepsilon_{it} \tag{3.5}$$

Where R_{it} is the realized return of stock i in month t. X'_{it} denotes a vector of beta and other firm specific variables. In a cross-sectional regression $\mathrm{X}'_{\mathrm{it}} = [\mathrm{Beta}, \ln(\mathrm{ME}), \ln(\mathrm{BE/ME})]$. $IV'_{\mathrm{it}} = [E(IVOL), Ln(IVOL)_{t-1}]$, is a vector of conditional idiosyncratic volatility and one-month lagged idiosyncratic volatility.

The conditional cross-sectional regression allows the market beta of stocks and risk premia to change on the market condition. The economic intuition of contemporaneous association of returns with the market risk is to examine investors' asymmetric response to upside and downside market risk. In this setting, the upside and downside market beta constructed following the procedures for computing unconditional market beta as in Fama and French (1992). I estimate monthly firm upside betas (β^{+}) from the first stage regression of a market model using the previous 60 months of returns, where market return being above 1 standard deviation of its mean. Then each stock grouped into 10x10 two-way sort portfolios based on size and upside betas. I then calculate equal-weighted portfolio monthly returns for 100 portfolios. Finally, I estimate the upside betas as the sum of the slopes on the current and prior month's upside market returns, then upside beta is allocated to individual stocks in the portfolio. The same procedures applied to generate downside beta(β^{-}), where market return being below 1 standard deviation of its mean. The conditional cross-sectional regressions that incorporates conditional market beta, idiosyncratic volatility and other time-varying factors are the following from

$$R_{it} = \gamma_{0t} + \gamma_{Xt} X_{it} + \gamma_{IVt} IV_{it} + \varepsilon_{it} \quad ; \qquad \mathrm{X}'_{\mathrm{it}} = [\beta^{+}, \ln(\mathrm{ME}), \ln(\mathrm{BE/ME})] \quad (3.6)$$

$$R_{it} = \gamma_{0t} + \gamma_{Xt} X_{it} + \gamma_{IVt} IV_{it} + \varepsilon_{it} \quad ; \qquad \mathrm{X}'_{\mathrm{it}} = [\beta^{-}, \ln(\mathrm{ME}), \ln(\mathrm{BE/ME})] \quad (3.7)$$

In the Fama-MacBeth regressions, the first stage regression estimates upside market beta (β^{+}_{it}), downside market beta (β^{-}_{it}), size and value coefficients. The second stage regression estimates the upside and downside marker risk premia along with other risk premia using the ex-ante regression coefficients. Hence, it allows to estimate the variation in average returns conditional on the market movements.

3.4 Empirical results

This section presents several tests of idiosyncratic volatility and Fama-MacBeth cross-sectional regression results.

3.4.1 Descriptive statistics

Panel A of Table 3.2 presents the pooled descriptive statistics of stock reruns, idiosyncratic volatilities and other candidate variables. The mean monthly return is 1.2% with a standard deviation of 10.61%.

The mean skewness and excess kurtosis of returns is 1.69 and 24.23, which implies that on average stock returns are positively skewed and leptokurtic. The mean excess return is 1.08% per month. Systematic risk measure beta, size and book-to market ratio are on average 1.23, 13.96 and -0.72, respectively. Average monthly idiosyncratic volatility(IVOL) returns is 9.54% with a standard deviation of 6.56%. The distribution of monthly idiosyncratic volatility is substantially positively skewed. However, the natural logarithm of idiosyncratic volatility ln(IVOL) has a distribution close to symmetric, and it will be used in the cross-sectional regression. Conditional idiosyncratic volatility(E(IVOL)) has a mean and standard deviation of 10.10% and 5.36%, respectively.

Panel B shows the time-series mean of the cross-sectional Pearson correlations. The mean correlation between stock returns and idiosyncratic volatility is 0.03. While the correlation between returns and one-month lagged ln(IVOL) is -0.05, which is in line with the negative return-idiosyncratic volatility association reported in AHXZ. This relationship reversed when the second measure of idiosyncratic volatility, conditional idiosyncratic volatility is applied. The correlation between E(IVOL) and returns is 0.06, which confirms the results of Fu (2009). Among all candidate variables, the highest correlation exists between IVOL and E(IVOL), 0.50. For book-to-market equity, the correlation test implies a positive relationship between returns and ln(BE/ME). Along with the findings of Fama and French (1992), the mean cross-sectional correlations between ln(ME) and ln(BE/ME) is negative, -0.30. The negative relationship is also apparent between beta and ln(ME). Conditional idiosyncratic volatility is negatively correlated with ln(ME), which implies that small firms have higher idiosyncratic volatility than large firms. Furthermore, the positive correlation between ln(BE/ME) and E(IVOL) shows high idiosyncratic volatility is more prevalent in value firms than growth firms.

Figure 3.1 shows the cross-sectional returns and average idiosyncratic volatilities over time. Alternative idiosyncratic volatility measures, IVOL and E(IVOL), are reported separately in the figure. The mean stock returns are more volatile during the 2008 Global financial crisis. Idiosyncratic volatility also experienced higher volatility during the same period.

Table 3.2: *Descriptive statistics and cross-sectional correlations for the pooled sample*

Panel A: Variables descriptive statistics

Variables	**Mean**	**Std dev.**	**Skew**	**Kurt**	**Q1**	**Median**	**Q3**
RET	1.20	10.61	1.69	24.23	-4.21	0.71	5.86
XRET	1.08	10.66	1.68	24.07	-4.34	0.58	5.76
BETA	1.23	0.28	0.14	-0.78	1.01	1.19	1.46
Ln(ME)	13.96	1.99	0.12	-0.19	12.57	13.94	15.27
Ln(BE/ME)	-0.72	0.75	-1.59	8.41	-1.09	-0.63	-0.26
IVOL	9.54	6.56	3.98	40.58	5.67	7.82	11.34
Ln(IVOL)	-0.33	41.90	0.10	2.00	-25.55	-0.68	24.27
E(IVOL)	10.10	5.36	2.93	23.55	6.71	8.96	12.21

Panel B: Cross-sectional correlation

Variables	**RET**	**BETA**	**Ln(ME)**	**Ln(BE/ME)**	**IVOL**	**Ln(IVOL)**	**E(IVOL)**
RET	1						
BETA	0.02	1					
Ln(ME)	0.00	-0.21	1				
Ln(BE/ME)	0.01	0.11	-0.30	1			
IVOL	0.03	0.22	-0.44	0.12	1		
Ln(IVOL)	-0.05	0.00	0.00	0.00	0.38	1	
E(IVOL)	0.06	0.36	-0.34	0.04	0.50	-0.02	1

The table reports sample statistics for the pool data. Panel A presents the variables descriptive statistics and Panel B the time-series mean of the cross-sectional Pearson correlations. RET is monthly stock returns. XRET is monthly stock excess return, stock return minus one-month government T-bill rate. The variable BETA, ME and BE/ME are constructed following the procedures as in Fama and French (1992). BETA is the coefficient in the full sample regression of 10x10 size-pre-ranking β portfolio returns on the prior and current month's market return. ME is the market capitalization, the product of closing price and outstanding shares. BE/ME is the book-to-market equity ratio. Idiosyncratic volatility (IVOL) calculated as the standard deviation of regression residuals from the Fama and French (1992) three-factor model estimated using the daily stock returns with in a month. The logarithm of idiosyncratic volatility ln(IVOL) computed as $\ln(\mathrm{IVOL_t}/\mathrm{IVOL_{t-1}})$. E(IVOL) is the conditional idiosyncratic volatility estimated using EGARCH model. The ME, BE/ME and IVOL variables are transformed into natural logarithm to mitigate high skewness. RET, XRET and idiosyncratic volatility variables are reported in percentage. The sample includes of stocks traded in NYSE and NASDAQ from March 2000 to December 2016.

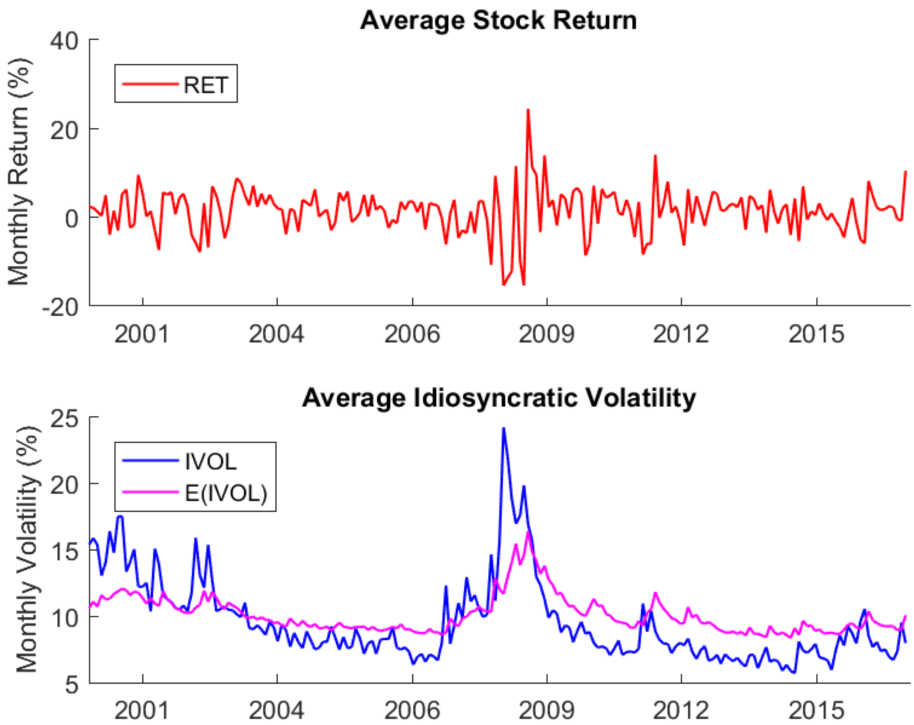

Figure 3.1: *Cross-sectional average returns and idiosyncratic volatilities over time.*

Furthermore, both return and idiosyncratic volatility show a relatively high volatility following the bursting of the Dotcom bubble in the early 2000s. This supports the result of positive correlation between stock returns and idiosyncratic volatility in Table 3.2.

3.4.2 Portfolio returns formed on idiosyncratic volatilities

Portfolio sorts are the most widely approach in finance to examine the systematic patterns of expected returns related to some stock characteristics. I examine the cross-sectional relation between idiosyncratic volatilities and returns using stock portfolios sorted on idiosyncratic volatility. The procedure for constructing stock portfolios are as follows. In each month, stocks are sorted into 12 portfolios based on their idiosyncratic volatilities. The first two portfolios (1A and 1B) split the bottom decile into half that contains stocks with the lowest idiosyncratic volatilities. The middle 8 portfolios composed of stocks with the next deciles of idiosyncratic volatilities. The last two extreme portfolios (10A and 10B) divided the top decile into two that consists of stocks with the highest idiosyncratic volatilities.

Table 3.3: *Properties of portfolios formed on idiosyncratic volatility*

Panel A: Portfolios formed on E(IVOL)												
Variables	**1A**	**1B**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10A**	**10B**
RET	0.77	0.62	0.65	0.73	0.76	0.89	0.95	1.07	1.13	1.55	1.86	2.72
BETA	1.05	1.02	1.08	1.12	1.19	1.20	1.26	1.30	1.33	1.40	1.42	1.41
Ln(ME)	14.80	15.21	15.10	14.85	14.58	14.45	14.16	13.79	13.62	13.09	12.76	12.31
Ln(BE/ME)	-0.71	-0.77	-0.76	-0.76	-0.71	-0.75	-0.74	-0.67	-0.62	-0.61	-0.64	-0.68
Panel B: Portfolios formed on ln(IVOLt-1)												
Variables	**1A**	**1B**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10A**	**10B**
RET	1.05	1.20	0.99	0.92	1.06	1.11	1.15	1.05	0.94	1.06	1.24	1.36
BETA	1.26	1.24	1.24	1.22	1.23	1.21	1.23	1.22	1.24	1.24	1.27	1.27
Ln(ME)	13.98	14.26	14.24	14.28	14.26	14.32	14.32	14.24	14.12	13.85	13.63	13.49
Ln(BE/ME)	-0.72	-0.79	-0.72	-0.71	-0.69	-0.72	-0.72	-0.70	-0.67	-0.67	-0.68	-0.72

This table presents the summary statistics of portfolios formed on idiosyncratic volatilities. The sample period is from March 2000 to December 2016. In panel A, stocks are sorted into decile on the basis of their expected or conditional idiosyncratic volatility, the E(IVOL) estimated using EGARCH model. In Panel B, stocks are sorted using one-month lagged idiosyncratic volatility, the ln($IVOL_{t-1}$) calculated as the logarithm of the standard deviation of regression residuals from Fama and French (1992) three-factor model estimated using the daily stock returns with in a month. All portfolios are rebalanced each month and are equally weighted. The first two portfolios (1A and 1B) split the bottom decile into half that contains stocks with the lowest idiosyncratic volatilities. Portfolio 2-9 composed of stocks with the next deciles of idiosyncratic volatilities. The last two extreme portfolios (10A and 10B) split the top decile into half that consists of stocks with the highest idiosyncratic volatilities. RET is the time-series of monthly average portfolio returns. BETA is the coefficient in the full sample regression of 10x10 size-pre-ranking β portfolio returns on the prior and current month's market return. ME is the market capitalization, the product of closing price and outstanding shares. BE/ME is the book-to-market ratio.

A zero-investment portfolio can be computed by deducting the returns of high idiosyncratic volatility portfolio from the return of low idiosyncratic volatility portfolio. If the return of this portfolio is positive, buying stocks with the highest idiosyncratic volatilities and selling stocks with lowest idiosyncratic volatilities provide abnormal positive returns.

Panel A of Table 3.3 shows the properties of portfolios formed on conditional idiosyncratic volatility. Average monthly returns rises from low E(IVOL) portfolio to high E(IVOL) portfolio. This monotonic pattern in portfolio returns implies a strong positive relation between idiosyncratic volatility and stock returns. Fu (2009) also reports a positive relationship between stock return and idiosyncratic volatility using the same measure of firm-specific risk, E(IVOL). Similar pattern is evident for the market beta, beta value increases when moving from low E(IVOL) to high E(IVOL) portfolio, which indicate a positive relationship between beta and idiosyncratic volatilities. As for size (ME), a monotonically declining patter is observed in ME from the bottom to top ranked portfolios.

Panel B of Table 3.3 reports portfolios sorted using one-month lagged idiosyncratic volatility ln(IVOL) following AHXZ. There is an increase in return from the bottom 1A portfolio to 1B portfolio by around 15 base points per month, from the third to six portfolios by 23 base points and from decile eight to 10B by another 42 base points per month. The test result shows that the positive relationship between idiosyncratic volatility and stock return is much weaker. Moreover, a systematic pattern is not observed in beta and other firm-specific characteristics such as size and book-to-market equity ratio from bottom to top decile portfolio. This indicates lack of strong relationship between these variables and idiosyncratic volatility.

The portfolios formed on pre-ranking beta and other firm characteristics are also examined using the procedures in Fama and French (1992). Table A3 reports the properties of portfolios formed on size, pre-ranking beta and book-to-market in the appendix. Consistent with the findings of Fama and French (1992), the result shows a strong positive relation between beta and average stock returns, and between book-to-market ratio and average returns. However, there is no strong reliable relationship between average returns and size.

3.4.3 Cross-sectional analysis

Next, I investigate the existence of idiosyncratic risk premia in the cross-section of stock returns, hence if compensation exist for under-diversified investors with idiosyncratic risk. Table 3.4 reports the result of unconditional Fama and MacBeth regressions of monthly stock returns on idiosyncratic volatilities and other candidate variables. Model 1 is univariate regression of returns on conditional idiosyncratic volatility. The average slope of conditional idiosyncratic volatility from regression is 11.36% with a t-statistics of 8.42. This reliable positive coefficient with the corresponding significant t-statistics illustrates a positive relationship between stock returns and conditional idiosyncratic volatility. Hence idiosyncratic volatility appears to have useful information in explaining stock returns. Fu (2009) also find a positive relationship between idiosyncratic risk and returns using conditional idiosyncratic volatility as a proxy of firm-specific risk.

Table 3.4: *Cross-sectional regressions: Unconditional test*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
BETA			1.13	1.10					0.63	0.67
			(5.90)	(5.55)					(1.61)	(1.67)
Ln(ME)					0.10	-0.01			0.04	0.03
					(5.03)	(-0.81)			(1.73)	(1.59)
Ln(BE/ME)							0.12	0.18	0.07	0.06
							(3.32)	(4.57)	(4.36)	(4.22)
E(IVOL)	11.36		-0.39		12.61		11.1		0.18	
	(8.42)		(-1.02)		(8.64)		(8.27)		(0.80)	
Ln(IVOLt-1)		-0.04		0.06		-0.05		-0.04		0.02
		(-0.88)		(2.02)		(-0.97)		(-0.74)		(0.84)
R^2(%)	3.81	0.75	0.12	0.13	4.13	2.01	10.16	7.13	0.32	0.31

The table reports the time-series average of coefficients and the corresponding t-statistics from monthly Fama-MacBeth regressions of stock returns on idiosyncratic volatility and firm-specific characteristics. The dependent variable is monthly stock returns RET. BETA is the coefficient in the full sample regression of 10x10 size-pre-ranking β portfolio returns on the prior and current month's market returns. ME is the market capitalization, the product of closing price and outstanding shares. BE/ME is the book-to-market equity ratio. BETA, ME, and BE/ME variables are constructed following the procedures of Fama and French (1992). E(IVOL) is conditional idiosyncratic volatility estimated using EGARCH model. Ln($IVOL_{t-1}$) is the logarithm of one-month lagged idiosyncratic volatility, calculated as the standard deviation of regression residuals from the Fama and French (1992) three-factor model estimated using the daily stock returns with in a month. The sample period is from March 2000 to December 2016.

Model 2 regress stock returns on one-month lagged idiosyncratic volatility. The average negative slope from regression is not statistically significant, thus one-month lagged idiosyncratic volatility does not help to capture the cross-section of stock returns. While, AHXZ report a negative relationship between average return and lagged idiosyncratic volatility, the regression result shows the absence of reliable negative relationship between the two variables. This is against the argument of idiosyncratic risk puzzle, idiosyncratic risk priced negatively in the cross-section of returns. One possible explanation suggested by Fu (2009) why one-month lagged idiosyncratic volatility may not explain expected returns is that since idiosyncratic volatility is time-varying, last month idiosyncratic volatility cannot be a good proxy to explain the average return of next month.

In Model 3 and 4, I introduce another risk factor in the cross-sectional regression. The result shows that adding unconditional beta in the regression changes the relationship between average returns and idiosyncratic volatility reported in Model 1 and 2. Specifically, the coefficient of conditional idiosyncratic volatility become negative and statistically insignificant, and the average slope of one-month lagged idiosyncratic volatility changes to positive with the corresponding significant t-statistics. A significant beta coefficient in Model 3 and 4 shows the importance of market risk factor in explaining the variation of stock returns.

The cross-sectional regression in Model 5 suggests that including size factor in the regression improve the explanatory power of conditional idiosyncratic volatility in Model 1. The average conditional idiosyncratic volatility slop rises to 12.61% with the associated t-statistic of 8.64. The size effect is also significant in explaining the cross-section of returns. However, the result in Model 6 prevails that after controlling the size effect, one-month lagged idiosyncratic volatility can not help to explain average returns. The coefficients of size and one-month lagged idiosyncratic volatility are insignificant, similar to the regression result in Model 2, that no reliable negative relationship exists between stock returns and idiosyncratic volatility.

Model 7 and 8 regress returns on book-to-market ratio and idiosyncratic volatility. The coefficients of book-to-market and conditional idiosyncratic volatility in Model 7 are positive and statistically significant. Both candidate variables add explanatory power to the average stock returns. The regression result in Model 8, however, reveals that one-month lagged idiosyncratic volatility fails to capture the variation of stock returns. The average slope and the corresponding t-statistics of lagged idiosyncratic volatility is similar to the univariate regression. This implies that, there is no significant relationship between one-month lagged idiosyncratic volatility and stocks returns after controlling for the value effect.

The last two columns of Table 3.4 controls for beta, firm size and book-to-market ratio in examining the effect of idiosyncratic risk on expected returns. The regression result provides striking evidence that the coefficient of neither factors is different from zero, except book-to-market value. Both idiosyncratic risk measures found statistically insignificant in explaining stock returns.

The overall result in Table 3.4 suggests that the effect of idiosyncratic volatility on stock return is sensitive to the idiosyncratic risk measures. When conditional idiosyncratic volatility used as a proxy of idiosyncratic risk, a significant positive relationship found between expected return and idiosyncratic risk in most regression models. This implies that investors demand a positive risk premium to hold an asset with high idiosyncratic risk. On the other hand, when idiosyncratic risk measured as one-month lagged idiosyncratic volatility following AHXZ, idiosyncratic risk adds no explanatory power to the expected returns in most regressions. This implies that a negative return-idiosyncratic risk relationship suggested by AHXZ is not statistically significant, inferring idiosyncratic risk puzzle do not exist. Rather investors demand compensation when they are under-diversified and unable to eliminate idiosyncratic risk.

I investigate further the pricing of idiosyncratic risk in a conditional market setting. The conditional relationship between beta and stock returns is to account for investors' asymmetric treatment towards risk across upside and downside market movements. Upside and downside market betas computed using a threshold when market return is above or below 1 standard deviation of its mean. Table 3.5 reports the conditional cross-sectional regression of stock returns on idiosyncratic volatility, upside-market beta and other candidate variables as shown in equation 3.6.

Table 3.5: *Cross-sectional regressions: Up-market*

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
UP-BETA			1.13	1.08					0.77	0.69
			(6.18)	(5.71)					(2.06)	(1.75)
Ln(ME)					0.10	-0.01			0.03	0.03
					(5.03)	(-0.81)			(1.28)	(1.40)
Ln(BE/ME)							0.12	0.18	0.04	0.05
							(3.32)	(4.57)	(2.64)	(3.14)
E(IVOL)	11.36		-0.92		12.61		11.10		-0.44	
	(8.42)		(-2.24)		(8.64)		(8.27)		(-2.01)	
Ln(IVOLt-1)		-0.04		0.09		-0.05		-0.04		0.06
		(-0.88)		(3.84)		(-0.97)		(-0.74)		(2.38)
R^2(%)	3.81	0.75	0.19	0.11	4.13	2.01	10.16	7.13	0.37	0.46

The table reports the time-series average of coefficients with the corresponding t-statistics from monthly Fama-MacBeth cross-sectional regressions of returns on idiosyncratic volatility and firm characteristics. The dependent variable is monthly stock returns RET. The upside beta(UP-BETA) calculated as follows. First, I estimate monthly pre-ranking upside betas from the first-pass regression of a market model where market return being above 1 standard deviation of its mean. Then UP-BETA is computed as the sum of coefficients in the full sample regression of 10x10 size-pre-ranking upside beta portfolio returns on the prior and current month's upside market return. ME, BE/ME, E(IVOL) and Ln($IVOL_{t-1}$) variables are defined in Table 3.4. The sample period ranges from March 2000 to December 2016.

Regression models that do not include beta factor have the same results with the unconditional test in Table 3.4. Model 3 of Table 3.5 add upside-market beta in the regression. The average slope of conditional idiosyncratic volatility become negative and statistically significant from insignificant coefficient in unconditional regression. While, the upside market beta positively related to average return with a strong t-statistics of 6.18 from 5.90. Model 4 examines the effect of one-month lagged idiosyncratic volatility on stock returns after controlling for upside-market beta. The coefficient reveals a significant positive relationship between one-month lagged idiosyncratic volatility and stock returns.

The regression in Model 9 and 10 controls for upside beta, size and book-to-market factors in the pricing of idiosyncratic volatility. The negative coefficient on conditional idiosyncratic volatility suggests the negative relationship with the average returns. The estimated upside beta and book-to-market coefficients are also a significant determinants of stock returns.

Table 3.6: *Cross-sectional regressions: Down-market*

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
DOWN-BETA			1.18	1.19					0.60	0.77
			(5.82)	(5.52)					(1.49)	(1.86)
Ln(ME)					0.10	-0.01			0.04	0.03
					(5.03)	(-0.81)			(1.72)	(1.21)
Ln(BE/ME)							0.12	0.18	-0.03	-0.04
							(3.32)	(4.57)	(-1.74)	(-2.19)
E(IVOL)	11.36		0.32		12.61		11.10		0.79	
	(8.42)		(0.83)		(8.64)		(8.27)		(3.54)	
Ln(IVOLt-1)		-0.04		0.01		-0.05		-0.04		-0.02
		(-0.88)		(0.19)		(-0.97)		(-0.74)		(-0.80)
R^2(%)	3.81	0.75	0.48	0.49	4.13	2.01	10.16	7.13	0.49	0.51

The table presents the time-series average of coefficients with the corresponding t-statistics from Fama-MacBeth cross-sectional regressions of returns on idiosyncratic volatility and firm characteristics. The dependent variable is monthly stock returns RET. The downside beta (DOWN-BETA) computed as follows. First, I estimate monthly pre-ranking downside betas from the first-pass regression of a market model where market return being below 1 standard deviation of its mean. Then DOWN-BETA is computed as the sum of coefficients in the full sample regression of 10x10 size-pre-ranking downside beta portfolio returns on the prior and current month's downside market return. ME, BE/ME, E(IVOL) and Ln($IVOL_{t-1}$) variables are defined in Table 3.4. The sample period ranges from March 2000 to December 2016.

In Model 10, book-to-market value and one-month lagged idiosyncratic volatility factors positively and significantly priced in average returns. Looking at the regressions in Table 3.5, it is evident that conditional association of beta with the return alter the relationship between idiosyncratic volatility and average returns in upside market setting.

Table 3.6 reports the cross-sectional regression of stock returns on downside-market beta, idiosyncratic volatility and other variables. In Model 3, I include downside-market beta in the idiosyncratic volatility regression. The time-series average slope of conditional beta is strongly significant, which confirms a non-zero risk premium. The average risk premium for a unit of downside-market beta is 1.18% per month. While, the conditional idiosyncratic volatility failed to be priced in stock returns. Similar results are also shown in Model 4, where only downside-risk beta has explanatory power of average returns.

The regression in Model 9 reveals that conditional idiosyncratic volatility is the only determinant factor of returns. Conditional idiosyncratic volatility positively related with average stock returns. The regression result in Model 10 shows that book-to-market is the only variable do a fine job in explaining stock returns, other factors are not different from zero. In both conditional and unconditional cross-sectional regression test, book-to-market ratio is the consistent candidate variable that has a premium in the cross-section of stock returns. The overall result in Table 3.6 illustrates that the average premium for conditional idiosyncratic volatility is positive after controlling for size and value factors, while the risk premium for one-month lagged idiosyncratic volatility is essentially zero when downside-market beta included in the regression.

In summary, the conditional Fama-MacBeth regressions demonstrates that while asymmetric treatment of market return do not bring major changes in the market beta-return relationship, it alters the risk premium associated with idiosyncratic volatilities. Including, upside-market beta in the regressions change insignificant conditional idiosyncratic volatility coefficient to a statistically significant negative coefficients, which suggest a negative association between idiosyncratic volatility and stock returns. The average slope of lagged idiosyncratic volatility found to be positive and significant, yet it is small. On the other hand, the downside market test shows a reliable positive relationship between conditional idiosyncratic volatility and stock returns. The result of univariate regressions also prevails that high conditional idiosyncratic volatility compensated by high average returns over the same period, while the reward for one-month lagged idiosyncratic volatility is fragile.

3.5 Conclusions

In this paper, I investigate the pricing of idiosyncratic volatility in the cross-section of stock returns. Beside the unconditional cross-sectional test, conditional regressions are employed to characterize the behavior of investors' asymmetric response to upside and downside market risk. Hence, the conditional relations of idiosyncratic risk and stock returns captured by the association of returns with the conditional market return. Moreover, I use conditional idiosyncratic volatility and one-month lagged idiosyncratic volatility as a proxy of idiosyncratic risk in the analysis.

I find that average stock returns increase monotonically with an increase in the conditional idiosyncratic volatility. This implies that investors require a positive risk premium to hold an asset with high idiosyncratic risk. However, when one-month lagged idiosyncratic volatility used as a proxy of idiosyncratic risk, there is no strong significant relationship between idiosyncratic risk and average returns. The cross-sectional regression shows that, conditional market setting alters the sign of risk premium associated with idiosyncratic volatility. Including upside-market beta in the regression results a significant negative relationship between conditional idiosyncratic volatility and average returns, but this relationship flips in the downside market setting. The over result shows that firm-specific risk priced more strongly in the cross-section of returns when conditional idiosyncratic volatility used as a proxy of idiosyncratic risk, furthermore investors demand compensation when they are under-diversified and unable to eliminate idiosyncratic risk.

CONCLUSIONS

In the realm of asset pricing characterizing investors' attitude towards risk is very important. I investigate the cross-section of asset returns and downside risk for multiple asset classes. Investors are more averse to downside loss as compared with upside gain, and asymmetric treatment of downside and upside risk appear to characterize the risk aversion of representative investors. An increase in average returns is associated with a contemporaneous increase in downside risk. Asset pricing models that distinguish market factor between upside and downside components successfully explain the cross-section of equities, currencies, bonds, commodities and CDS returns than the traditional asset pricing models. Moreover, the variation in asset returns better captured by extended downside risk asset pricing models.

Momentum strategy generate implausible higher Sharpe ratio in equity and currency markets. However, the distribution of momentum return is characterized by fat left tails coupled with considerable negative skewness, which reflects high exposure of this strategy to crash risk. Plain equity momentum experience huge crash as the market rebound following server collapse such as Great depression and Global financial crisis. Managing the risk of momentum enables to mitigate crash risk and generate persistent returns. Optimal risk management strategy, hedging the time-varying risk exposure of momentum then scaling the hedged long-short portfolio by its forecasted semi-variance, increases the Sharpe ratio and reduces momentum crash considerably. Looking at currency markets, huge crash risk is not prevalent in currency momentum. The result shows that idiosyncratic risk accounts the main source of currency momentum risk.

I investigate the existence of idiosyncratic risk premia in the cross-section of stock returns. Average stock returns increase monotonically with an increase in the conditional idiosyncratic volatility. This positive monotonic trend suggests that investors require a positive risk premium to hold assets with high idiosyncratic risk. However, the relationship between idiosyncratic risk and stock returns is sensitive to idiosyncratic risk measures and market setting. I find a significant positive relationship between expected returns and conditional idiosyncratic volatility, while lagged idiosyncratic volatility has no significant explanatory power of expected returns. In a downside market, conditional idiosyncratic volatility positively priced in the cross-section of stock returns. Overall, investors demand compensation to hold assets with idiosyncratic risk.

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APPENDIX

Table A1: *Currency momentum risk decomposing*

Variable	α t(α)	ρ t(ρ)	R^2	R^2_{oos}
RV_{WML}	0.04 (1.15)	0.23 (1.83)	5.30	40.17
RV_{RMRF}	0.00 (0.73)	0.91 (18.21)	85.90	94.32
β^2	0.01 (2.76)	0.36 (2.92)	12.65	2.11
β^2 RV_{RMRF}	0.00 (3.53)	0.04 (0.32)	0.17	-10.58
RV_{ε}	0.04 (1.14)	0.23 (1.82)	5.35	40.09

The table shows AR (1) for each component of risk currency momentum following Pedro Barroso and Pedro Santa-Clara(2015). α and ρ are estimated coefficients from AR(1). The first row of the tables shows the realized variance of currency WML portfolio. The second row is realized variance of market(RMRF) portfolio. The third one is squared beta, which is estimated by regression of WML portfolio on market using six months' daily returns. The forth row is systematic component of market risk. The last row is, specific component of risk. R^2 and R^2_{oos}denotes in-sample and out-of-sample coefficient of determination. The t-statistics are in prentices. All statistics are computed using currency data from February 1986 to March 2017.

Table A2: *Average returns and post-ranking betas for portfolios formed on size and then beta*

Panel A: Portfolios formed on size and pre-ranking betas

Panel A: Average Monthly Return (in percent)

	All	Low-β	β-2	β-3	β-4	β-5	β-6	β-7	β-8	β-9	High-β
All	1.07	0.97	1.00	1.21	1.30	1.15	0.98	1.10	1.05	1.02	0.93
Small-ME	1.05	1.68	0.92	1.04	1.05	1.04	1.11	1.27	0.95	0.83	0.61
ME-2	0.78	0.48	0.25	0.86	1.07	1.18	0.93	0.75	0.83	0.68	0.74
ME-3	0.73	0.21	0.43	1.10	0.80	0.71	0.73	0.73	0.95	0.79	0.84
ME-4	0.80	0.16	0.63	1.12	0.91	1.10	0.66	0.89	0.76	0.92	0.88
ME-5	0.88	0.25	0.70	1.04	1.03	1.37	0.57	0.94	0.95	1.10	0.83
ME-6	0.97	0.81	0.50	1.38	1.11	1.03	0.92	1.06	1.19	0.77	0.90
ME-7	1.12	1.16	0.87	1.25	1.45	1.08	1.10	0.90	1.09	1.19	1.07
ME-8	1.16	1.24	1.17	1.12	1.37	1.23	0.74	1.53	1.30	0.86	1.02
ME-9	1.48	1.21	2.45	1.72	1.89	0.96	1.43	1.55	0.87	1.62	1.05
Large-ME	1.76	2.48	2.09	1.45	2.30	1.79	1.64	1.43	1.60	1.41	1.37

Panel B: Post-ranking betas

	All	Low-β	β-2	β-3	β-4	β-5	β-6	β-7	β-8	β-9	High-β
All	0.00	1.28	1.22	1.30	1.36	1.26	1.23	1.25	1.24	1.16	1.03
Small-ME	1.07	1.66	0.95	1.15	1.16	1.02	1.02	1.13	0.95	0.73	0.91
ME-2	1.01	0.82	1.14	1.09	1.09	1.15	1.02	1.01	1.19	0.81	0.81
ME-3	0.97	0.97	0.72	0.96	1.13	1.13	1.02	1.01	1.08	0.94	0.80
ME-4	1.10	1.01	1.27	1.08	1.27	1.18	1.03	0.93	1.15	1.14	0.93
ME-5	1.14	0.99	1.31	1.01	1.42	1.13	1.07	1.10	1.08	1.15	1.12
ME-6	1.23	1.47	0.87	1.37	1.57	1.19	1.10	1.23	1.21	1.23	1.06
ME-7	1.36	1.42	1.29	1.53	1.50	1.31	1.33	1.57	1.25	1.38	1.06
ME-8	1.38	1.26	1.13	1.58	1.26	1.44	1.48	1.58	1.52	1.37	1.19
ME-9	1.48	1.61	1.98	1.71	1.42	1.31	1.36	1.55	1.45	1.45	0.96
Large-ME	1.59	1.62	1.51	1.48	1.76	1.77	1.84	1.45	1.54	1.44	1.49

The table reports monthly average returns and post-ranking beta for the stock portfolios formed on size then beta. The procedure for construction of post-ranking beta and portfolio sorting are the same with Fama and French (1992). I estimate monthly pre-ranking betas (β) from the first-pass regression of a market model using the previous 60 months of returns. Next, all stocks are allocated to 10 size(ME) portfolios then size decile portfolios further sub-divided into 10 beta portfolios based on betas. I then calculate equal-weighted portfolio monthly returns for 100 portfolios. Finally, I estimate the betas as the sum of the slopes in the full sample regression of size-β portfolio returns on the prior and current month's market return. The average monthly return is the time-series average of equal-weighted portfolio returns. The all column and all row presents statistics for equal-weighted size-decile and beta-decile portfolios, respectively.

Table A3: *Properties of portfolios formed on size, pre-ranking beta and book-to-market*

Panel A: Portfolios formed on Size

Variables	**1A**	**1B**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10A**	**10B**
RET	0.95	0.98	1.00	1.21	1.30	1.15	0.98	1.10	1.05	1.02	1.02	0.84
BETA	1.20	1.22	0.86	0.82	0.97	0.99	0.90	1.15	1.05	1.03	0.93	0.89
Ln(ME)	10.32	11.24	12.03	12.75	13.33	13.87	14.37	14.89	15.45	16.25	17.03	18.23
Ln(BE/ME)	-0.05	-0.25	-0.40	-0.58	-0.68	-0.77	-0.75	-0.85	-0.87	-0.94	-0.97	-1.10

Panel B: Portfolios formed on pre-ranking betas

Variables	**1A**	**1B**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10A**	**10B**
RET	0.69	0.71	0.74	0.82	1.02	0.90	1.00	1.09	1.16	1.36	1.67	2.16
BETA	0.84	0.83	0.86	0.87	0.90	0.94	0.99	1.05	1.11	1.15	1.18	1.19
Ln(ME)	13.31	13.87	14.17	14.31	14.31	14.34	14.25	14.24	14.25	14.06	13.78	13.56
Ln(BE/ME)	-0.69	-0.75	-0.77	-0.75	-0.72	-0.73	-0.68	-0.69	-0.68	-0.67	-0.60	-0.63

Panel B: Portfolios formed on book-to-market

Variables	**1A**	**1B**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10A**	**10B**
RET	1.24	0.97	0.88	0.97	1.08	0.94	0.91	1.00	0.97	1.16	1.21	2.19
BETA	0.98	0.97	0.99	0.99	1.01	0.98	0.95	0.96	0.96	0.99	1.06	1.12
Ln(ME)	14.82	15.00	15.01	14.78	14.69	14.33	14.01	13.85	13.62	13.40	13.08	12.10
Ln(BE/ME)	-2.54	-1.63	-1.29	-1.05	-0.87	-0.69	-0.53	-0.40	-0.25	-0.09	0.07	0.40

This table reports the summary statistics of portfolios formed on beta and other firm-specific characteristics. In panel A of the table, stocks are sorted into decile based on size. In Panel B and C, stocks are sorted using pre-ranking beta and book-to-market value, respectively. All portfolios are rebalanced each month and are equally weighted. The first two portfolios (1A and 1B) split the bottom decile into half. Portfolio 2-9 composed of stocks with the next deciles. The last two extreme portfolios (10A and 10B) split the top decile into half. RET is monthly average portfolio returns. BETA is the coefficient in the full sample regression of 10x10 size-pre-ranking β portfolio returns on the prior and current month's market return. ME is the market capitalization, the product of closing price and outstanding shares. BE/ME is the book-to-market equity ratio. The sample period ranges from March 2000 to December 2016.