Asset Pricing Implications of the Volatility Term Structure

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ABSTRACT

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This dissertation aims to investigate the asset pricing implications of the stock option's implied volatility term structure. We mainly focus on two directions: the volatility term structure of the market and the volatility term structure of individual stocks.

The market volatility term structure, which is calculated from prices of index options with different expirations, reflects the market's expectation of future volatility of different horizons. So the market volatility term structure incorporates information that is not captured by the market volatility itself. In particular, the slope of the volatility term structure captures the expected volatility trend. In the first part of the thesis, we investigate whether the market volatility term structure slope is a priced source of risk or not. We find that stocks with high sensitivities to the proxies of the VIX term structure slope exhibit high returns on average. We further estimate the premium for bearing the VIX slope risk to be approximately 2.5% annually and statistically significant. The effect cannot be explained by other common risk factors, such as the market excess return, size, book-to-market, momentum, liquidity and market volatility. We extensively investigate the robustness of our empirical results and find that the effect of the VIX term structure risk is robust. Within the context of ICAPM, the positive price of VIX term structure risk indicates that it is a state variable which positively affects the future investment opportunity set.

In the second part of the thesis, we provide a stylized model that explains our empirical

results. We build a regime-switching rare disaster model that allows disasters to have short and long durations. Our model indicates that a downward sloping VIX term structure corresponds to a potential long disaster and an upward sloping VIX term structure corresponds to a potential short disaster. It further implies that stocks with high sensitivities to the VIX slope have high loadings on the disaster duration risk, thus earn higher risk premium. These implications are consistent with our empirical results.

In the last part, we study the relationship between individual stock's volatility term structure and the stock's future return. We use a measure of stock's implied volatility term structure slope, defined as the difference between 3-month and 1-month implied volatility from at-the-money options, to demonstrate that option prices contain important information for the underlying equities. We show that option volatility term structure slopes are significant in explaining future equity returns in the cross-section. And we further find evidence that the implied volatility term structure is a measure of event risk: firms with the most negative volatility term structure are those for which the market anticipates news that may affect stock price within one month. Relevant events include, but are not limited to, earnings announcements.

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Chapter 1

Introduction

This dissertation aims to investigate the asset pricing implications of the stock option's implied volatility term structure. We mainly focus on two directions: the market volatility term structure and the individual stocks' volatility term structure. For the first direction, we study both the empirical implications and theoretical models. For the second direction, we only focus on the empirical studies.

1.1 Market Volatility Term Structure

The time-varying market volatility term structure slope reflects the changes of expectation of future market risk-return trade-off trend, thus it should induce changes in the investment opportunity set and should be a state variable. The Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973) then predicts that innovations in market volatility term structure must be a priced risk factor in the cross-section of risky asset returns, and stocks with different sensitivities to changes of the volatility term structure slope should have different expected returns. Therefore the first goal of this paper is to investigate how the market volatility term structure is priced in the cross-section of expected stock returns. We want to both determine whether the market volatility term structure is a priced risk factor and estimate the price of volatility term structure risk.

Ang, Hodrick, Xing and Zhang (2006) demonstrates that market volatility risk is priced in the cross-section of stock returns. While past studies have been focusing on pricing models of the volatility term structure (Britten-Jones and Neuberger (2006), Jiang and Tian (2005), Carr and Wu (2009), among others), the implication of the market volatility term structure on the cross-section of stock returns has yet to be studied.

We use the VIX term structure to proxy for the market volatility term structure and we find that by controlling the loadings on the market excess returns and changes in VIX, the stocks with high sensitivities to changes in the volatility term structure exhibit high returns on average. The average return on the high-minus-low VIX slope portfolio is around 0.2% per month. The price of volatility term structure risk is statistically significant and it cannot be explained by other common risk factors, such as the market excess return, size, book-to-market, momentum, liquidity, and market volatility. We extensively test the empirical results and find the effect of the volatility term structure risk to be robust.

1.2 Rare Disaster Models

Most recent studies on VIX or the VIX term structure focus on stochastic volatility and jump models (Ait-Sahalia, Mustafa and Loriano (2012), Duan and Yeh (2011), Amengual (2009), and Egloff, Leippold and Wu (2010)). These models lack the connection with the fundamental economy. In order to connect the fundamental economy with the volatility term structure, we propose a stylized model. We build a regime-switching rare disaster model. In this framework, the VIX term structure contains information about the length of a potential disaster.

Rare disasters were proposed by Rietz (1988) as the major determinant of asset risk premia. It could be economic depression or war which occur rarely but is disastrous in terms of magnitude. Barro (2006) supports the hypothesis by showing that disasters were frequent and large enough to account for the high risk premium on equities. And Gabaix (2012) incorporates a time-varying severity of disaster into the baseline model by Barro (2006) to solve many of asset-pricing puzzles in a unified framework. We extend Gabaix (2012) by adding in durations of disaster to explain VIX term structures.

In Chapter 3, we build a regime swithching rare disaster model to explain the positive price of VIX term structure risk. Our model follows with Gabaix (2012), which assumes hidden probability p_t at period t of entering into a disaster at next period $t+1$. What differentiates our model from Gabaix Model is that we not only assume probability of entering into a disaster at $t+1$, but also of getting out of the potential disaster at $t+1$. In the model, $p_{in,t}$ is defined as the probability of entering in a disaster at $t+1$ and $p_{out,t}$ is defined as the probability of exit the potential disaster starting at $t+1$ at each period after $t+1$. By introducing p_{out} we bring duration of disaster into our model.

We show by simulation that, assuming p_{in} doesn't change, higher p_{out} (shorter crisis duration) corresponds to a steeper VIX term structure while lower p_{out} (longer crisis duration) corresponds to flatter VIX term structure. This is consistent with our empirical results in Chapter 2.

1.3 Individual Stock's Volatility Term Structure

Previous studies (Bali, Hu and Murray (2014), Xing, Zhang, and Zhao (2010)) find that the stock option's implied volatility and skewness are predictive of future stock returns. In Chapter 4, we study the relationship between individual stock's volatility term structure and the stock's future return. We use a measure of stock's implied volatility term structure slope ($SLOPE$), defined as the difference between 3-month and 1-month implied volatility from at-the-money (ATM) options, to demonstrate that option prices contain important information for the underlying equities. We show that option volatility term structure slopes are significant in predicting future equity returns in the cross-section.

The pattern of volatility term structure for stock index options has been examined in numerous papers. For instance, past studies have focused on calibrations of pricing models with the volatility term structure (Britten-Jones and Neuberger (2006), Jiang and Tian (2005), Carr and Wu (2009), among others). Chapter 2 and 3 address implications of the market volatility term structure on the cross-section of stock returns. While index options volatility term structure may capture a macro risk, the individual stock option's volatility term structure may reflect a firm specific risk.

We find that the stock's volatility term structure can predict future returns. Previous studies find relationships between the earnings announcements, stock and option trading volumes and the option's implied volatility. Frazzini and Lamont (2007) finds strong relationships between earnings announcements and stocks trading volumes. Amin and Lee (1997) document that option trading volume is related to price discovery of earnings news. And Leung and Santoli (2014) study the implied volatility surface of the stocks' approaching to the earnings announcements. In this paper, we find evidence that the implied volatility term structure is a measure of event risk: firms with the most negative volatility term structure are those for which the market anticipates news that may affect stock price within one month. Relevant events include, but are not limited to, earnings announcement.

1.4 Outline

In Chapter 2, we investigate whether the market volatility term structure slope is a source of risk or not. We find that stocks with high sensitivities to the proxies of the VIX term structure slope exhibit high returns on average. In Chapter 3, we provide a stylized model that explains our empirical results. We build a regime-switching rare disaster model that allows disasters to have short and long durations. Our model indicates that a downward sloping VIX term structure corresponds to a potential long disaster and an upward sloping VIX term structure corresponds to a potential short disaster. In Chapter 4, we study the relationship between individual stock's volatility term structure and the stock's future return. We show that option volatility term structure slopes are significant in predicting future equity returns in the cross-section.

Chapter 2

Empirical Implications of VIX Term Structure

It is well known that the market volatility is an indicator of market-wide risk. Ang, Hodrick, Xing and Zhang (2006) finds that market volatility risk is priced in the cross-section of stock returns. The market volatility term structure, which is calculated from prices of options with different expirations, reflects the market's expectation of future volatility of different horizons. We investigate in this paper whether the market volatility term structure slope is a source of risk or not.

The first goal of this chapter is to investigate how the market volatility term structure is priced in the cross-section of expected stock returns. We want to both determine whether the market volatility term structure is a priced risk factor and estimate the price of volatility term structure risk.

We use the VIX term structure to proxy for the market volatility term structure. The VIX is the market's 30-day volatility implied from S&P 500 index option prices. And the VIX term structure is the market's implied volatilities on different time horizons. We use the VIX slope to represent the VIX term structure and we introduce two measures for the VIX slope. We do not directly use the VIX slope as the proxy because it is highly correlated with the VIX and thus could affect the robustness of the empirical test results. The first measure we use is the "slope" principal component of the VIX term structure, which we call *PSlope*. The second measure is proposed as the return of a VIX futures trading strategy that we propose. The strategy captures VIX futures roll yields by long and short VIX futures with different expirations, and we refer to this measure as $VStrat$. Both measures worth studying. *PSlope* mimics the VIX slope very well and has the longer possible sample period between 1996 and August 2013. $VStrat$ is a return-based factor and can be directly used as a trading strategy which captures the volatility term structure premium. So $VStrat$ can be used to compare the strategy performance with other volatility related strategies. Because the VIX futures were introduced to market since 2004, the sample period is shorter. The two measures are constructed from different methodologies, so it is meaningful to check the consistency of the results corresponding to the two measures.

We conduct two types of empirical tests. First, we triple-sort all stocks on the NYSE, AMEX, and the NASDAQ into terciles with respect to their sensitivities to market excess returns, changes in VIX and changes in the volatility term structure (*PSlope* or $VStrat$). The triple-sort is intended to isolate the effect of each risk factor. We construct hedge portfolio with respect to the volatility term structure risk. By design, the hedge portfolio has equal loadings on the other two factors. We find that by controlling the loadings on the market excess returns and changes in VIX, the stocks with high sensitivities to changes in the volatility term structure exhibit high returns on average. The average return on the high-minus-low *PSlope* ($VStrat$) portfolio is 0.21% (0.18%) per month. Second, we estimate the price of risk for the volatility term structure by running Fama-MacBeth regressions with different test portfolios and different rolling windows. We find that estimates of the price of *PSlope* ($VStrat$) risk is positive and it is approximately 2.5% annually. The price of volatility term structure risk is statistically significant and it cannot be explained by other common risk factors, such as the market excess return, size, book-to-market, momentum, liquidity, and market volatility. We extensively test the empirical results and find the effect of the volatility term structure risk to be robust.

Furthermore, we investigate whether the volatility term structure premium is explained by the variance risk premium (VRP). VRP is defined as the risk-neutral expectation and the objective expectation of stock return variation. Empirically, we follow several recent studies including Carr and Wu (2009), Bollerslev, Tauchen and Zhou (2009), Drechsler and Yaron (2011) on estimating VRP as the difference between model-free option-implied variance and realized variance. We construct hedge portfolios by triple-sorting all stocks on the NYSE, AMEX, and the NASDAQ in terciles with respect to their sensitivities to market excess returns, changes in VRP, and changes in the volatility term structure. Even with the loadings on the other two risk factors controlled, the high-minus-low average return on the volatility term structure risk hedge portfolio still exists and is significant. Thus the VRP cannot explain the volatility term structure and they are different risk factors.

The second goal of this paper is to explain the implications of the volatility term structure risk. Most recent studies on VIX or the VIX term structure focus on stochastic volatility and jump models (Ait-Sahalia, Mustafa and Loriano (2012), Duan and Yeh (2011), Amengual (2009), and Egloff, Leippold and Wu (2010)). These models lack the connection with the fundamental economy. In order to connect the fundamental economy with the volatility term structure, we propose a stylized model. We build a regime-switching rare disaster model. In this framework, the VIX term structure contains information about the length of a potential disaster.

The rare disasters literature (Rietz (1988), Barro (2006), Gabaix (2012), and Wachter (2013)) argues that asset prices and risk premia can be explained by rare disasters, which are any large decline in consumption and/or GDP. Our model is most related to the Gabaix model, which assumes a hidden probability p of entering into a disaster in the next period.

What differentiates our model from the Gabaix model is that we not only assume a probability of entering into a disaster, but also a probability of exiting from a disaster. Because of this difference, the disaster is an instant downside jump in the Gabaix model, but it has a finite length in our model. In our model, there are two types of disasters: one with a short duration (e.g., months) and the other with a long duration (e.g., years). The economy has a high probability to exit the short disaster but has lower probability to exit the long disaster. The model indicates that a downward sloping volatility term structure corresponds to a potential long disaster, and an upward sloping volatility term structure corresponds to a potential short disaster. Stocks with high sensitivities to the VIX slope have high loadings on the disaster duration risk, thus earn higher risk premium. Therefore the model implications and the empirical findings are consistent.

The rest of this chapter is organized as follows. In Section 2.1, we introduce the empirical model. In Section 2.2, we describe the data and introduce two measures that serve as proxies of the volatility term structure. Section 2.3 presents the methodology and empirical results of constructing hedge portfolios with loadings only to the VIX term structure factor. Section 2.4 estimates the price of volatility term structure risk. Section 2.5 explains the robust tests.

2.1 ICAPM Model

In this section, we first introduce the ICAPM setup, and subsequently discuss alternative theoretical perspectives on the model's specification, as well as existing research that provides guidance regarding the prices of volatility term structure risk.

Following the intuition of the ICAPM, the equilibrium expected returns of risky assets in the cross-section are determined by the conditional covariances between the asset returns and the changes in state variables that allow investors to hedge against changes in the investment opportunity set. Our hypothesis is that the volatilety term structure is a state variable in

ICAPM. We empirically investigate this hypothesis with two empirical tests.

The first empirical test is to create hedge portfolios with triple-sorting. We use a sample of returns and moments for a time period, $t = 1, ..., T$, to estimate the cross-section stock returns' loadings on changes in the volatility term structure, through time-series regressions of the following form:

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i (r_{m,t} - r_{f,t}) + \beta_{\Delta VIX}^i \Delta VIX_t + \beta_{\Delta VSlope}^i \Delta VSlope_t + \varepsilon_{i,t}, \qquad (2.1)$$

where $r_{i,t}$, $r_{m,t}$, and $r_{f,t}$ are daily return on the stock i, the market portfolio, and the risk-free asset. $\Delta VIX_t = VIX_t - VIX_{t-1}$, $\Delta VSlope_t = VSlope_t - VSlope_{t-1}$, where $VSlope$ represents either of the two measures of the volatility term structure. The coefficients of the regression, β_{MKT}^i, $\beta_{\Delta VIX}^i$, $\beta_{\Delta VSlope}^i$ are the ith stock's loadings to market excess return, VIX, and the volatility term structure.

At the end of each month, we run regression (2.1). We group the stocks into terciles based on β_{MKT}^i (lowest in tercile 1 and highest in tercile 3), and then group each of these three portfolios into terciles based on $\beta_{\Delta VIX}^i$, which yields $3 \times 3 = 9$ portfolios. We subsequently group each of these nine portfolios into terciles based on $\beta_{\Delta VSlope}^i$, which yields $3 \times 3 \times 3 = 27$ portfolios in total. The high-minus-low portfolios on $\Delta VSlope$ risk is constructed as goes long the 9 high-exposure portfolios and go short the 9 low-exposure portfolios with respect to the $\Delta VSlope$ factor.

The second empirical test is based on Fama-MacBeth regressions. We use regression coefficients for stock $i = 1, ..., N$ obtained from time series regression (2.1) to estimate the price of factor risk from the following cross-sectional regression:

$$E[r_i] - r_f = \lambda_0 + \lambda_{MKT} \beta_{MKT}^i + \lambda_{\Delta VIX} \beta_{\Delta VIX}^i + \lambda_{\Delta VSlope} \beta_{\Delta VSlope}^i \qquad (2.2)$$

Within ICAPM context, the prices of risk of the factors depend on whether they reflect improvements or deteriorations in the economy's opportunity set. For instance, if a flat market volatility term structure today is related to an unfavorable investment opportunity set tomorrow, then an asset whose return is negatively related to changes in the market volatility slope provides a hedge against a deterioration in the investment opportunity set. When investors are risk averse, the hedge provided by this asset is desirable, resulting in a lower expected return for such asset. The price of market volatility term structure risk is then positive. In the opposite scenario, in which flat market volatility term structure is related to a favorable future investment opportunity set, the price of market volatility term structure risk will be negative.

A previous study by Johnson (2011) found that the slope of the VIX term structure is positively correlated with future market return. We should expect the sign of the price of market volatility risk, $\lambda_{\Delta VSlope}$ to be positive.

2.2 Data and Measurement

2.2.1 Data

VIX is designed to measure the market's expectation of 30-day volatility. The calculation of VIX is based on S&P 500 index option prices in a model-free approach discussed in Chicago Board Options Exchange (2009) to replicate the risk-neutral variance of a fixed 30-day maturity. We introduce two measures of the VIX slope from different approaches. The first measure is constructed with the VIX term structure, and the second measure is based on the VIX futures term structure. We compute the VIX term structure by replicating the VIX calculation, but with multiple maturities (1, 2, 3, 6, 9, and 12 months) rather than only 30 days. We use the closing option quotes of S&P 500 index options and risk-free rates available from 1996 through August 2013 via OptionMetrics to compute VIX term structure. Summary statistics are shown in Table 2.1.

We plot the VIX term structure from Sept 15th, 2008 and July 9th, 2014 in Figure 2.1 and 2.2. The former one represents a day which the market is under turmoil (the day Lehman Brother went bankruptcy) and the latter represents a normal day. As we can see from the graphs, the VIX term structure is downward sloping and convex in the turmoil day and is upward sloping and concave in the normal day.

	Obs	Mean	Std. Dev.	Min	Max
VIX	4448	21.92	8.57	9.90	78.28
VIX^{2m}	4448	21.96	7.93	10.24	75.01
VIX^{3m}	4448	22.15	7.54	10.40	69.55
VIX^{6m}	4448	22.36	6.99	10.43	61.66
VIX^{9m}	4448	22.17	6.65	11.89	56.85
VIX^{12m}	4448	22.09	6.80	12.03	53.16

Table 2.1: Descriptive Statistics of the VIX Term Structure
The table presents descriptive statistics of the daily VIX term structure (1, 2, 3, 6, 9, and 12 months) from January 1996 to August 2013.

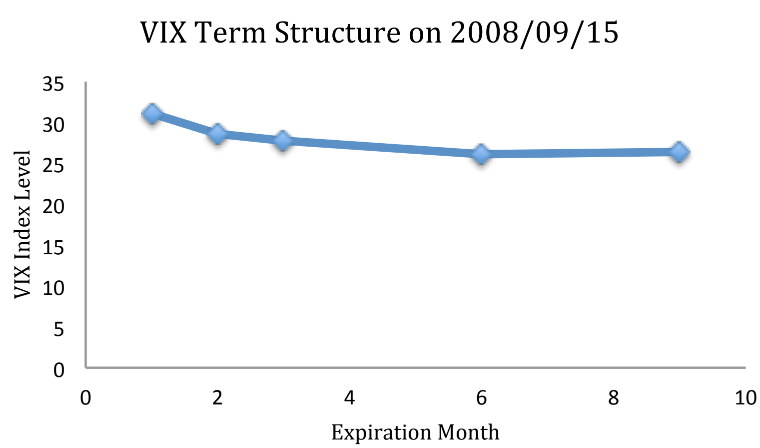

Figure 2.1: VIX Term Structure on 2008/09/15

VIX futures began trading on the CBOE Futures Exchange (CFE) on March 26, 2004.

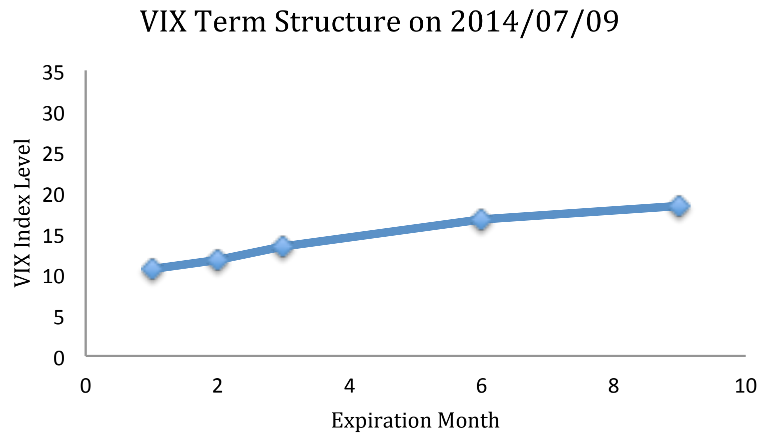

Figure 2.2: VIX Term Structure on 2014/07/09

We use the VIX futures daily closing data with different expirations from 2004 through 2013 via Bloomberg. We use returns on all stocks included in the CRSP NYSE/AMEX/NASDAQ daily stock file.

2.2.2 Measures of the Volatility Term Structure

We use $VSlope$ to represent the volatility term structure and we focus on the "slope" component of the volatility term structure. We introduce two measures as proxies for the VIX slope. We construct the first measure as changes in the second principal component ("slope") of VIX term structure. We run a principal component test on the VIX term structure and the results are shown in Table 2.2. We call the "level" principal component of the VIX term structure $PLevel$ and the "slope" principal component $PSlope$. As shown in the table, $PLevel$ loads relatively equal amounts on 1-12 months VIX term structure, and $PSlope$ loads a positive amount on shorter term VIX but a negative amount on longer term VIX. Therefore, $PSlope$ should positively correlates with the VIX slope. As for the variance of the VIX term structure, 95.12% of the variance could be explained by $PLevel$ and 3.86% could be explained by $PSlope$.

	PLevel	PSlope
VIX	0.40	-0.57
VIX^{2m}	0.41	-0.36
VIX^{3m}	0.41	-0.20
VIX^{6m}	0.41	0.17
VIX^{9m}	0.40	0.39
VIX^{12m}	0.40	0.57
% of var	95.12%	3.86%

Table 2.2: Principal Components of the VIX Term Structure
The table presents the first two principal components of the VIX term structure. The first block shows the coefficients defining each principal component. The second block gives the fraction of term structure variance explained by each principal component. The sample is daily from January 1996 to August 2013.

The second measure of the volatility term structure is a return-based factor which is a simple VIX futures trading strategy we develop. In order to understand the strategy, it is important for us to understand the roll yield of trading futures.

Futures contracts have specific expiration dates, in order to maintain exposure, the investor needs to sell a futures contracts as it gets close to expiration and purchase another contract with a later expiration date. This process is known as "rolling" the futures position. This rolling activity gives investor a return called "roll yield", which refers to the difference between log price of the maturing contract they roll from and the deferred contract they roll into, following Mou (2010).

When a futures curve is in contango (upward sloping), an investor in a long futures position pays a higher price to buy a later expiration futures contract than the price at which the investor sells the contract as it nears expiration, thus suffering negative returns, by which we call a negative roll yield. Since the VIX term structure is often in contango, the long VIX future position is often associated with a negative roll yield. Our trading strategy aims to profit from this negative roll yield.

The trading strategy is defined by maintaining a long position at the 2-month point on the VIX futures curve by continuously rolling between the second and third month futures contracts and a short position at the 1-month point on the VIX futures curve by continuously rolling between the first and second month futures contracts.

If the VIX futures curve stays upward sloping, the long position at the 2-month point on the VIX futures curve keeps rolling the futures from the second month futures to the third month futures, thus suffers a negative roll yield, while the short position at the 1-month point on the VIX futures curve keeps rolling the short position between the first month futures to the second month futures, thus earning a positive roll yield. The future curve is concave while it is upward sloping, thus the positive roll yield earned from the short 1-month VIX futures position is bigger than the long 2-month VIX futures position, thus making a profit. If the VIX futures slope becomes steeper, the strategy will make higher profits and vice versa. Therefore the strategy's return is expected to be highly positively correlated with the VIX slope and $PSlope$. We define the return of this strategy as $VStrat$.

Table 2.3 reports the correlation of ΔVIX, $\Delta PLevel$, $\Delta PSlope$, and $VStrat$ with various factors. Although we use the principal component method to get $PLevel$ and $PSlope$, the changes of $PLevel$ and $PSlope$ are still highly correlated. We present more tests corresponding to this issue in Section 2.5.

2.3 Portfolio Construction and Tests

As discussed in Section 2.2, we develop two measures as proxies of the VIX term structure. The first is $\Delta PSlope$ and the second is $VStrat$. We run each of the tests described in Section 2.1 corresponding to the two measures.

Panel A: 1996-2013

	$\Delta PLevel$	$\Delta PSlope$
$\Delta PLevel$	1.00	
$\Delta PSlope$	-0.73	1.00
MKT	-0.67	0.51
HML	-0.10	0.12
SMB	-0.20	0.14
UMD	0.23	-0.19
ΔVIX	0.93	-0.83

Panel B: 2006-2013

	$VStrat$
$VStrat$	1.00
MKT	0.61
HML	0.08
SMB	0.21
UMD	-0.16
ΔVIX	0.73

Table 2.3: Correlations of Factors

Panel A reports the correlations of monthly changes in VIX, $PLevel$, and $PSlope$ with various factors. The variable ΔVIX represents the monthly change in VIX, and $\Delta PLevel$, $\Delta PSlope$ are the monthly changes of the first two principal components of the VIX term structure. The factors MKT, SMB, HML are the Fama and French (1993) factors, the momentum factor UMD is constructed by Kenneth French, and LIQ is the Pastor and Stambaugh (2003) liquidity factor. The sample period is January 1996 to August 2013. Panel B reports the correlations of monthly changes in VIX, $PLevel$, and $PSlope$, $VStrat$, and with various factors, where $VStrat$ is the monthly return of the VIX slope strategy we introduced in Section 2.2. The sample period is April 2006 to August 2013.

2.3.1 Constructing Hedge Portfolios

Table 2.3 shows high correlations among MKT, VIX, and $VSlope$ factors. If sensitivities to these factors are correlated, it is important to separate the pricing effects of different factors to identify the implication of each market moment separately. For this reason we use triple-sorting to help construct the portfolios following Fama and French (1993), Cochrane (2005), and Chang, Christoffersen and Jacobs (2013).

At the end of each month, we run the following regressions with the two measures:

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i (r_{m,t} - r_{f,t}) + \beta_{\Delta PLevel}^i \Delta PLevel_t + \beta_{\Delta PSlope}^i \Delta PSlope_t + \varepsilon_{i,t} \quad (2.3)$$

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i (r_{m,t} - r_{f,t}) + \beta_{\Delta VIX}^i \Delta VIX_t + \beta_{VStrat}^i VStrat_t + \varepsilon_{i,t} \quad (2.4)$$

We first group the stocks into terciles based on β_{MKT}^i (lowest in tercile 1 and highest in tercile 3). Then we group each of these three portfolios into terciles based on $\beta_{\Delta PLevel}^i$ (or $\beta_{\Delta VIX}^i$), which yields $3 \times 3 = 9$ portfolios. We subsequently group each of these nine portfolios into terciles based on $\beta_{\Delta PSlope}^i$ (or β_{VStrat}^i), which yields $3 \times 3 \times 3 = 27$ portfolios in total.

This grouping procedure allows me to obtain portfolios that have varying exposures to one factor, but have equal loadings on the other two factors. In Table 2.4, the row H-L reports the average returns and alphas of the high-minus-low portfolios that is long 9 high-exposure portfolios and short 9 low-exposure portfolios to the $\Delta VSlope$ factor.

The average return of the $\Delta VSlope$ H-L portfolio is 0.21% per month for the $PSlope$ measure and 0.18% per month for the $VStrat$ measure. The H-L return is statistically significant at the 5% level with a t-statistic of 2.31 for the $PSlope$ measure and at the 10% level with a t-statistic of 1.64 for the $VStrat$ measure. We also report the Carhart 4-factor alpha of the H-L portfolios for both measures to check if the return spread is captured by these factors. We find that the alphas of H-L portfolios show consistent results with the

Panel A: $\Delta PSlope$, 1996-2013, $nobs = 211$

	Tercile Portfolios			
	L	M	H	H-L
Mean	0.61	0.73	0.82	0.21
	(1.39)	(1.89)	(1.73)	(**2.31**)
Carhart 4-Factor Alpha	0.16	0.27	0.35	0.18
	(1.10)	(**2.78**)	(**2.43**)	(**2.22**)

Panel B: $VStrat$, 2006-2013, $nobs = 81$

	Tercile Portfolios			
	L	M	H	H-L
Mean	0.11	0.28	0.29	0.18
	(1.15)	(1.37)	(1.32)	(1.64)
Carhart 4-Factor Alpha	-0.15	0.03	0.04	0.19
	(-1.24)	(1.25)	(1.17)	(1.62)

Table 2.4: Sorting on VIX Term Structure Loadings

At the end of each month, we run regression (2.6) and (2.7) on daily returns of each stock. We form 27 portfolios with varying sensitivities to $r_m - r_f$, $\Delta PLevel$ (ΔVIX), $\Delta PSlope$ ($VStrat$) by sequentially grouping the stocks into terciles sorted on β_{MKT}, $\beta_{\Delta PLevel}$ ($\beta_{\Delta VIX}$), $\beta_{\Delta PSlope}$ (β_{VStrat}), (lowest in tercile L and highest in tercile H). We then group the 27 portfolios into the group that contains stocks with low (L), medium (M) or high (H) exposures to only $\Delta PSlope$ ($VStrat$). We report the average monthly returns, the Carhart-4 Factor alpha, and the respective Newey-West t-statistics with lag 12 for the L, M, H, H-L (High-minus-Low) portfolios. Panel A reports the results with measure $\Delta PSlope$ and Panel B reports the results with measure $VStrat$.

average returns. The H-L portfolio alpha is 0.18% per month for the $PSlope$ measure and 0.19% per month for the $VStrat$ measure. In summary, the exposure portfolio on $VSlope$ shows increasing patterns in average returns and Carhart 4-factor alphas.

The results suggest that $VSlope$ is a risk factor. The higher the loadings a stock has on $VSlope$, the more risk it takes. And the difference in return between high and low $\Delta VSlope$ exposure portfolios cannot be explained by market excess return, size, book-to-market, or momentum factors.

2.3.2 Constructing Return-Based Factors

Following procedures similar to those of Fama and French (1993), we construct return-based risk factors from the hedge portfolios constructed in the previous subsection. We construct two sets of risk factors corresponding to the $PSlope$ and $VStrat$ measures.

We define $FPLevel$ as the return of the $PLevel$ hedge portfolio, $FPSlope$ as the return of the $PSlope$ hedge portfolio: $FPLevel = (1/9)\left(r\beta_{\Delta PLevel,H} - r\beta_{\Delta PLevel,L}\right)$, $FPSlope = (1/9)\left(r\beta_{\Delta PSlope,H} - r\beta_{\Delta PSlope,L}\right)$, where $r\beta_{\Delta PLevel,H(L)}$ $(r\beta_{\Delta PSlope,H(L)})$ represents the sum of the return of the 9 portfolios with highest (lowest) loadings on $\Delta PLevel$ ($\Delta PSlope$).

And we define $FVIX$ as the return of the VIX hedge portfolio, and $FVStrat$ as the return of the $VStrat$ hedge portfolio: $FVIX = (1/9)\left(r\beta_{\Delta VIX,H} - r\beta_{\Delta VIX,L}\right)$, $FVStrat = (1/9)\left(r\beta_{VStrat,H} - r\beta_{VStrat,L}\right)$, where $r\beta_{\Delta VIX,H(L)}$ $(r\beta_{VStrat,H(L)})$ represents the sum of the return of the 9 portfolios with highest (lowest) loadings on ΔVIX ($\Delta VStrat$).

2.4 Price of Volatility Term Structure Risk

In the previous section, we constructed hedge portfolios corresponding to $VSlope$ risk. We estimated the price of $PSlope$ ($VStrat$) risk to be 0.21% (0.18%) per month. And we constructed the return-based factors $FPSlope$ and $FVStrat$. In this section, we estimate the price of $VSlope$ risk by running Fama-Macbeth regressions.

2.4.1 Fama-MacBeth Regressions

We first apply the two-pass regressions of Fama and MacBeth (1973) to the 27 portfolios we constructed in Section 2.3. In the first stage, we regress the time series of post-ranking monthly excess returns of each of the 27 portfolios on the pricing factors to estimate the portfolio's factor betas. In the second stage, we regress the cross-section of excess returns of the 27 portfolios on their estimated factor betas to obtain the estimated price of risk each month. The monthly estimates of the price of risk are then averaged to yield the final estimate.

$$E[r_i] - r_f = \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{\Delta VIX}\beta^i_{\Delta VIX} + \lambda_{\Delta VSlope}\beta^i_{\Delta VSlope} \tag{2.5}$$

We run two Fama-MacBeth tests corresponding to the two measures of $VSlope$. The pricing factors include $r_m - r_f$, SMB, HML, UMD, $FPLevel$ ($FVIX$), $FPSlope$ ($FVStrat$), and LIQ. The factors $r_m - r_f$, SMB, HML are the Fama and French (1993) factors, the momentum factor UMD is constructed by Kenneth French, and LIQ is the Pastor and Stambaugh (2003) liquidity factor.

We run multiple Fama-MacBeth tests on different combinations of the pricing factors, which include: (1) CAPM, (2) CAPM+$FPSlope$ ($FVStrat$), (3) CAPM+$FPSlope$ ($FVStrat$)+$FPLevel$ ($FVIX$), (4) FF-3, (5) FF-3+$FPSlope$ ($FVStrat$)+$FPLevel$ ($FVIX$), (6) Carhart-4, (7) Carhart-4+$FPSlope$ ($FVStrat$)+$FPLevel$ ($FVIX$), and (8) Carhart-4+$FPSlope$ ($FVStrat$)+$FPLevel$ ($FVIX$)+LIQ.

The results of the Fama-MacBeth regressions based on the 27 portfolios are shown in Table 2.5. In the panel A, the price of $FPSlope$ risk's magnitude is around 0.20% and it remains significant as we add in more factors. The price of $FVStrat$ risk in panel B has similar magnitude and significance as the price of $FPSlope$ risk in panel A. Both sets of results suggest a positive price of $VSlope$ risk and are statistically significant. They are also consistent with the results in Section 2.3 with regard to magnitude, sign, and significance.

It is important to check the robustness of the test results using other sets of test portfolios. We consider another set of test portfolios: 48 industry portfolios. The results are provided in Table 2.6. The price of risk for $FPSlope$ and $FVStrat$ factors remain positive and significant.

2.4.2 Fama-MacBeth Regressions with Rolling Betas

In the previous subsection, we ran Fama-MacBeth tests with constant betas. To check if varying betas would affect the previous results, we use the following method to run Fama-MacBeth tests with rolling betas. At the end of each rolling period (1, 3, or 6 months), we run the following regression on the daily returns of each stock:

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i(r_{m,t} - r_{f,t}) + \beta_{\Delta PLevel}^i \Delta PLevel_t + \beta_{\Delta PSlope}^i \Delta PSlope_t + \varepsilon_{i,t} \quad (2.6)$$

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i(r_{m,t} - r_{f,t}) + \beta_{\Delta VIX}^i \Delta VIX_t + \beta_{VStrat}^i VStrat_t + \varepsilon_{i,t} \quad (2.7)$$

We include all six factors in all our robustness tests in this section. The results of the regressions are reported in Table 2.12. Panel A uses 1-month betas, Panel B uses 3-month betas, and Panel C uses 6-month betas. The price of $FPSlope$ risk's magnitude and significance is around the same range for the 1-month to 6-month rolling beta windows as in Table 2.5. The price of $FVStrat$ risk in panel 2 has a larger magnitude and significance than in Table 2.5.

Panel A: $\Delta PSlope$, 1996-2013

$FPSlope$	0.21	0.21	0.20	0.20	0.20
	(1.85)	(**1.98**)	(**2.07**)	(**2.08**)	(**2.10**)
$FPLevel$		0.11	0.13	0.13	0.13
		(0.58)	(0.95)	(0.95)	(0.96)
$r_m - r_f$	-0.37	-0.32	-0.67	-0.67	-0.58
	(-0.61)	(-0.53)	(-0.88)	(-0.91)	(-0.87)
HML			0.39	0.37	0.28
			(0.61)	(0.70)	(0.59)
SMB			0.40	0.41	0.45
			(0.61)	(0.67)	(0.74)
UMD				-0.05	0.04
				(-0.06)	(0.04)
LIQ					0.00
					(0.03)
$Constant$	0.94	0.90	0.90	0.90	0.84
	(1.95)	(1.85)	(1.71)	(**2.04**)	(**2.14**)

Panel B: VStrat, 2006-2013

$FVStrat$	0.21	0.21	0.20	0.19	0.18
	(**2.05**)	(**2.11**)	(**1.97**)	(1.94)	(1.84)
$FVIX$		-0.02	0.02	0.05	0.05
		(-0.19)	(0.18)	(0.36)	(0.34)
$r_m - r_f$	-0.13	-0.17	-0.31	-0.08	-0.05
	(-0.16)	(-0.18)	(-0.25)	(-0.09)	(-0.06)
HML			0.40	0.39	0.34
			(1.32)	(1.30)	(0.86)
SMB			-0.33	-0.26	-0.30
			(-1.21)	(-0.91)	(-1.20)
UMD				-0.13	-0.04
				(-0.01)	(-0.03)
LIQ					0.00
					(-0.51)
$Constant$	0.34	0.41	0.75	0.55	0.55
	(0.64)	(0.70)	(1.21)	(1.81)	(1.79)

Table 2.5: The Price of VIX Term Structure Risk

The table reports the estimated prices of risk for $3 \times 3 \times 3$ portfolios sorted by β_{MKT}, $\beta_{\Delta PLevel}$, $\beta_{\Delta PSlope}$ with $FPLevel$, $FPSlope$, $r_m - r_f$, HML, SMB, UMD and LIQ as factors. We estimate the prices of risk by applying the two-pass regression procedure of Fama-MacBeth (1973) to the post-ranking monthly returns of the $3 \times 3 \times 3$ portfolios. We estimate the β's by running a time series regression on the full-sample post-ranking returns, then estimate λ's by running a cross-sectional regression every month. The Newey-West t-statistics with 12 lags are reported in the parentheses.

$FPSlope$	0.16	$FVStrat$	0.43
	(**1.97**)		(**2.07**)
$FPLevel$	-0.14	$FVIX$	-0.06
	(-0.60)		(-0.19)
$r_m - r_f$	0.22	$r_m - r_f$	-0.36
	(0.40)		(-0.40)
HML	0.05	HML	-0.49
	(0.13)		(-1.52)
SMB	-0.25	SMB	-0.19
	(-0.95)		(-0.75)
UMD	0.89	UMD	0.47
	(1.11)		(0.33)
LIQ	0.01	LIQ	0.01
	(1.79)		(**1.99**)
$Constant$	0.59	$Constant$	0.76
	(1.70)		(1.92)

Table 2.6: The Price of Volatility Term Structure Risk with 48 Industry Portfolios
We estimate the prices of risk by applying the two-pass regression procedure of Fama-MacBeth (1973) to the 48 industry portfolios provided by Kenneth French. We estimate the β's by running a time series regression on the full-sample post-ranking returns, then estimate λ's by running a cross-sectional regression every month. The Newey-West t-statistics with 12 lags are reported in the parentheses.

Panel A: $\Delta PSlope$, 1996-2013

	1month	3month	6month
$FPSlope$	0.19	0.21	0.18
	(**1.98**)	(**2.40**)	(**2.09**)
$FPLevel$	0.09	0.07	0.06
	(0.92)	(0.60)	(0.48)
$r_m - r_f$	0.07	0.11	0.04
	(0.13)	(0.18)	(0.08)
HML	0.63	0.66	0.47
	(1.72)	(1.48)	(1.05)
SMB	-0.37	-0.11	0.04
	(-1.34)	(-0.25)	(0.07)
UMD	0.46	0.17	0.18
	(0.26)	(0.30)	(0.28)
$Constant$	0.61	0.50	0.54
	(1.27)	(0.83)	(1.00)

Panel B: VStrat, 2006-2013

	1month	3month	6month
$FVStrat$	0.17	0.29	0.35
	(1.89)	(**2.63**)	(**3.26**)
$FVIX$	0.14	0.03	0.04
	(0.92)	(0.13)	(0.03)
$r_m - r_f$	0.17	-0.03	-0.02
	(0.61)	(-0.06)	(-0.05)
HML	0.36	0.13	0.22
	(0.55)	(0.24)	(0.31)
SMB	-0.76	-0.24	-0.49
	(-1.49)	(-0.49)	(-0.78)
UMD	0.37	0.73	0.88
	(0.71)	(0.89)	(1.15)
$Constant$	0.46	0.20	0.05
	(0.58)	(0.25)	(0.06)

Table 2.7: The Price of Volatility Term Structure Risk with Different Beta Rolling Periods The table reports the estimated prices of risk for 3×3×3 portfolios sorted by β_{MKT}, $\beta_{\Delta PLevel}$, $\beta_{\Delta PSlope}$ with $FPLevel$, $FPSlope$, $r_m - r_f$, HML, SMB, UMD and LIQ as factors. We estimate the prices of risk by applying the two-pass regression procedure of Fama-MacBeth (1973) to the post-ranking monthly returns of the $3 \times 3 \times 3$ portfolios. We estimate the β's by running a time series regression uses rolling 1, 3, and 6 months returns, then estimate λ's by running a cross-sectional regression every rolling period. The Newey-West t-statistics with 12 lags are reported in the parentheses.

2.5 Robustness

2.5.1 Robustness to Sub-Periods

To verify that our results are not driven by the particular circumstances in the sample period (1996-2013), we repeat the tests from Section 2.3 for two subperiods: 1996-2003 and 2004-2013. We only separate the testing period for the $PSlope$ measure. We do not separate the testing period for the $VStrat$ measure because the testing period is short (2003-2013), and the results for separate periods would not be useful. We present the results in Table 2.8, which shows that the H-L return difference and Carhart 4-factor alphas are still significant within the separate testing periods.

Panel A: $\Delta PSlope$, 1996-2003

	Tercile Portfolios			
	L	M	H	H-L
Mean	1.00	1.05	1.31	0.21
	(1.39)	(1.89)	(1.73)	(**2.31**)
Carhart 4-Factor Alpha	-0.15	0.13	0.27	0.18
	(1.10)	(**2.78**)	(**2.43**)	(**2.22**)

Panel B: $\Delta PSlope$, 2004-2013

	Tercile Portfolios			
	L	M	H	H-L
Mean	0.34	0.48	0.59	0.18
	(1.15)	(1.37)	(1.32)	(1.64)
Carhart 4-Factor Alpha	-0.08	0.00	0.17	0.19
	(-1.24)	(1.25)	(1.17)	(1.62)

Table 2.8: Sorting on $\Delta PSlope$ Loadings with Sub-Periods

At the end of each month, we run regression (2.6) on daily returns of each stock. We form 27 portfolios with varying sensitivities to $r_m - r_f$, $\Delta PLevel$, $\Delta PSlope$ by sequentially grouping the stocks into terciles sorted on β_{MKT}, $\beta_{\Delta PLevel}$, $\beta_{\Delta PSlope}$, (lowest in tercile L and highest in tercile H). We then group the 27 portfolios into the group that contains stocks with low(L), medium(M) or high(H) exposures to only $\Delta PSlope$. We report the average monthly returns, the Carhart-4 Factor alpha, and the respective Newey-West t-statistics with lag 12 for the L, M, H, H-L (High-minus-Low) portfolios. Panel A reports the results with sample period January 1996 to December 2003 and Panel B reports the results with sample period January 2004 to August 2013.

Another concern is that the VIX term structure risk premium may be earned during the most volatile periods in the market. To test for this possibility, we compute average monthly returns, Carhart four-factor alphas of the H-L portfolios conditioning on periods with $VIX \geq 30$ (volatile periods) or $VIX < 30$ (stable periods).

As shown in Table 2.9, for the portfolios constructed with regression (2.6) the difference in the Carhart four-factor alphas of the H and L portfolios is 0.19% (0.35%) per month during stable (volatile) periods. The differences in alphas during both stable and volatile periods are significant at the 5% level. As shown in Table 2.10, for the portfolios constructed with regression (2.7), during stable (volatile) periods, the difference in the Carhart four-factor alphas of the H and L portfolios is 0.33% (0.18%) per month. The differences in alphas during the stable period is significant at the 5% level, while those during the volatile periods are not.

The test result suggests that the VIX term structure risk premium is not concentrated during volatile periods. On the other hand, most of the VIX term structure risk premium is earned during normal periods.

2.5.2 Principal Components of Changes in VIX Term Structure

As mentioned in Section 2.2, we constructed the $PSlope$ measure as the "slope" principal component of the VIX term structure. As shown in Table 2.3, the correlation between $\Delta PLevel$ and $\Delta PSlope$ is very high, even though the correlation between $PLevel$ and $PSlope$ is zero because they are both principal components of the VIX index term structure. Therefore, we further check if a measure constructed as the principal component of the VIX term structure daily change would change the previous testing results.

We define $PDLevel$ as the first principal component of changes in the VIX term structure and $PDSlope$ as the second principal component of changes in the VIX term structure, which

Panel A: $\Delta PSlope$, 1996-2013, $VIX < 30$, $nobs = 162$

	Tercile Portfolios			
	L	M	H	H-L
Average Return	1.53	1.58	1.73	0.20
	(**3.33**)	(**4.10**)	(**3.49**)	(**1.98**)
Carhart 4-Factor Alpha	0.30	0.38	0.49	0.19
	(1.49)	(**2.81**)	(**2.52**)	(**2.03**)

Panel B: $\Delta PSlope$, 1996-2013, $VIX \geq 30$, $nobs = 49$

	Tercile Portfolios			
	L	M	H	H-L
Average Return	-1.82	-1.55	-1.53	0.29
	(-1.46)	(-1.19)	(-1.10)	(1.69)
Carhart 4-Factor Alpha	-0.55	-0.27	-0.20	0.35
	(-1.42)	(-0.35)	(-0.29)	(2.13)

Table 2.9: Sorting on $\Delta PSlope$ Loadings with Different VIX Levels

At the end of each month, we run regression 2.6 on daily returns of each stock. We form 27 portfolios with varying sensitivities to Rm-Rf, $\Delta PLevel$, $\Delta PSlope$ by sequentially grouping the stocks into terciles sorted on β_{MKT}, $\beta_{\Delta PLevel}$, $\beta_{\Delta PSlope}$ (lowest in tercile L and highest in tercile H). We then group the 27 portfolios into the group that contains stocks with low(L), medium(M) or high(H) exposures to only $\Delta PSlope$. Conditioning on $VIX < 30$ or $VIX \geq 30$, we report the average monthly returns, the Carhart-4 Factor alpha, and the respective Newey-West t-statistics with lag 12 for the L, M, H, H-L (High-minus-Low) portfolios.

Panel A: $VStrat$, 2006-2013, $VIX < 30$, $nobs = 58$

	Tercile Portfolios			
	L	M	H	H-L
Average Return	1.23	1.10	1.50	0.27
	(1.65)	(**2.07**)	(**2.01**)	(1.83)
Carhart 4-Factor Alpha	-0.15	0.09	0.18	0.33
	(-0.55)	(0.73)	(0.81)	(**2.04**)

Panel B: $VStrat$, 2006-2013, $VIX \geq 30$, $nobs = 23$

	Tercile Portfolios			
	L	M	H	H-L
Average Return	-1.77	-1.69	-1.68	0.09
	(-0.87)	(-0.76)	(-0.71)	(0.17)
Carhart 4-Factor Alpha	-1.10	-0.99	-0.92	0.18
	(-1.85)	(-1.70)	(-1.69)	(0.39)

Table 2.10: Sorting on $VStrat$ Loadings with Different VIX Levels

At the end of each month, we run regression 2.7 on daily returns of each stock. We form 27 portfolios with varying sensitivities to Rm-Rf, ΔVIX, $VStrat$ by sequentially grouping the stocks into terciles sorted on β_{MKT}, $\beta_{\Delta VIX}$, β_{VStrat} (lowest in tercile L and highest in tercile H). We then group the 27 portfolios into the group that contains stocks with low(L), medium(M) or high(H) exposures to only β_{VStrat}. Conditioning on $VIX < 30$ or $VIX \geq 30$, we report the average monthly returns, the Carhart-4 Factor alpha, and the respective Newey-West t-statistics with lag 12 for the L, M, H, H-L (High-minus-Low) portfolios.

has negative loadings on the shorter end but positive loadings on the longer end. Table 2.11 shows the principal components of changes in the VIX term structure.

	$\Delta PLevel$	$\Delta PSlope$
ΔVIX	0.44	-0.22
ΔVIX^{2m}	0.44	-0.29
ΔVIX^{3m}	0.41	-0.39
ΔVIX^{6m}	0.39	-0.05
ΔVIX^{9m}	0.41	0.31
ΔVIX^{12m}	0.35	0.79
% of var	72.18%	10.36%

Table 2.11: Principal Components of Changes in VIX Term Structure
We present principal components analysis with the first two components for the daily changes of the VIX term structure. The first block shows the coefficients defining each principal component. The second block gives the fraction of term structure variance explained by each principal component. $\Delta PLevel$ is the first principal component and $\Delta PSlope$ is the second principal component.

We also run regression (2.8) instead of regression (2.6):

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i(r_{m,t} - r_{f,t}) + \beta_{PDLevel}^i PDLevel_t + \beta_{PDSlope}^i PDSlope_t + \varepsilon_{i,t} \quad (2.8)$$

Table 2.12 shows the results, which are very similar those presented in Table 2.5, which implies that our previous principal component measure with $PLevel$ and $PSlope$ works even though $\Delta PLevel$ and $\Delta PSlope$ are highly correlated.

2.5.3 Robustness to Variance Risk Premium

The variance risk premium (VRP) is defined as the difference between the risk neutral expectation of the future return variance and the physical expectation of the return variance over the $[t, t+1]$ time interval, as $VRP_t = E^Q Var_{t,t+1} - E^P Var_{t,t+1}$.

There are two type of views on the VRP by recent studies. The first view it as an indicator of the representative agent's risk aversion (Rosenberg and Engle (2002), Bakshi

$FPDSlope$	0.21	0.20	0.19	0.19	0.19
	(**2.41**)	(**2.37**)	(**2.35**)	(**2.31**)	(**2.29**)
$FPDLevel$		-0.05	-0.04	-0.02	-0.02
		(-0.28)	(-0.27)	(-0.13)	(-0.13)
$Rm - Rf$	-0.18	-0.20	-0.35	-0.07	-0.13
	(-0.04)	(-0.31)	(-0.45)	(-0.09)	(-0.19)
HML			0.11	0.22	0.22
			(0.29)	(0.57)	(0.55)
SMB			0.17	-0.22	-0.26
			(0.25)	(-0.38)	(-0.44)
MOM				-0.92	-0.96
				(-1.10)	(-1.07)
LIQ					0.00
					(-0.44)
$Constant$	0.76	0.92	0.96	0.77	0.87
	(1.60)	(1.80)	(1.69)	(1.68)	(1.93)

Table 2.12: Prices of the VIX Term Structure Risk with Principal Components of Changes in VIX Term Structure

We report the estimated prices of risk for 3x3x3 Portfolios sorted by β_{MKT}, $\beta_{\Delta PDLevel}$, $\beta_{\Delta PDSlope}$ with $FDPLevel$, $FDPSlope$, Rm-Rf, HML, SMB, MOM and LIQ as factors. LIQ is the Pastor and Stambaugh (2003) liquidity factor. We estimate the prices of risk by applying the two-pass regression procedure of Fama-MacBeth (1973) to the post-ranking monthly returns of the 3x3x3 Portfolios. We estimate the β's by running a time series regression on the full-sample post-ranking returns, then estimate λ's by running a cross-sectional regression every month. The Newey-West t-statistics with 12 lags are reported in the parentheses.

and Madan (2006), Bollerslev, Gibson and Zhou (2011)). The other interpret it as a cause by macroeconomic uncertainty risk (Bollerslev, Tauchen and Zhou (2009), Drechsler and Yaron (2011)).

To estimate the VRP, we need to estimate both the risk neutral and physical expectations of the future return variance. $E^Q Var_{t,t+1}$ is typically estimated by the VIX^2 (Britten-Jones and Neuberger (2006), Jiang and Tian (2005), Carr and Wu (2009), among others), while $E^P Var_{t,t+1}$ has various ways of estimation. In this paper, $E^P Var_{t,t+1}$ is estimated by the annualized realized volatility of S&P 500 index from the past 1 month.

Though the VRP could be viewed as macroeconomic risk factor, it is different from $VSlope$. From definition, the VRP measures the difference between the risk neutral and physical expectation of the future return variance, while the $VSlope$ measures the difference between different terms of the risk neutral expectation of the future return volatility. Therefore, the $VSlope$ does not capture the physical expectation of the future return volatility, and the VRP does not capture the longer term of the risk neutral expectation of the future return variance. Next, we use empirical tests to justify that the VRP and $VSlope$ reflects different risks.

To check that $\Delta VSlope$ is a different risk factor from VRP, we run the procedure in Section 2.3 based on regression (2.9) or (2.10):

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i (r_{m,t} - r_{f,t}) + \beta_{\Delta VRP}^i \Delta VRP_t + \beta_{\Delta PSlope}^i \Delta PSlope_t + \varepsilon_{i,t} \tag{2.9}$$

$$r_{i,t} - r_{f,t} = \beta_0^i + \beta_{MKT}^i (r_{m,t} - r_{f,t}) + \beta_{\Delta VRP}^i \Delta VRP_t + \beta_{VStrat}^i VStrat_t + \varepsilon_{i,t} \tag{2.10}$$

As in Section 2.3, we first group the stocks into terciles based on β_{MKT}^i (lowest in tercile 1 and highest in tercile 3), and then group each of these three portfolios into terciles based on $\beta_{\Delta VRP}^i$ which yields $3 \times 3 = 9$ portfolios, and we subsequently group each of these nine portfolios into terciles based on $\beta^i_{\Delta PSlope}$ (or β^i_{VStrat}), which yields $3 \times 3 \times 3 = 27$ portfolios in total.

We construct the H-L portfolios as in Section 2.3, so that each portfolio is neutral to the other two factors (r_{MKT} and ΔVRP). The results in Table 2.13 show that the H-L significance still exists, which suggests that $\Delta VSlope$ and VRP are different measures.

Panel A: $\Delta PSlope$, 1996-2013, VRP, $nobs = 211$

	Tercile Portfolios			
	L	M	H	H-L
Mean	0.65	0.81	0.88	0.23
	(1.21)	(1.80)	(1.58)	(1.83)
Carhart 4-Factor Alpha	0.18	0.29	0.37	0.19
	(0.98)	(**2.09**)	(**2.11**)	(**2.13**)

Panel B: VStrat, 2006-2013, VRP, $nobs = 81$

	Tercile Portfolios			
	L	M	H	H-L
Mean	0.09	0.32	0.35	0.26
	(0.07)	(0.30)	(0.28)	(**2.05**)
Carhart 4-Factor Alpha	-0.16	0.03	0.05	0.21
	(-0.56)	(0.05)	(0.21)	(1.31)

Table 2.13: Robustness Test with the VRP

At the end of each month, we run regression 2.9 and 2.10 on daily returns of each stock. We form 27 portfolios with varying sensitivities to $r_m - r_f$, ΔVRP, $\Delta PSlope$ (VStrat) by sequentially grouping the stocks into terciles sorted on β_{MKT}, $\beta_{\Delta VRP}$, $\beta_{\Delta PSlope}$ (β_{VStrat}), (lowest in tercile L and highest in tercile H). We then group the 27 portfolios into the group that contains stocks with low(L), medium(M) or high(H) exposures to only $\Delta PSlope$ (VStrat) . I report the average monthly returns, the Carhart-4 Factor alpha, and the respective Newey-West t-statistics with lag 12 for the L, M, H, H-L (High-minus-Low) portfolios.

2.6 Conclusions

We find that stocks with high sensitivities to the proxies of the VIX term structure slope exhibit high returns on average. We further estimate the premium for bearing the VIX slope risk to be approximately 2.5% annually, statistically significant, and cannot be explained by other common risk factors, such as the market excess return, size, book-to-market, momentum, liquidity and market volatility. We extensively investigate the robustness of our empirical results and find that the effect of the VIX term structure risk is robust. Within the context of ICAPM, the positive price of VIX term structure risk indicates that it is a state variable which positively affects the future investment opportunity set.

Chapter 3

Regime-Switching Rare Disaster Model

3.1 Rare Disaster Literature

According to ICAPM, the prices of risk of the factors depend on whether they reflect improvements or deteriorations in the economy's opportunity set. If a downward sloping VIX term structure today is related to an unfavorable investment opportunity set in the future, then an asset whose return is negatively related to $\Delta VSlope$ provides a hedge against a deterioration in the investment opportunity set. When investors are risk averse, the hedge provided by this asset is desirable, resulting in a lower expected return for such asset. Therefore, we expect that stocks with negative sensitivities to the VIX term structure risk would have low average returns.

In previous sections, we used two measures for VIX term structure. The first measure is based on using the changes in the second principal component of the VIX term structure ($\Delta PSlope$), which has negative loadings on the shorter end but positive loadings on the longer end. The second relies on the return of a VIX slope strategy (VStrat), which captures the roll yield of the VIX futures term structure. From the test result showing that the price of VIX term structure risk is positive, we expect that a downward sloping VIX term structure today is related to an unfavorable investment opportunity set in the future according to ICAPM and vice versa. This is consistent with positive correlation between $\Delta PSlope$ (VStrat) and the market excess return as reported in Table 2.3.

There have been numerous studies on VIX and the VIX term structure (see, e.g., Ait-Sahalia, Mustafa and Loriano (2012), Duan and Yeh (2011), Amengual (2009), and Egloff, Leippold and Wu (2010)). However, they all use stochastic volatility and jump models, which lack a link with the fundamental economy. To link the fundamental macro economy with the VIX term structure, we suggest a regime-switching rare disaster model with which we show the previously mentioned ICAPM implications.

Rare disasters were proposed by Rietz (1988) as the major determinant of asset risk premia. A rare disaster, such as economic depression or war, occurs extremely infrequently but is calamitous in terms of magnitude. Barro (2006) supports the hypothesis by showing that disasters must be frequent and large to account for the high risk premium on equities. Gabaix (2012) incorporates a time-varying severity of disaster into the baseline model by Barro (2006), which solved many asset-pricing puzzles in a unified framework.

While the models of Rietz (1988), Barro (2006), and Gabaix (2012) all assume that disasters happen as an instant drop in the economy, the reality is that each disaster has a duration. Our model helps filling this gap by incorporating a time-varying hidden length of potential disasters, thus captures the time dimension embedded in the term structure of risks. The model generate an equity risk premium of a magnitude similar to that of the Gabaix model. At the same time, the model can generate stochastic volatility and changing VIX term structures. An upward sloping VIX term structure corresponds to a shorter hidden length of disaster and vice versa in our model.

Our model follows Gabaix (2012) and assumes probability $p_{in,t}$ at period t of entering into a disaster in the next period, $t+1$. What differentiates our model from the Gabaix model is that we introduce a probability of staying in the disaster state once it has been entered. By this difference we bring disaster length into our model, and we can generate a VIX term structure that is consistent with our empirical findings.

3.2 Macro Setting

We follow Gabaix (2012), and introduce a representative agent with a power utility function $E\left[\sum_{t=0}^{\infty} e^{-\rho t} \frac{C_t^{1-\gamma}-1}{1-\gamma}\right]$. $\gamma \geq 0$ is the coefficient of relative risk aversion, and $\rho > 0$ is the rate of time preference. The agent receives a consumption endowment C_t. At each period $t+1$, a disaster may happen with a probability $p_{in,t}$, meaning that the disaster probability is determined one period ahead of the potential disaster. If the disaster does not happen at period $t+1$, $\frac{C_{t+1}}{C_t} = e^{g_c}$, and g_c is the normal time growth rate of the economy. If the disaster happens at period $t+1$, it will have probability $p_{out,t}$ of exiting the disaster in each period after period $t+1$, and $\frac{C_{t+1}}{C_t} = e^{g_c} J_{c,t+1}$. $J_{c,t+1}$ is a random variable that represents the jump of the economy when a disaster happens. For example, if $J_{c,t+1} = 0.95$ then consumption drops by 5% if disaster happens at period $t+1$.

In sum, consumption follows

$$\frac{C_{t+1}}{C_t} = e^{g_c} \times \begin{cases} 1 & \text{if no disaster at t+1} \\ J_{c,t+1} & \text{if disaster at t+1} \end{cases} \tag{3.1}$$

The pricing kernel M_t is given by $M_t = e^{-\rho} \times \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}$, and it follows that

$$M_{t+1} = e^{-\delta} \times \begin{cases} 1 & \text{if no disaster at t+1} \\ J_{c,t+1}^{-\gamma} & \text{if disaster at t+1,} \end{cases} \tag{3.2}$$

where $\delta = \rho + \gamma g_c$, as in Gabaix model, is the Ramsey discount rate, which is the risk-free rate in an economy with a zero probability of disasters. And $\gamma \geq 0$ is the coefficient of relative risk aversion and $\rho > 0$ is the rate of time preference.

Similarly, we define the dividend of the ith stock at period t as $D_{i,t}$, and it follows that

$$\begin{aligned}\frac{D_{i,t}}{D_{i,t-1}} &= e^{g_{i,d}}(1+\epsilon_{i,d,t}) \\ &\times \begin{cases} 1 & \text{if no disaster at t+1} \\ J_{i,d,t+1} & \text{if disaster at t+1,} \end{cases}\end{aligned} \tag{3.3}$$

where $\epsilon_{i,d,t} > -1$ is a mean-zero shock that is independent of the disaster event. It matters only for the calibration of dividend volatility.

3.3 Four Regimes

Let p_t be the probability at period t that a disaster happens at period $t+1$. If the disaster happens at period $t+1$, it will have probability $p_{out,t}$ of exiting from the disaster in each period after period $t+1$. Assume that p_t has a constant value p and $p_{out,t}$ can only take two values, p_L and p_H with $p_L < p_H$.

There are two types of disaster regimes in our model. The first one has p_L for exiting a disaster if it enters and the second one has p_H for exiting disaster if it enters. Therefore, the first type of disaster is expected to be longer than the second type of disaster on average.

Thus we refer to the first type of disaster as the long-disaster (DL) regime. The other one has p_L to exit disaster if it enters, and we define it as the short-disaster (DS) regime. In our setup, there are two type of normal regimes, and each one could lead to either a normal regime, or one particular type of disaster regime. We call these two normal regimes as NL and NS. The NL regime may lead to either NL, NS, or DL regimes in the next period but it could not lead to a DS regime. And the NS regime may lead to either NS, NL, or DS regimes in the next period but it could not lead to a DL regime.

In sum, the four regimes in our model are the following:

$$\begin{cases} NS: & \text{normal regime which could lead to NS, NL, DS at next period} \\ NL: & \text{normal regime which could lead to NS, NL, DL at next period} \\ DS: & \text{disaster regime with short duration} \\ DL: & \text{disaster regime with long duration} \end{cases}$$

We let $S_t \in \{NS, NL, DS, DL\}$ denote the regime of period t. The transition probability matrix $\mathbf{P}$ is characterized as follows:

$$\begin{aligned} \mathbf{P} &= \mathbf{P}(S_t \mid S_{t-1}) \\ &= \begin{array}{c} \\ NS \\ NL \\ DS \\ DL \end{array} \begin{array}{c} \begin{array}{cccc} NS & NL & DS & DL \end{array} \\ \begin{pmatrix} \bar{p} \times A & \bar{p} \times \bar{A} & p & 0 \\ \bar{p} \times \bar{A} & \bar{p} \times A & 0 & p \\ p_H \times B & p_H \times \bar{B} & \bar{p}_L & 0 \\ p_L \times B & p_L \times \bar{B} & 0 & \bar{p}_L \end{pmatrix} \end{array}, \end{aligned}$$

where A and B are parameters with conditions $0 < A < 1$ and $0 < B < 1$.

If a disaster (either DS or DL) does not happen at period $t+1$, C_{t+1} will follow $\frac{C_{t+1}}{C_t} = e^{g_c}$, where g_c is the normal regime (either NS or NL) growth rate of the economy. If a disaster (either DS or DL) happens at period $t+1$, C_{t+1} will follow $\frac{C_{t+1}}{C_t} = e^{g_c} J_{c,t+1}$, where $0 < J_{c,t+1} < 1$ is the downside jump and is a random variable.

3.3.1 Model Implications

We only include the most important results from the model. Detailed derivations can be found in the Appendix.

From the settings of the model, we know that S_t is a Markov process. With the price of the ith stock defined as $P_{i,t}$, $P_{i,t}$ should satisfy: $P_{i,t} = D_{i,t} + E_t\left(M_{t+1}P_{i,t+1}\right)$, which can be written as

$$\frac{P_{i,t}}{D_{i,t}} = 1 + E_t\left(\left(M_{t+1}\frac{D_{i,t+1}}{D_{i,t}}\right) \times \frac{P_{i,t+1}}{D_{i,t+1}}\right) \tag{3.4}$$

S_t is a Markov process, and thus the price-dividend ratio is constant within each regime. Following Cecchetti, Lam and Mark (1990), we conjecture the following solution:

$$\frac{P_{i,t}}{D_{i,t}} = \rho(i, S_t),\ S_t = NS, NL, DS, DL \tag{3.5}$$

And we solve the price-dividend ratios within each regime. The results are included in the Appendix.

The ith stock's return on period t+1 is defined as $r_{i,t+1} = \frac{P_{i,t+1}}{P_{i,t}-D_{i,t}}$, and it can be transformed as: $r_{i,t+1} = \frac{\rho(i,S_{t+1})}{\rho(i,S_t)-1} \times \frac{D_{i,t+1}}{D_{i,t}}$. The expected return at period t can be defined as $r^e_{i,t} = E_t\left(r_{i,t+1}\right)$. Based on the price-dividend ratios we solved for the four regimes, we are able to calculate the expected return as in the Appendix.

Following Carr and Wu (2009), the realized variance is defined as:

$$RV_{i,t,t+n} = \sum_{k=t+1}^{t+n}\left(\frac{P_{i,k} - P_{i,k-1}}{P_{i,k-1}}\right)^2 \tag{3.6}$$

And the expected realized volatility $RV^e_{i,S_{t+k-1}}$ is defined as:

$$RV^e_{i,S_{t+k-1}} = E_{S_t}\left\{\left(\frac{\rho(i,S_{t+1})}{\rho(i,S_t)} \times \frac{D_{i,t+1}}{D_{i,t}} - 1\right)^2\right\} \tag{3.7}$$

Variance swap rate is defined as:

$$VS_{i,t,t+n} = E^Q_t RV_{i,t,t+n} \tag{3.8}$$

And T months VIX from t can be expressed as:

$$VIX^T_t = \left(\frac{252}{T \times 21} \times VS_{t,t+T\times 21}\right)^{\frac{1}{2}} \tag{3.9}$$

3.4 Calibrated Parameters

We propose the following calibration of the model's parameters. The calibrated inputs are summarized in Table 3.1.

We chose most parameters so that they are consistent with Barro and Ursua (2008)'s findings and calibration parameters from Gabaix (2012). In normal times, consumption and stock dividend grow at rate $g_c = 2.5\%$ and $g_d = 2.5\%$ (Gabaix (2012)'s estimate). And the probability of a disaster is constant at $p = 3.5\%$ (Barro and Ursua (2008)'s findings). We choose $\gamma = 3$ for the risk aversion (Gabaix (2012)'s estimate). Volatility of dividend in the normal regime is $\sigma_d = 2\%$ (Gabaix (2012)'s estimate).

The major input we chose specifically for our model are the distribution of jumps in consumption and stock dividend, the probabilities of exiting a short/long disaster, and the transition parameters. We chose the following parameter inputs so that the model generates the equity risk premiums which are consistent with Gabaix (2012) results. We assume the distribution of jumps in consumption when disaster occurs to be uniformly distributed from 0.81 to 0.99. And we assume the probabilities of exiting a disaster to be $p_L = 0.15\%$ daily and $p_S = 3\%$ daily so that the average length of short disaster is 33 days and average length of long disaster is 1.8 years. We set the transition parameters $A = 0.95$ and $B = 0.5$. This means that when moving from a normal regime (NS or NL) yesterday to a normal regime (NS or NL) today, there is a 95% chance of entering the same normal regime as existed yesterday. This setting makes sense because we do not expect the fundamental economy to change so frequently.

Variables	Values (annualized)
Time preference	$\rho = 6.5\%$
Risk aversion	$\gamma = 3$
Growth rate of consumption	$g_c = 2.5\%$
Growth rate of dividends	$g_d = 2.5\%$
Volatility of dividends	$\sigma_d = 2\%$
Probability of disaster	$p = 3.5\%$
Probability of exiting disaster	$p_H = 3\%$ (daily)
	$p_L = 0.15\%$ (daily)
Consumption jumps on disaster	$J_c \sim Uniform(0.81, 0.99)$
Dividends jumps on disaster	$J_d \sim Uniform(0.81, 0.99)$
A	0.95
B	0.5

Table 3.1: Variables Used in the Calibration

3.4.1 Model Implications

A unique feature that the model generates is an upward sloping VIX term structure of NS and DS regimes and a downward sloping VIX term structure of NL and DL regimes. We will illustrate why the model could generate the above mentioned features.

According to equation (A.9), the term structure of the expected realized variance can be written in the following form:

$$E_t RV_{i,t,t+n} = \sum_{k=1}^{n} \sum_{S_{t+k-1}} P_{S_t,S_{t+k-1}}^{k-1} RV_{i,S_{t+k-1}}^{e} \tag{3.10}$$

where $RV_{i,S_{t+k-1}}^{e}$ is defined as:

$$RV_{i,S_{t+k-1}}^{e} = E_{S_t} \left\{ \left(\frac{\rho(i,S_{t+1})}{\rho(i,S_t)} \times \frac{D_{i,t+1}}{D_{i,t}} - 1 \right)^2 \right\} \tag{3.11}$$

The difference between $E_t RV_{i,t,t+n}$ and $E_t RV_{i,t,t+n-1}$ can be calculated as:

$$E_t RV_{i,t,t+n} - E_t RV_{i,t,t+n-1} = \sum_{S_{t+n-1}} P_{S_t,S_{t+n-1}}^{n-1} RV_{i,S_{t+n-1}}^{e} \tag{3.12}$$

As n goes to infinity, equation (3.12) becomes

$$\lim_{n\to\infty} E_t RV_{i,t,t+n} - E_t RV_{i,t,t+n-1} = \sum_{S_{t+n-1}} \pi\left(S_{t+n-1}\right) RV_{S_{t+n-1}}^{e} \tag{3.13}$$

where π represents the stable distribution.

For simplicity, we call $\lim_{n\to\infty} E_t RV_{i,t,t+n} - E_t RV_{i,t,t+n-1}$ as RV_{∞}^{e}. By requiring $RV_{DL}^{e} > RV_{NL}^{e} > RV_{\infty}^{e} > RV_{DS}^{e} > RV_{NS}^{e}$, our model can generate an upward sloping expected realized variance term structure of NS and DS regimes and a downward sloping expected realized variance term structure of NL and DL regimes.

Similar analysis applies to the VIX term structure, by equation (A.15),

$$VS_{i,t,t+n} = \sum_{k=1}^{n} \frac{1}{E_t M_{t,t+k}} \sum_{S_{t+k-1}} P_{S_t,S_{t+k-1}}^{*k-1} VS_{i,S_{t+k-1}} \tag{3.14}$$

Then we can calculate the difference:

$$VS_{i,t,t+n} - VS_{i,t,t+n-1} = \frac{1}{E_t M_{t,t+n}} \sum_{S_{t+n-1}} P^{*k-1}_{S_t,S_{t+n-1}} VS_{i,S_{t+n-1}} \quad (3.15)$$

As n goes to infinity, equation (3.15) becomes

$$\lim_{n\to\infty} VS_{i,t,t+n} - VS_{i,t,t+n-1} = VS_\infty \quad (3.16)$$

where similar requirements would also be needed for VS_{S_t} in order to have the term structure we expect.

As shown in Table 3.2, the price-dividend ratio in a normal regime is greater than in a disaster regime, which is consistent with empirical studies. The equity risk premium is also higher in the NL regime than in the NS regime. This is consistent because investors need more compensation in a normal regime when it is linked with a hidden long disaster compared with a short disaster. This is consistent with equity risk premium being lower in an DL regime than in an DS regime.

As shown in Figures 3.1, 3.2, and 3.3, we have four patterns of the VIX term structure corresponding to the four regimes in our model with γ=2,3,4.

The NS regime and the DS regime are accompanied by an upward sloping VIX term structure, and the other two regimes (NL, DL) are accompanied by a downward sloping VIX term structure. This supports our hypothesis that length of hidden disaster determines the slope of the VIX term structure.

Variables	Values (annualized)
Ramsey discount rate	$\delta = 14\%$
price-dividend ratio(NS)	18.92
price-dividend ratio(NL)	16.37
price-dividend ratio(DS)	11.54
price-dividend ratio(DL)	13.80
equity premium(NS)	4.3%
equity premium(NL)	4.5%
equity premium(DS)	6.8%
equity premium(DL)	7.3%
equity premium(unconditional)	4.3%
volatility(NS)	15.8%
volatility(NL)	18.1%
volatility(DS)	16.9%
volatility(DL)	23.3%
volatility(unconditional)	17.2%

Table 3.2: Variables Generated by the Calibration

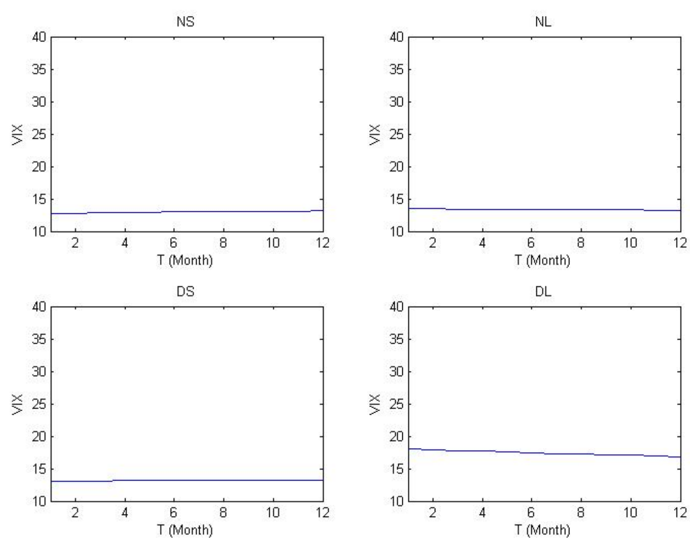

Figure 3.1: VIX Term Structure in Four Regimes (Gamma=2)

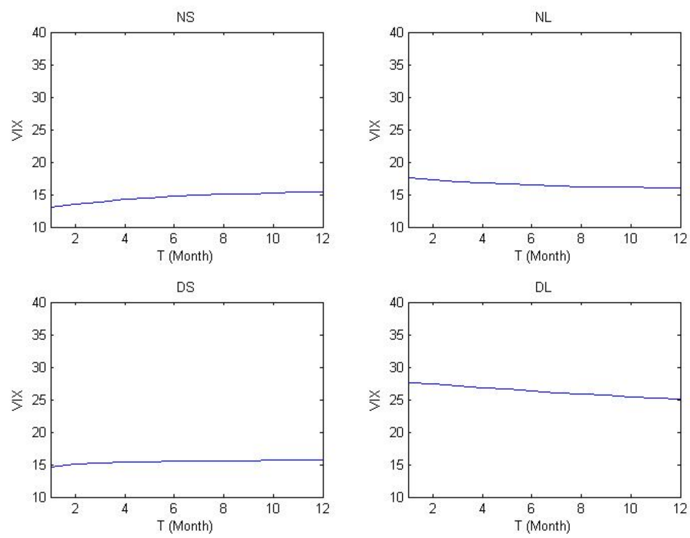

Figure 3.2: VIX Term Structure in Four Regimes (Gamma=3)

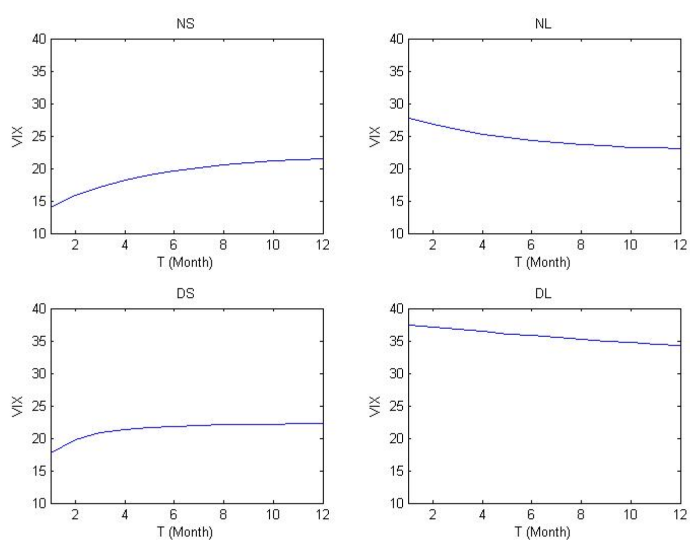

Figure 3.3: VIX Term Structure in Four Regimes (Gamma=4)

3.5 Conclusions

We propose a stylized model to explain the empirical findings in Chapter 2. We build a regime-switching rare disaster model that allows disasters to have short and long durations. Our model indicates that a downward sloping VIX term structure corresponds to a potential long disaster and an upward sloping VIX term structure corresponds to a potential short disaster. It further implicates that stocks with high sensitivities to the VIX slope have high loadings on the disaster duration risk, thus earn higher risk premium. These implications are consistent with our empirical results.

Chapter 4

Individual Stock's Volatility Term Structure

Our first goal is to understand whether the stock's volatility term structure can predict future returns. We construct sorted portfolios on *SLOPE* to study the low-minus-high portfolio returns on *SLOPE*. At the end of each month, we sort all stocks on the NYSE, AMEX, and the NASDAQ into quintiles with respect to their *SLOPE*. We construct quintile portfolios with respect to *SLOPE* with holding period of one month. The average return on the low-minus-high *SLOPE* portfolio is 0.63% per month and remains statistically significant after adjustment by the Fama-French 3-factor model. We further check the robustness of our results and we find that the *SLOPE* does not pick up risks from other risk characteristics, such as implied volatility, implied volatility skew.

The second goal of this paper is to explain the implications of the volatility term structure on individual equity returns. To understand the nature of the information embedded in *SLOPE*, we examine whether the predictability persists or reverses quickly. We find that the positive correlation between volatility slope and future one month stock returns is quickly reversed after two months. Therefore the behavior of *SLOPE* is very different from option's implied volatility skew (Xing, Zhang, and Zhao (2010)), whose predictive power lasts for more than 3 months. The reverting property of the predictability from *SLOPE* leads us to investigate the relationship between negative *SLOPE* and short term events of the company. We find that companies with most negative *SLOPE* have higher chances of announcing earnings in the next month.

Previous studies find strong relationships between earnings announcements, asset returns, and stock options (Amin and Lee (1997), Frazzini and Lamont (2007)). In this paper, we want to investigate whether the volatility term structure slope predicts something not captured in earnings announcements. We specifically set the timing to be one month, thus to check whether the volatility term structure slopes predicts an event which happens within future one month. We divide stocks in to two groups. The first group consists of stocks which are going to announce earnings release in the next month. The second group consists of the rest of the stocks. We further sort stocks from each group into quintile portfolios based on their *SLOPE*. The average low-minus-high return from the "earnings announcement" group becomes insignificant but the low-minus-high return from the "no earnings announcement" group remains significant. This observation leads us to the explanation that the implied volatility term structure of individual stocks indicates near term events, which reflect in the expected returns.

To examine the hypothesis that implied volatility term structure is an indicator of near term company events, we run two tests. In the first test, we introduce an ex-post event studies approach that checks the relationship between firm-specific events and implied volatility term structure. It is nearly impossible to investigate all firm-specific events, since not all events are reflected in publicly available news. Since here we are only interested in events which could cause a change in expected return of the stock, we assume there is a firm-specific event if there is an abnormal jump in a stock's idiosyncratic risk. Idiosyncratic volatility is a useful proxy for idiosyncratic risk. Therefore the results suggest that a lower *SLOPE* helps to predict an earnings announcement within future one month.

The second event studies test is based on pharmaceutical stocks' Phase III trial announcements. Clinical trials have three main phases: Phase I, II and III. As described by FDA (2014), in Phase III trials, the drug is studied in a larger number of people with the disease (approximately 1,000-3,000). This phase further tests the product's effectiveness, monitors side effects and, in some cases, compares the product's effects to a standard treatment, if one is already available. As suggested by Berlin (2012), Phase III trials are the best way to find a new standard for treatment. Therefore we focus on the tests with Phase III trials. We study whether the announcement of results from Phase III trials could actually explain part of volatility slope strategy gains. We define an "event" here as a Phase III trial data release from the pharmaceutical company. In the test, we select the stocks on NYSE, AMEX, and the NASDAQ with options trading and have announced a Phase III results in the period between 1996 and 2013. And we find the stocks have on average a significant lower *SLOPE* one month ahead of the announcement of Phase III trial results.

The third test is to check the relationship between stock trading volume and *SLOPE*. Beaver (1968) finds trading volume to yield unique insights on earnings announcements. Since we find that *SLOPE* is related to earnings announcements and firm specific events, it is important that we check whether the *SLOPE* is related with stock's trading volume. As a higher trading volume predicts a higher return around earning announcements and a lower *SLOPE* predict a higher return, we would expect a negative correlation between volume and *SLOPE*. And the results are consistent.

The rest of this paper is organized as follows. In Section 4.1, we describe the data and the proxies for volatility term structure and volatility skew. Section 4.2 presents the methodology and empirical results of quintile portfolios with only difference in *SLOPE*. Section 4.3 performs robustness checks on the relationship between *SLOPE* and portfolio returns and suggests that firm-specific events could explain part of the low-minus-high *SLOPE* premiums. Section 4.4 performs two tests on the relationship between firm-specific events and *SLOPE*. Section 4.5 concludes.

4.1 Data and Measurement

Our sample period is from 1996 (due to limitations by OptionMetrics) to 2013. Equity returns and earnings announcement dates are from CRSP. Options data are from OptionMetrics, which provides end-of-day quotes, implied volatilities surface. We also collect pharmaceutical stocks Phase III trials announcements from BioCentury Archives database.

We calculate the implied volatility slope measure for firm i at day t, $SLOPE_{i,t}$, as the difference between 3-month and 1-month average implied volatilities of ATM calls and puts, denoted by $IV_{i,t}^{3m,avg} = 0.5IV_{i,t}^{3m,call} + 0.5IV_{i,t}^{3m,put}$, respectively. That is, $SLOPE_{i,t} = IV_{i,t}^{3m,avg} - IV_{i,t}^{1m,avg}$.

We follow similar approach with Xing, Zhang, and Zhao (2010) by defining $SKEW$ as the difference between implied volatilities of out-of-the-money put (delta = -0.25) and out-the-money call (delta = 0.25). That is, $SKEW_{i,t} = IV_{i,t}^{delta=-0.25} - IV_{i,t}^{delta=0.25}$.

Summary statistics of $SLOPE$ are shown in Table 4.1. As we can see, the average state of the volatility term structure is downward sloping for individual stocks.

In Table 4.2, we show the *SLOPE* by industries. As we can see although different industries have different *SLOPE*s, the range is very small. The Finance industry has the lowest *SLOPE* while the Healthcare, Medical Equipment, and Drugs industry has the highest *SLOPE*. The average of the *SLOPE*s in all industries are negative. The implied volatility and *SLOPE* are not very negatively correlated in Table 4.2. For example, the Finance industry has the lowest *SLOPE* but it has a relatively low implied volatility compared with other industries.

Variables	Mean	Std. Dev.	5%	25%	50%	75%	95%
IV	0.455	0.224	0.190	0.290	0.395	0.542	0.871
SLOPE	-0.012	0.081	-0.096	-0.024	-0.002	0.014	0.051
SKEW	0.092	0.257	-0.240	0.014	0.101	0.183	0.376
Ret	0.008	0.139	-0.196	-0.056	0.009	0.074	0.220
SIZE	8.794	26.157	0.173	0.610	1.681	5.521	38.147

Table 4.1: Descriptive Statistics of the *SLOPE*

Data is obtained from CRSP and OptionMetrics (for options). Our sample period is 1996 to 2013. Variable *IV* is the implied volatility of at-the-money call and put options. *SLOPE* is the measure of individual stock's volatility term structure slope. *SKEW* is the measure of individual stock's implied volatility skew. SIZE is the firm market capitalization in $ billions.

Rank	*SLOPE*	Ret	IV	SIZE	IC	Number	Industry
low	-0.015	0.012	0.36	10.72	11	250	Finance
2	-0.014	0.011	0.43	26.15	7	49	Telephone and Television Transmission
3	-0.014	0.010	0.26	6.71	8	67	Utilities
4	-0.017	0.016	0.55	8.28	6	293	Computers, Software, and Electronic Equipment
5	-0.012	0.013	0.48	4.62	12	262	Other
6	-0.011	0.012	0.42	7.42	2	36	Consumer Durables
7	-0.011	0.014	0.43	6.18	9	158	Wholesale, Retail, and Some Services
8	-0.010	0.013	0.43	5.25	3	151	Manufacturing
9	-0.010	0.012	0.36	9.81	5	45	Chemicals and Allied Products
10	-0.009	0.012	0.38	11.09	1	70	Consumer NonDurables
11	-0.008	0.015	0.43	15.51	4	97	Oil, Gas, and Coal Extraction and Products
high	-0.007	0.015	0.54	10.23	10	154	Healthcare, Medical Equipment, and Drugs

Table 4.2: *SLOPE* by Industry

We use industries as defined by Fama-French 12 Industries. Data is obtained from CRSP and OptionMetrics (for options). Our sample period is 1996 to 2013. SIZE is the firm market capitalization in $ billions. Number is the average of number of companies per industry over the whole period. IC is the industry code by Fama French.

4.2 Can Volatility Term Structure Predict Future Stock Returns?

In this section, we check whether the stock option's implied volatility term structure slope is predictive of the stock's future returns. We construct monthly long-short trading strategies based on the volatility term structure measure *SLOPE*. And we find that the stocks with the most upward sloping volatility term structure in their traded options underperform stocks with the most negative volatility term structures in their options by 7.6% per year.

4.2.1 Sorted Portfolios

We demonstrate that *SLOPE* predicts future stock returns using the portfolio sorting approach. Each month, we sort all sample firms into quintile portfolios based on their *SLOPE* on the last trading day of the previous month. Portfolio 1 (low) includes firms whose stock options have the most negative *SLOPE*, and portfolio 5 (high) includes firms with the highest *SLOPE*. We then compute the value-weighted quintile portfolio returns for the next month. The return on this long-short investment strategy heuristically illustrates the economic significance of the sorting *SLOPE* variable.

In Table 4.3, we present the monthly quintile portfolio returns and the *SLOPE*. Each quintile portfolio has 101 stocks on average. Portfolio "low", containing firms with the lowest *SLOPE*, has a highest monthly average return, and portfolio "high", containing firms with the highest *SLOPE*, has a lowest monthly average return. Portfolio "high" underperforms portfolio "low" by 0.63% per month (7.6% per year) which is significant. The Fama-French 3-factor alpha of low-minus-high portfolio is also positive and significant.

To summarize, we find that firms with high implied volatility slopes underperform firms with low implied volatility slopes. The return difference is economically large and statistically

Period: 1996-2013, $nobs = 211$

	Quintile Portfolios					
	low	2	3	4	high	low-high
SLOPE	-0.06	-0.02	0.00	0.01	0.03	-0.09
Ret	1.11	1.19	0.95	0.73	0.48	0.62
t-stat	1.85	**2.72**	**2.39**	**2.22**	1.72	**1.98**
Alpha	1.23	1.17	0.95	0.68	0.37	0.86
t-stat	1.79	**2.58**	**2.35**	1.62	1.05	**2.21**

Table 4.3: Quintile Portfolios Sorted by *SLOPE*
Data is obtained from CRSP and OptionMetrics (for options). Our sample period is 1996 to 2013. Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. For each month, we form quintile portfolios based on the *SLOPE* from last trading day of last month. We then hold the quintile portfolios for another month. On average, each quintile portfolio contains 101 firms. The t-statistics are adjusted using Newey-West (1987) with 12 lags.

significant.

4.2.2 Fama-Macbeth Tests

In order to run a cross-sectional research on the relationship between the stock option's implied volatility slope and the stock's future returns, we use Fama-Macbeth regressions. The standard Fama-Macbeth regression has two stages. In the first stage, we estimate the following regression in cross-section for each month t. $Ret_{i,t} = b_{0,t} + b1_{1,t}SLOPE_{i,t-1} + b_{2,t}CONTROLS_{i,t-1} + e_{i,t}$ where $Ret_{i,t}$ is stock i's return for month t. $SLOPE_{i,t-1}$ is stock i's implied volatility slope measure for month $t-1$ and $CONTROLS_{i,t-1}$ is a vector of control variables for stock i at month $t-1$. In the second stage, we conduct inference on the time-series of the coefficients by assuming the coefficients over time are i.i.d. For $CONTROLS$, we pick IV which is the implied volatility and $SKEW$ which is the implied volatility skew measure of the stock.

In Table 4.4, we report the results for Fama-Macbeth regressions. The coefficient of

SLOPE is negative and significant even after including the implied volatility and implied volatility skew. The negative sign is consistent with our previous results that a low *SLOPE* predicts a high return. Here we give an estimate of the annualized return difference for the *SLOPE* portfolios' inter-quartile. The magnitude of coefficient of *SLOPE* is around -0.09 and as shown in Table 4.1 the 75^{th} and 25^{th} percentile values of *SLOPE* are 0.014 and -0.024. The corresponding annualized difference in expected returns is around $(0.014 - (-0.024)) * 0.09 * 12 = 4.10\%$. Therefore we should expect the difference in return between stock portfolios with *SLOPE* at 75^{th} and 25^{th} percentile to be around 4% per year.

	SLOPE	IV	*SKEW*
coef	-0.096		
t-stat	**-2.52**		
coef	-0.090	0.013	-0.008
t-stat	**-2.30**	1.91	**-2.96**

Table 4.4: Fama-Macbeth Regression

In the first stage, we estimate the following regression in cross-section for each month t. $Ret_{i,t} = b_{0,t} + b1_{1,t}SLOPE_{i,t-1} + b_{2,t}IV_{i,t-1} + b_{3,t}SKEW_{i,t-1} + e_{i,t}$ where $Ret_{i,t}$ is stock i's return for month t. $SLOPE_{i,t-1}$ is stock i's implied volatility slope measure for month t-1. We pick IV which is the implied volatility and $SKEW$ which is the implied volatility skew measure of the stock as the controls. The t-statistics are adjusted using Newey-West (1987) with 12 lags.

4.3 Robustness Tests

In this section, we run robustness checks for the results in the previous section. We investigate the sorted portfolios by ruling out the effects of implied volatility and implied volatility skew. We also check if the earnings announcements could be one source where the *SLOPE* portfolios low-minus-high return comes from. Our hypothesis is that *SLOPE* helps to predict whether a stock is going to announce its earnings or not in the future one month and it is due to the earnings announcement that the stock on average achieves a higher return.

4.3.1 Implied Volatility

Implied volatility indicates the expectations on future stock volatility and is a measure of risk for individual stocks. Several studies have documented that high (low) implied volatility forecasts high (low) returns for individual stocks (Dennis, Stewart and Chris (2006), An, Ang, Bali and Cakici (2014)).

As shown in the previous section, firms with high implied volatility slopes underperform firms with low implied volatility slopes. We want to check whether this is simply because the high implied volatility slope stocks have low current implied volatility and the low implied volatility slope stocks have high implied volatility. In order to filter out the possible influence of implied volatility, we double-sort all stocks on the NYSE, AMEX, and the NASDAQ into quintiles with respect to their implied volatility and *SLOPE*.

The double-sort is intended to isolate the effect of each risk factor. At the end of each month, we group the stocks into quintiles based on their option's implied volatility (lowest in quintile 1 and highest in quintile 5), and then group each of these five portfolios into quintiles based on *SLOPE*, which yields $5 \times 5 = 25$ portfolios in total. The low-minus-high portfolios on *SLOPE* is constructed as goes long the 5 low-*SLOPE* portfolios and go short the 5 high-*SLOPE* portfolios. By design, the hedge portfolio has equal loadings on the implied volatility.

As shown in Table 4.5, we find that by controlling the implied volatility, the low-minus-high portfolio return remains significant and positive. Therefore the results suggest that the implied volatility and volatility term structure slope captures different risks.

Period: 1996-2013, $nobs = 211$

	Quintile Portfolios					
	low	2	3	4	high	low-high
SLOPE	-0.05	-0.01	0.00	0.02	0.03	-0.08
IV	0.44	0.44	0.44	0.43	0.44	0.00
Ret	1.09	1.20	0.97	0.74	0.50	0.59
t-stat	1.57	1.92	1.28	1.31	1.23	**1.99**

Table 4.5: Portfolios Sorted by IV and *SLOPE*
Our sample period is 1996 to 2013. Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. And variable *IV* is the implied volatility of at-the-money call and put options. At the end of each month, we double sort (5x5) the stocks by *IV* and *SLOPE* and I form 25 portfolios. We then group the 25 portfolios into the group that contains stocks with low to high *SLOPE*. We then hold the quintile portfolios for another month. Data is obtained from CRSP and OptionMetrics (for options). The t-statistics are adjusted using Newey-West (1987) with 12 lags.

4.3.2 Implied Volatility Skew

The pattern of volatility skew for both stock index options and individual stock options has been examined in numerous papers. For instance, Pan (2002) documents that the volatility smile for an S&P 500 index option with about 30 days to expiration is roughly 10% on a median volatility day. Xing, Zhang, and Zhao (2010) find that stocks with the most upward sloping volatility smile in options underperform stocks with the least smiles in their options by 10.9% per year.

Since the term structure and smiles both capture the higher moments of implied volatility, it is important to check the double sorted portfolios by their implied volatility skew and *SLOPE*. We construct a hedge portfolio with respect to the volatility term structure risk. At the end of each month, we group the stocks into quintiles based on their option's implied volatility skew (lowest in quintile 1 and highest in quintile 5), and then group each of these five portfolios into quintiles based on *SLOPE*, which yields $5 \times 5 = 25$ portfolios in total. The low-minus-high portfolios on *SLOPE* is constructed by going long the 5 low-*SLOPE* portfolios and going short the 5 high-*SLOPE* portfolios. By design, the hedge portfolio has equal loadings on the implied volatility skew.

As shown in Table 4.6, we find that after controlling the implied volatility skew, the low-minus-high portfolio return remains significant and positive. Therefore the results suggest that the implied volatility skew and volatility term structure slope capture different risks.

Period: 1996-2013, $nobs = 211$

	Quintile Portfolios					
	low	2	3	4	high	low-high
SLOPE	-0.04	-0.01	0.00	0.02	0.03	-0.07
SKEW	-0.09	-0.10	-0.09	-0.11	-0.10	0.01
Ret	0.94	1.07	0.83	0.79	0.43	0.51
t-stat	1.18	1.56	1.42	1.50	1.64	**2.03**

Table 4.6: Portfolios Sorted by *SKEW* and *SLOPE*
Our sample period is 1996 to 2013. Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. And variable $SKEW$ is the measure of implied volatility skew. At the end of each month, we double sort (5x5) the stocks by *SKEW* and *SLOPE* and I form 25 portfolios. We then group the 25 portfolios into the group that contains stocks with low to high *SLOPE*. We then hold the quintile portfolios for another month. Data is obtained from CRSP and OptionMetrics (for options). The t-statistics are adjusted using Newey-West (1987) with 12 lags.

4.3.3 Short-term Reversals

In Table 4.7, we compare the current and next month return for the *SLOPE* quintile portfolios constructed in Section II. As we find in the table, the portfolio which has the lowest (highest) *SLOPE* has the lowest (highest) return in the current (next) month. Therefore it is possible that the portfolios capture part of the short-term reversals return.

A short-term return reversal strategy buys and sells stocks on the basis of their prior-month returns and holds them for one month in the stock market. It is a well-established phenomenon for more than 40 years, has been shown to be both robust and of economic significance. Jegadeesh (1990) finds that the short-term reversal strategy has profits of about 2% per month over 1934-1987. In fact, Pastor and Stambaugh (2003) suggest directly measuring the degree of illiquidity by the occurrence of an initial price change and subsequent reversal.

In order to sort out the effects by short-term reversals, we double-sort all stocks on the NYSE, AMEX, and the NASDAQ into quintiles with respect to their past one month return and *SLOPE*. We then construct a hedge portfolio with respect to the short term reversals. At the end of each month, we group the stocks into quintiles based on their past one month return (lowest in quintile 1 and highest in quintile 5), and then group each of these five portfolios into quintiles based on *SLOPE*, which yields $5 \times 5 = 25$ portfolios in total. The low-minus-high portfolios on *SLOPE* is constructed as goes long the 5 low-*SLOPE* portfolios and go short the 5 high-*SLOPE* portfolios. By design, the hedge portfolio has equal loadings of the past one month return.

As shown in Table 4.8, we find that by controlling the short term reversals, the low-minus-high portfolio return remains significant and positive. Therefore the short term reversals and volatility term structure slope captures different risks.

Period: 1996-2013, $nobs = 211$

	Quintile Portfolios				
	low	2	3	4	high
SLOPE	-0.06	-0.02	0.00	0.01	0.03
Ret (t)	-0.88	0.44	1.05	1.37	1.75
Ret (t+1)	1.09	1.20	0.97	0.74	0.50

Table 4.7: *SLOPE* and Current Return

In this table we compare the *SLOPE* portfolio's current month return and next month return. Data is obtained from CRSP and OptionMetrics (for options). Our sample period is 1996 to 2013. We follow the same methodology of constructing the *SLOPE* quintile portfolios as in Section 4.2.

Period: 1996-2013, $nobs = 211$

	Quintile Portfolios					
	low	2	3	4	high	low-high
SLOPE	-0.06	-0.01	0.00	0.01	0.02	-0.08
Ret	0.97	0.93	0.89	0.72	0.48	0.49
t-stat	1.57	1.82	1.58	1.71	1.60	**2.19**

Table 4.8: Portfolios Sorted by RET_{t-1m} and *SLOPE*

Our sample period is 1996 to 2013. Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. And variable RET_{t-1m} is the past one month return. At the end of each month, we double sort (5x5) the stocks by RET_{t-1m} and *SLOPE* and I form 25 portfolios. We then group the 25 portfolios into the group that contains stocks with low to high *SLOPE*. We then hold the quintile portfolios for another month. Data is obtained from CRSP and OptionMetrics (for options). The t-statistics are adjusted using Newey-West (1987) with 12 lags.

4.3.4 Earnings Announcements

The implied volatility of stock options reflects expectations of risk for the stock, and the stock's implied volatility term structure suggests expectations on individual assets' future trends of risk. As earnings announcements belong to one category of events which may affect the asset risks and prices, it is possible that the earnings announcements can explain our empirical findings on volatility term structure and expected returns.

There are many articles on the relationship between earnings announcements, asset returns, and stock options. For example, Amin and Lee (1997) examine trading activities in the four-day period just before earnings announcements and document that option trading volume is related to price discovery of earnings news. Frazzini and Lamont (2007) show that the equity premium during earnings announcement is large, robust, and strongly related to the fact that volume surges around announcement dates.

We investigate the low-minus-high *SLOPE* portfolios returns by filtering out the earnings announcement events. In order to run the tests, at the end of each month, we separate stocks into two portfolios. One portfolio consists of stocks that are going to have an earnings release announced the next month. The other portfolio consists of stocks that do not have an earnings announced the next month. We are interested in finding is that whether the two portfolios have similar or different average volatility slopes, and whether the two portfolios have significantly different expected returns for the next month. From Table 4.9, we can see the average volatility slope is less negative for Panel A (no announcement) than than for Panel B (with announcement). This is consistent in that the more negative volatility slope implies more risk in the near future, which the stocks going to have earnings announcements should embed.

In each panel, we further divide stocks into five quintile portfolios based on their *SLOPE*. From the table, the "low-minus-high" returns (around 0.4% per month) for the portfolios within Panel A and B are significantly smaller than the "low-minus-high" returns for previous tests. This suggests that part of the "low-minus-high" returns we receive in previous tests are due to the "earnings release" effect. Even among firms with forthcoming earnings announcements, the implied volatility slope is predictive of expected returns.

4.4 Volatility Term Structure and Events

We argue that volatility term structure reflects investors' expectation of a price jump due to a future event. Given that the implied volatility slope is predictive of expected returns, the next natural question becomes: What is the nature of the information embedded in the volatility term structure? Since the volatility term structure is a firm-specific variable, we focus on firm-level events rather than on aggregate information. Our hypothesis is that the volatility term structure is related to firm-level events and that the anticipated events cause the volatility slope to change and result in a significant positive expected return. We apply different approaches to test it.

Panel A: $ER = 0$, Period: 1996-2013, $nobs = 211$

	Quintile Portfolios					
	low	2	3	4	high	low-high
SLOPE	-0.04	-0.02	0.00	0.01	0.01	-0.05
Ret	0.89	0.91	0.72	0.69	0.47	0.42
t-stat	1.38	1.79	1.35	1.20	1.16	1.73

Panel B, $ER = 1$, Period: 1996-2013, $nobs = 211$

	Quintile Portfolios					
	low	2	3	4	high	low-high
SLOPE	-0.12	-0.10	-0.07	-0.04	-0.02	-0.10
Ret	1.31	1.25	1.17	0.90	0.98	0.33
t-stat	1.23	**2.15**	1.48	1.74	1.72	**2.11**

Table 4.9: Portfolios Sorted by ER and *SLOPE*

Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. Variable ER is the indicator if a stock has an earnings release next month. For each month, we first separate stocks into two portfolios based on their ER and then we form quintile portfolios based on the *SLOPE* from last trading day of last month. We then hold the quintile portfolios for another month. The t-statistics are adjusted using Newey-West (1987) with 12 lags.

4.4.1 Ex-post Events Approach

The first approach we run is based on ex-post tests on firm-level events. We define ex-post events based on different measures and we test our hypothesis by filtering stocks based on the events.

There are both events which the information is publicly available and which the information is private. Both events can cause the change of volatility (or risk) of an equity and it is impossible to count in all the events corresponding to a company. Thus we take a different approach. We do not directly track all the events but we treat the stock which has one week significant return or idiosyncratic volatility as undergoing an "event". We further filter stocks based on if they're going through an "event" or not to study them.

Our hypothesis is that, the volatility slope strategy returns can be explained by the risk premiums on stock related events. Therefore we expect to see the "event" stocks to have a relatively low *SLOPE* one month ahead of the "event". The two measures we use to define the "event" are idiosyncratic volatility and up/down return percentile.

Idiosyncratic Volatility Approach

Idiosyncratic volatility is a useful proxy for idiosyncratic risk. The definition and measurement of idiosyncratic volatility vary among authors. Campbell, Lettau, Malkiel and Xu (2001) define idiosyncratic volatility as firm-specific volatility with the decomposition from the volatility loadings from market and industry. Ang, Hodrick, Xing and Zhang (2006) use the Fama-French three factor model to calculate idiosyncratic volatility, and we follow their approach. We look into the *SLOPE* of these stocks one month prior to the "events" and we show the average *SLOPE* one month prior to an event to be significantly lower than the average *SLOPE* in history.

We follow Ang, Hodrick, Xing and Zhang (2006) in calculating idiosyncratic volatility, relative to the Fama-French 3-factor model. Studies show that idiosyncratic volatility is related to firm-specific events. Wong (2011) finds that a substantial portion of the idiosyncratic volatility discount can be explained by earnings momentum and post-formation earnings shocks. Yang, Zhang and Zhang (2015) find that the idiosyncratic volatility changes around earnings announcement days are correlated with stock returns during the same periods.

We use idiosyncratic volatility as the measure to tell if the stock is having an "event" or not. At the beginning of each month, we first use rolling past 12-month daily returns and the Fama-French 3-factor model to calculate the market beta of this month. With the beta we calculate the daily residuals and thus calculate the weekly idiosyncratic volatility. For each week, we determine that there is an "event" if the week's idiosyncratic volatility is greater than or equal to the second largest idiosyncratic volatility of the past 24 weeks. We determine that there is an "event" in a month if there is at least one week which has an "event". As we can tell, this is an ex-post measure of event. And we don't separate scheduled announcements from news surprises.

As shown in the Table 4.10, "event" stocks have a lower *SLOPE* one month prior to the "event". It is consistent with our hypothesis that the *SLOPE* helps to predict a future event.

Period: 1996-2013

Event	Ret	*SLOPE*(t)	*SLOPE*(t-1)
Yes	1.24	-0.018	-0.021
t-stat	**2.17**	**-1.98**	**-2.34**
No	0.78	-0.015	-0.010
t-stat	1.80	-1.93	-1.82

Table 4.10: Portfolios Sorted by Event (Idiosyncratic Vol) and *SLOPE*
Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. Variable Event is the indicator if a stock's weekly idiosyncratic volatility is greater or equal to the second largest weekly idiosyncratic volatility in the past 24 weeks.

Up/Down Return Percentile Approach

As many studies (Hong, Tu and Zhou (2007), Daniel and Moskowitz (2013)) suggest, it is meaningful to study the up and down returns separately. This suggests an alternative definition of an event. We follow similar approaches as the idiosyncratic volatility approach. We calculate the weekly returns of each stock. If the return is positive or zero we define it as an up return. If it is negative we call it a down return. We define an event to be an up return in the top 5% of up returns over the previous 24 weeks or a down return in the bottom 5% of down returns over the same period. Although the two approaches have different definitions of an "event", around 60% of both their "events" happen in the same month.

As shown in the Table 4.11, "event" stocks have a lower *SLOPE* one month prior to the "event". It is consistent with our hypothesis that the *SLOPE* helps to predict a future event.

Period: 1996-2013

Event	Ret	*SLOPE*(t)	*SLOPE*(t-1)
Yes	1.31	-0.013	-0.023
t-stat	1.94	-1.79	**-2.06**
No	0.73	-0.011	-0.014
t-stat	1.38	-1.82	**-1.97**

Table 4.11: Portfolios Sorted by Event (Ret) and *SLOPE*
Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. Variable Event is the indicator if a stock's weekly up (down) return is greater or equal than the 95^{th} percentile of the up (down) return in the past 24 weeks.

4.4.2 Event Studies on Pharmaceutical Stocks

In the previous subsection, we've shown that "earnings release" is a category of events which can explain part of the volatility slope strategy gains. The result implies that other events may explain the volatility slope gains too. So in this subsection we run event studies on pharmaceutical stocks, more specifically, on pharmaceutical stocks which has at least one medicine undergoing Phase III clinical trials. There are several studies on the relationship between stock prices and clinical trials. Shortridge (2004) finds that the R&D of successful pharmaceutical producers to be valued more by the market than the R&D of non-successful producers. Sarkar and de Jong (2006) indicate that investors react positively to positive signals from the FDA and negatively to rejection indicators. Moreover, the magnitude of the negative reaction tends to be larger than the positive reaction.

There are three main phases for clinical trials and they are Phase I, II and III. As mentioned by Food and Drug Administration (FDA (2014)), in Phase III trials, the drug is studied in a larger number of people with the disease (approximately 1,000-3,000). This phase further tests the product's effectiveness, monitors side effects and, in some cases, compares the product's effects to a standard treatment, if one is already available. As more and more participants are tested over longer periods of time, the less common side effects are more likely to be revealed. And as suggested by Berlin (2012), Phase III trials are the best way to find a new standard for treatment. Therefore we focus on Phase III trials, because we expect them to have the most direct effect on stock prices. We want to study if the announcement of results from Phase III trials could actually explain part of volatility slope strategy gains when restricted to pharmaceutical stocks. We define an "event" here as a Phase III trial data release from the pharmaceutical company.

We use BioCentury Archive Database. It records the releases from pharmaceutical companies on their trials. We set the criteria into the filter of the news on BioCentury Archive website from 1996 to 2013 to only find news related to "Phase III" and "results". We then manually pick the news from the filtered results to include only news related to Phase III announcements. We record the news date, ticker, and we match it with CRSP and OptionMetrics. The screening gives us a total of 837 events and 270 stocks.

We compare the average *SLOPE*s for the pharmaceutical stocks conditioning on it is around the Phase III announcement dates and other times. Our hypothesis is that the Phase III announcements belong to the category of events which affect stocks returns, and that the *SLOPE* should be able to help predict Phase III announcements. We report the results in Table 4.12. As we can see, the average *SLOPE* one month prior to the Phase III announcements is much lower than the average for non-announcement dates. Thus the results are consistent with our hypothesis.

Period: 1996-2013

Announcement	*SLOPE*(t)	*SLOPE*(t-1)
Yes	-0.004	-0.020
t-stat	-1.58	**-2.04**
No	-0.000	-0.000
t-stat	-1.15	-0.39

Table 4.12: Event Study on Phase III Announcements
We find pharmaceutical stocks from Biocentury Archive with Phase III announcements which trade on NYSE, NASDAQ, and AMEX and have options trading.

4.4.3 Trading Volume

In this subsection we study the relationship between trading volume and the implied volatility term structure. Previous studies show stock's trading volume reflect information of earnings announcements (Beaver (1968), Frazzini and Lamont (2007)). As we have shown in previous results that *SLOPE* is related to earnings announcement, it is interesting to check the relationship between volume and *SLOPE*.

Here we use a relative measure of stock's trading volume, which is defined as monthly trading volume divided by common shares outstanding. From Table 4.13, we report the relationship between Relative Volume and *SLOPE*. As shown in the table, stocks with the lowest *SLOPE* have the highest relative trading volume on average. And the results are consistent with our hypothesis.

Period: 1996-2013, $nobs = 211$

	Quintile Portfolios				
	low	2	3	4	high
SLOPE (t)	-0.06	-0.01	0.00	0.01	0.02
Relative Volume (t)	0.18	0.13	0.11	0.11	0.12
t-stat	**2.24**	**2.03**	**1.99**	1.84	1.89
Relative Volume (t-1)	0.17	0.13	0.11	0.12	0.12
t-stat	**2.41**	**2.16**	1.95	1.31	1.48

Table 4.13: Volume and *SLOPE*

Relative volume is calculated as monthly volume over common shares outstanding. Variable *SLOPE* is the difference between 3-month and 1-month implied volatilities of at-the-money call and put options. And we display the average relative volume and *SLOPE* for the quintile portfolios sorted by *SLOPE*. Relative Volume is calculated as the monthly volume divided by shares outstanding.

4.5 Conclusions

We find that stocks with the most positive volatility term structure in their traded options underperform stocks with the most negative volatility term structures in their options by 7.6% per year. And the result is robust to various characteristics. With further checks we find that earnings announcements could explain part of the results but can not explain all the abnormal returns. Therefore we suggest the hypothesis that the implied volatility term structure is a measure of risk that is related to firm's future events. Event studies on pharmaceutical companies' Phase III trial results suggest consistent results with the hypothesis. What's more, we propose a systematic approach on testing the hypothesis by assuming a stock undergoing an "event" if it currently has a relatively high idiosyncratic volatility. And this systematic approach suggests that firms with the most negative volatility term structure are those expecting an event which may affect stock price in one month.

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Appendix A

Appendix for Chapter 2

A.1 Calculating Price-dividend Ratios

Define the price of the ith stock as $P_{i,t}$, and $P_{i,t}$ should satisfy $P_{i,t} = D_{i,t} + E_t\left(M_{t+1}P_{i,t+1}\right)$. And it is as same as

$$\frac{P_{i,t}}{D_{i,t}} = 1 + E_t\left(\left(M_{t+1}\frac{D_{i,t+1}}{D_{i,t}}\right) \times \frac{P_{i,t+1}}{D_{i,t+1}}\right) \tag{A.1}$$

Following Cecchetti, Lam and Mark (1990), we conjecture the following solution to equation (A.1):

$$\frac{P_{i,t}}{D_{i,t}} = \rho(i, S_t),\ S_t = NS, NL, DS, DL \tag{A.2}$$

by which we assume price-dividend ratio is constant within each regimes.

Suppose the current regime is NS, with equation (A.2), we have

$$\begin{aligned}
\rho(NS) &= \frac{P_{i,S_t=NS}}{D_{i,S_t=NS}} \\
&= 1 + pE_{t,S_t=NS}\left(M_{t+1}\frac{D_{t+1}}{D_t} \mid S_{t+1} = DS\right)\rho(i,DS) \\
&\quad +\bar{p}E_t\left(M_{t+1}\frac{D_{t+1}}{D_t} \mid S_{t+1} = NSorNL\right)\left(A\times\rho(i,NS)+\bar{A}\times\rho(i,NL)\right) \\
&= 1 + pe^{g_d-\delta}E\left(J_{c,t}^{-\gamma}J_{d,t}\right)\rho(i,DS) + \bar{p}e^{g_d-\delta}\left(A\times\rho(i,NS)+\bar{A}\times\rho(i,NL)\right)
\end{aligned}$$

Same way we get the following four equations:

$$\begin{aligned}
\rho(i,NS) =& 1 + pe^{g_{i,d}-\delta}E\left(J_{i,c,t}^{-\gamma}J_{i,d,t}\right)\rho(i,DS) + \bar{p}e^{g_{i,d}-\delta}\left(A\times\rho(i,NS)+\bar{A}\times\rho(i,NL)\right) \\
\rho(i,NL) =& 1 + pe^{g_{i,d}-\delta}E\left(J_{i,c,t}^{-\gamma}J_{i,d,t}\right)\rho(i,DL) + \bar{p}e^{g_{i,d}-\delta}\left(\bar{A}\times\rho(i,NS)+A\times\rho(i,NL)\right) \\
\rho(i,DS) =& 1 + \bar{p}_He^{g_{i,d}-\delta}E\left(J_{i,c,t}^{-\gamma}J_{i,d,t}\right)\rho(i,DS) + p_He^{g_{i,d}-\delta}\left(B\times\rho(i,NS)+\bar{B}\times\rho(i,NL)\right) \\
\rho(i,DL) =& 1 + \bar{p}_Le^{g_{i,d}-\delta}E\left(J_{i,c,t}^{-\gamma}J_{i,d,t}\right)\rho(i,DL) + p_Le^{g_{i,d}-\delta}\left(B\times\rho(i,NS)+\bar{B}\times\rho(i,NL)\right)
\end{aligned}$$

By solving equations above, we get $\rho(i,NS)$, $\rho(i,NL)$, $\rho(i,DS)$, $\rho(i,DL)$, which established that equation (A.2) is solution for equation (A.1).

Based on the price-dividend ratios we solved corresponding to the four regimes, we can calculate expected return.

A.2 Calculating Expected Returns

The ith stock's return on period $t+1$ is defined as $r_{i,t+1} = \frac{P_{i,t+1}}{P_{i,t}-D_{i,t}}$, and it can be written as:

$$r_{i,t+1} = \frac{\rho(i,S_{t+1})}{\rho(i,S_t)-1}\times\frac{D_{i,t+1}}{D_{i,t}} \tag{A.3}$$

Define the expected return of the ith stock at period t to be $r^e_{i,t}$, and $r^e_{i,t}$ should satisfy:

$$\begin{aligned} r^e_{i,t} &= E_t\left(r_{i,t+1}\right) && \text{(A.4)} \\ &= E\left(\frac{\rho(i,S_{t+1})}{\rho(i,S_t)-1} \times \frac{D_{i,t+1}}{D_{i,t}} \mid S_t\right) && \text{(A.5)} \end{aligned}$$

After solving equation (A.5) for four regimes, we get the following equations for expected return in corresponding regimes:

$$\begin{aligned} r^e_{i,S_t=NS} =& \frac{e^{g_{i,d}}}{\rho(i,NS)-1}\left\{p\rho(i,DS)E_tJ_{i,d,t+1} + \bar{p}\left(A\rho(i,NS) + \bar{A}\rho(i,NL)\right)\right\} \\ r^e_{i,S_t=NL} =& \frac{e^{g_{i,d}}}{\rho(i,NL)-1}\left\{p\rho(i,DL)E_tJ_{i,d,t+1} + \bar{p}\left(\bar{A}\rho(i,NS) + A\rho(i,NL)\right)\right\} \\ r^e_{i,S_t=DS} =& \frac{e^{g_{i,d}}}{\rho(i,DS)-1}\left\{\bar{p}_H\rho(i,DS)E_tJ_{i,d,t+1} + p_H\left(B\rho(i,NS) + \bar{B}\rho(i,NL)\right)\right\} \\ r^e_{i,S_t=DL} =& \frac{e^{g_{i,d}}}{\rho(i,DL)-1}\left\{\bar{p}_L\rho(i,DL)E_tJ_{i,d,t+1} + p_L\left(B\rho(i,NS) + \bar{B}\rho(i,NL)\right)\right\} \end{aligned}$$

A.3 Calculating Expected Realized Volatility

Following Carr and Wu (2009), we define annualized realized variance to be $RV_{i,t,t+n} = \sum_{k=t+1}^{t+n}\left(\frac{P_{i,k}-P_{i,k-1}}{P_{i,k-1}}\right)^2$, and

$$RV_{i,t,t+n} = \sum_{k=t+1}^{t+n}\left(\frac{\rho(i,S_k)}{\rho(i,S_{k-1})} \times \frac{D_{i,k}}{D_{i,k-1}} - 1\right)^2 \tag{A.6}$$

We define $E_t RV_{i,t,t+n}$ as the expected annualized realized volatility, which is:

$$\begin{aligned}
E_t RV_{i,t,t+n} &= E_t \sum_{k=t+1}^{t+n} \left(\frac{\rho(i,S_k)}{\rho(i,S_{k-1})} \times \frac{D_{i,k}}{D_{i,k-1}} - 1 \right)^2 && \text{(A.7)} \\
&= \sum_{k=1}^{n} \sum_{S_{t+k}} P_{S_t,S_{t+k}} \left(\frac{\rho(i,S_{t+k})}{\rho(i,S_{t+k-1})} \times \frac{D_{i,S_{t+k}}}{D_{i,S_{t+k-1}}} - 1 \right)^2 && \text{(A.8)} \\
&= \sum_{k=1}^{n} \sum_{S_{t+k-1}} P^{k-1}_{S_t,S_{t+k-1}} RV^e_{i,S_{t+k-1}} && \text{(A.9)}
\end{aligned}$$

where $RV^e_{i,S_{t+k-1}}$ is defined as

$$RV^e_{i,S_{t+k-1}} = E_{S_t} \left\{ \left(\frac{\rho(i,S_{t+1})}{\rho(i,S_t)} \times \frac{D_{i,t+1}}{D_{i,t}} - 1 \right)^2 \right\} \quad \text{(A.10)}$$

Corresponding to each of the four regimes, there are $RV^e_{i,NS}$, $RV^e_{i,NL}$, $RV^e_{i,DS}$, $RV^e_{i,DL}$.

A.4 Calculating Variance Swap

We define variance swap rate $VS_{i,t,t+n}$ as $VS_{i,t,t+n} = E^Q_t RV_{i,t,t+n}$, and

$$\begin{aligned}
VS_{i,t,t+n} &= E^Q_t RV_{i,t,t+n} && \text{(A.11)} \\
&= E_t \sum_{k=1}^{n} \left\{ \frac{M_{t,t+k}}{E_t M_{t,t+k}} \left(\frac{\rho(i,S_{t+k})}{\rho(i,S_{t+k-1})} \times \frac{D_{i,t+k}}{D_{i,t+k-1}} - 1 \right)^2 \right\} && \text{(A.12)} \\
&= \sum_{k=1}^{n} E_t \left\{ \frac{M_{t,t+k}}{E_t M_{t,t+k}} \left(\frac{\rho(i,S_{t+k})}{\rho(i,S_{t+k-1})} \times \frac{D_{i,t+k}}{D_{i,t+k-1}} - 1 \right)^2 \right\} && \text{(A.13)} \\
&= \sum_{k=1}^{n} \frac{1}{E_t M_{t,t+k}} \sum_{S_{t+k}} P^{*k}_{S_t,S_{t+k}} \left(\frac{\rho(i,S_{t+k})}{\rho(i,S_{t+k-1})} \times \frac{D_{i,S_{t+k}}}{D_{i,S_{t+k-1}}} - 1 \right)^2 && \text{(A.14)} \\
&= \sum_{k=1}^{n} \frac{1}{E_t M_{t,t+k}} \sum_{S_{t+k-1}} P^{*k-1}_{S_t,S_{t+k-1}} VS_{i,S_{t+k-1}} && \text{(A.15)}
\end{aligned}$$

where P^* is transition matrix with $P^*_{(i,j)} = P_{(i,j)}M_j$. And VS_{i,S_t} is defined as:

$$VS_{i,S_t} = E_{S_t}\left\{M_{t+1}\left(\frac{\rho(i,S_{t+1})}{\rho(i,S_t)} \times \frac{D_{i,t+1}}{D_{i,t}} - 1\right)^2\right\} \tag{A.16}$$

After solving equation (A.16) for each of the four regimes, we get $VS_{i,NS}$, $VS_{i,NL}$, $VS_{i,DS}$, $VS_{i,DL}$.

We define the T months VIX from t as

$$VIX_t^T = \left(\frac{252}{T \times 21} \times VS_{t+T\times 21}\right)^{\frac{1}{2}} \tag{A.17}$$

By equation (A.17), the term structure of VIX will be determined by the term structure of the variance swap rate.

A.5 Discussions on Price-Dividend Ratios

The price-dividend ratio serves a very important role in our model. In order to better understand how the price-dividend ratio differs in the four regimes that our model generates, we use a simplified two regime model to analyze. The implications of four regimes model follows two regime model naturally.

There is only one type of disaster in our two regime model and one normal state that could lead to this disaster. The two regimes are:

$$\begin{cases} N: & \textit{normal regime} \\ D: & \textit{disaster regime} \end{cases}$$

And the transition probability matrix $\mathbf{P}$ is characterized as following:

$$
\begin{aligned}
\mathbf{P} &= \mathbf{P}\left(S_t \mid S_{t-1}\right) \\
&= \begin{array}{c c} & \begin{array}{cc} N & D \end{array} \\ \begin{array}{c} N \\ D \end{array} & \begin{pmatrix} \bar{p} & p \\ p_{out} & \bar{p}_{out} \end{pmatrix} \end{array}
\end{aligned}
$$

Nothing else related to the settings of the model differs from the previous four regime model. By the similar calculation procedures we can get the following equations:

$$\rho(i,N) = 1 + pe^{g_{i,d}-\delta}E\left(J_{i,c,t}^{-\gamma}J_{i,d,t}\right)\rho(i,D) + \bar{p}_H e^{g_{i,d}-\delta}\rho(i,N) \tag{A.18}$$

$$\rho(i,D) = 1 + \bar{p}_{out}e^{g_{i,d}-\delta}E\left(J_{i,c,t}^{-\gamma}J_{i,d,t}\right)\rho(i,D) + p_{out}e^{g_{i,d}-\delta}\rho(i,N) \tag{A.19}$$

By solving equations (A.19) we get the following solutions:

$$\rho(i,N) = \frac{1 + E_D\left(1 - p - p_{out}\right)}{1 - E_D\bar{p}_{out} - E_N\bar{p} + E_D \times E_N\left(p + p_{out} - 1\right)} \tag{A.20}$$

$$\rho(i,D) = \frac{1 + E_N\left(1 - p - p_{out}\right)}{1 - E_D\bar{p}_{out} - E_N\bar{p} + E_D \times E_N\left(p + p_{out} - 1\right)} \tag{A.21}$$

where

$$E_N = E\left(M_{t+1}\frac{D_{i,t+1}}{D_{i,t}}|S_{t+1} = N\right) \tag{A.22}$$

$$E_D = E\left(M_{t+1}\frac{D_{i,t+1}}{D_{i,t}}|S_{t+1} = D\right) \tag{A.23}$$

According to equations (A.21), the denominator $1 - E_D\bar{p}_{out} - E_N\bar{p} + E_D \times E_N\left(p + p_{out} - 1\right) < 0$. So $\rho(i,N) = \rho(i,D)$ if $E_N = E_D$. And $\rho(i,N) > \rho(i,D)$ if $E_N > E_D$ and $\rho(i,N) < \rho(i,D)$

if $E_N < E_D$. The results stays the same if we replace the two regime model with the four regime model.

We focus on the situation where $\rho(i,N) > \rho(i,D)$, that is $E_N > E_D$ in the following study.

A.6 Calculating Risk Premium

Next we study the mechanism that cause a positive equity risk premium in our model and the factors that affect the magnitude of equity risk premium. By definition we have the following equation:

$$1 = E_t\left(M_{t+1} r_{i,t+1}\right) = Cov_t\left(M_{t+1}, r_{i,t+1}\right) + E_t\left(M_{t+1}\right) E_t\left(r_{i,t+1}\right) \tag{A.24}$$

By transformation we get:

$$\begin{aligned} E_t\left(r_{i,t+1}\right) &= \frac{1}{E_t\left(M_{t+1}\right)} - \frac{Cov_t\left(M_{t+1}, r_{i,t+1}\right)}{E_t\left(M_{t+1}\right)} && \text{(A.25)} \\ &= r_{f,t} - r_{f,t} Cov_t\left(M_{t+1}, r_{i,t+1}\right) && \text{(A.26)} \end{aligned}$$

, where $r_{f,t} = E_t^{-1}\left(M_{t+1}\right)$.

Define equity risk premium to be $r_{p,t} = E_t\left(r_{i,t+1}\right) - r_{f,t}$. Therefore the equity risk premium will follow the equation:

$$r_{p,t} = -r_{f,t} Cov_t\left(M_{t+1}, r_{i,t+1}\right) \tag{A.27}$$

We can write equation (A.5) as:

$$r_{p,t} = -r_{f,t} Vol_t\left(r_{i,t+1}\right) Vol_t\left(M_{t+1}\right) Corr_t\left(M_{t+1}, r_{i,t+1}\right) \tag{A.28}$$

where

$$Corr_t\left(M_{t+1}, r_{i,t+1}\right) = Corr_t\left(e^{-\rho} \times \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}, \frac{\rho(i, S_{t+1})}{\rho(i, S_t) - 1} \times \frac{D_{i,t+1}}{D_{i,t}}\right) \tag{A.29}$$

From equation (A.28) we can see there are three factors that can affect equity risk premium, which are, $Vol_t\left(M_{t+1}\right)$, $Vol_t\left(r_{i,t+1}\right)$, and $Corr_t\left(M_{t+1}, r_{i,t+1}\right)$. Among those three factors, $Corr_t\left(M_{t+1}, r_{i,t+1}\right)$ determines the sign of equity risk premium. In order to keep equity risk premium positive, there has to be a negative correlation between M_{t+1} and $r_{i,t+1}$.

First consider the correlation between M_{t+1} and $\frac{D_{i,t+1}}{D_{i,t}}$. The jumps in consumption and dividend when disaster comes happen at the same period in our model, so $Corr_t\left(e^{-\rho} \times \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}, \frac{D_{i,t+1}}{D_{i,t}}\right)$ is negative. Since price-dividend ratio in our settings changes as the same direction as dividend($\rho(i, N) > \rho(i, D)$), the model can generate a negative $Corr_t\left(M_{t+1}, r_{i,t+1}\right)$.

The magnitude of the equity risk premium are affected by the absolute value of $Vol_t\left(M_{t+1}\right)$, $Vol_t\left(r_{i,t+1}\right)$, and $Corr_t\left(M_{t+1}, r_{i,t+1}\right)$.

A.7 Model Comparison

Previously, we used a two regime model to explain the mechanism of the four regime model. We are going to discuss why we still need the four regime model than the two regime model.

In a two regime model there are only two price-dividend ratios corresponding to the normal and disaster regimes, while in the four regime model there are four price-dividend ratios.

The extra price-dividend ratios that the four regime model generates are very important and necessary.

As discussed previously, the four regime model generates RV^e_{DL}, RV^e_{NL}, RV^e_{DS}, and RV^e_{NS}. By requiring $RV^e_{DL} > RV^e_{NL} > RV^e_{\infty} > RV^e_{DS} > RV^e_{NS}$, our four regime model can generate an upward sloping expected realized variance term structure for NS and DS regimes and a downward sloping expected realized variance term structure for NL and DL regimes.

In the two regime model, the model generates RV^e_N and RV^e_D. By requiring $RV^e_D > RV^e_{\infty} > RV^e_N$ the model can generate a downward sloping expected realized variance term structure for disaster regime and upward sloping expected realized variance term structure for normal regime. However, based on our empirical observations, the downward sloping expected realized variance term structure also happen in normal regimes. That's why we need to bring in the four regime model, by which the sign of slope of term structure is not determined by disaster or normal regime but is determined by potential disaster lengths.

Next let us compare our four regime model with Barro model. The main difference between our four regime model and the Barro model is that the disaster has duration longer than one period in our model but doesn't have one in Barro model. The jump in output when disaster happens follows a distribution which is not time varying. And the price-earnings ratio is constant. The volatility is brought in solely by the volatility of earnings. And the expected realized variance term structure is flat in the model.

Gabaix (2012) model also has a disaster which only lasts one period. It did more than Barro model in that it introduces a time varying "Resilience" to model the time variation in the asset's recovery rate when disaster happens. The time varying "Resilience" makes the price-dividend ratio to move by time as mean reverting. And this mean reverting price-dividend ratio is the main source of the volatility in stock returns in Gabaix model. Because of this mean reverting price-dividend ratio, Gabaix model could generate time varying expected realized variance term structure.

Appendix B

Appendix for Chapter 2

```
*------------------------------------------*
Merge S&P Index Option Prices for Test Period
*------------------------------------------*;

libname opm '/wrds/optionm/sasdata';
libname opn '/local';

Proc sql;

CREAT VIEW opn.newopv AS
SELECT * from opm.Opprcd1996
UNION ALL SELECT * from opm.Opprcd1997
UNION ALL SELECT * from opm.Opprcd1998
UNION ALL SELECT * from opm.Opprcd1999
UNION ALL SELECT * from opm.Opprcd2000
```

```
UNION ALL SELECT * from opm.Opprcd2001
UNION ALL SELECT * from opm.Opprcd2002
UNION ALL SELECT * from opm.Opprcd2003
UNION ALL SELECT * from opm.Opprcd2004
UNION ALL SELECT * from opm.Opprcd2005
UNION ALL SELECT * from opm.Opprcd2006
UNION ALL SELECT * from opm.Opprcd2007
UNION ALL SELECT * from opm.Opprcd2008
UNION ALL SELECT * from opm.Opprcd2009
UNION ALL SELECT * from opm.Opprcd2010
UNION ALL SELECT * from opm.Opprcd2011
UNION ALL SELECT * from opm.Opprcd2012
UNION ALL SELECT * from opm.Opprcd2013

quit;

libname opm '/data/data1/optionm/sasdata';
libname opn '/user/user2/cxie15';

Proc sql;

CREAT VIEW opn.newspv AS
SELECT * from opm.Secprd1996
UNION ALL SELECT * from opm.Secprd1997
UNION ALL SELECT * from opm.Secprd1998
UNION ALL SELECT * from opm.Secprd1999
```

```
UNION ALL SELECT * from opm.Secprd2000
UNION ALL SELECT * from opm.Secprd2001
UNION ALL SELECT * from opm.Secprd2002
UNION ALL SELECT * from opm.Secprd2003
UNION ALL SELECT * from opm.Secprd2004
UNION ALL SELECT * from opm.Secprd2005
UNION ALL SELECT * from opm.Secprd2006
UNION ALL SELECT * from opm.Secprd2007
UNION ALL SELECT * from opm.Secprd2008
UNION ALL SELECT * from opm.Secprd2009
UNION ALL SELECT * from opm.Secprd2010
UNION ALL SELECT * from opm.Secprd2011
UNION ALL SELECT * from opm.Secprd2012
UNION ALL SELECT * from opm.Secprd2013

quit;

Proc sql;
CREAT VIEW opn.newrv AS
SELECT * from opm.Hvold1996
UNION ALL SELECT * from opm.Hvold1997
UNION ALL SELECT * from opm.Hvold1998
UNION ALL SELECT * from opm.Hvold1999
UNION ALL SELECT * from opm.Hvold2000
UNION ALL SELECT * from opm.Hvold2001
UNION ALL SELECT * from opm.Hvold2002
```

```
UNION ALL SELECT * from opm.Hvold2003
UNION ALL SELECT * from opm.Hvold2004
UNION ALL SELECT * from opm.Hvold2005
UNION ALL SELECT * from opm.Hvold2006
UNION ALL SELECT * from opm.Hvold2007
UNION ALL SELECT * from opm.Hvold2008
UNION ALL SELECT * from opm.Hvold2009
UNION ALL SELECT * from opm.Hvold2010
UNION ALL SELECT * from opm.Hvold2011
UNION ALL SELECT * from opm.Hvold2012
quit;

Proc sql;
create table test4 as
select x.date as date, x.exdate as expiration,
INTCK('day',x.date,x.exdate) as diff,x.cp_flag
as flag,x.strike_price/1000 as strike,
(x.best_bid+x.best_offer)/2 as mbbo,
x.best_bid as bid, x.best_offer as offer, y.close as close
from opm.MIDXOPPRCD x
inner join opm.MIDXPRCD y on x.secid=y.secid
and x.date=y.date
where x.secID = 108105
order by x.date;
quit;
```

```
Proc sql;
CREATE TABLE opn.realvolspx as
SELECT * from opn.newrv x
WHERE x.secid=108105
ORDER by x.date;
quit;

Proc sql;
CREATE TABLE opn.vixrvspx as
SELECT x1.date, x1.vix, x2.volatility, x2.date as date2,
x2.days from opn.vixindex2 x1
INNER JOIN opn.realvolspx x2
ON
x1.date=x2.date
AND
x2.days=30
ORDER by x1.date;
quit;

Proc sql;
CREATE TABLE opn.sp500listnew as
SELECT x1.PERMNO, x1.start, x1.ending, x2.PERMNO
as permno2,x2.DLSTDT,x2.NEXTDT from opm.Dsp500list x1
INNER JOIN opm2.Dsedelist x2
ON x1.PERMNO=x2.PERMNO;
quit;
```

```
PROC SQL;
CREATE TABLE opm.test13 AS
SELECT * , (480+510+1440*(x.diff-1))/525600 as T,
x.strike+exp((480+510+1440*(x.diff-1))/525600
) as a FROM opm.test12 x
ORDER BY
x.date, x.diff, x.flag, x.strike;
QUIT;

Proc sql;
CREATE TABLE opn.tbilnewl as
SELECT x.datadate, x.TBILL3M,x.TBILL6M,
x.TBILL12M from opm.Ecind_mth x
WHERE x.ECONISO="USA"
AND x.datadate>'01JAN1990'd;
quit;

PROC SQL;
CREATE TABLE opm.test14 AS
SELECT x.date, x.expiration, x.diff, x.flag, x.strike,
x.mbbo, x.bid, x.offer, x.close, x.datadate,
x.TBILL3M, x.T  FROM opm.test13 x
ORDER BY
x.date, x.diff, x.flag, x.strike;
QUIT;
```

```
PROC SQL;
CREATE TABLE opm.test15 AS
SELECT x.date, x.expiration, x.diff, x.flag, x.strike,
x.mbbo, x.bid, x.offer, x.close, x.datadate,
x.TBILL3M, x.T  FROM opm.test14 x
WHERE x.diff LE 100
AND x.diff GE 7
ORDER BY
x.date, x.diff, x.flag, x.strike;
QUIT;

Proc sql;
create table opm.test16strike as
select x1.date, x1.diff, x1.flag, x1.strike, x1.mbbo,
x2.date as date2, x2.diff as diff2, x2.flag as flag2,
x2.strike as strike2, x2.mbbo as mbbo2, x1.close,
x2.close as close2
from opm.Test10strike x1
INNER JOIN opm.Test10strike x2
ON x1.date=x2.date
AND x1.strike=x2.strike
AND x1.diff=x2.diff
AND x1.flag="C"
AND x2.flag="P"
order by x1.date, x1.diff, x1.strike;
```

```
quit;

Proc sql;
create table opm.test17strike as
select *, INTNX('day',x1.date,x1.diff) FORMAT=DATE9. as expiration
FROM opm.test16strike x1
order by x1.date, x1.diff, x1.strike;
quit;

PROC SQL;
CREATE TABLE opm.test18strike AS
SELECT * , (480+510+1440*(x.diff-1))/525600 as T,
y.datadate,y.TBILL3M as a FROM opm.test17strike x
INNER JOIN opm.Tbillnew y
ON
INTCK('month',x.expiration,y.datadate)=0
ORDER BY
x.date, x.diff, x.flag, x.strike;
QUIT;

PROC SQL;
CREATE TABLE opm.test19F AS
SELECT x.date, x.expiration, x.diff, x.flag, x.strike, x.mbbo,
x.flag2, x.mbbo2, x.close, x.datadate, (x.TBILL3M)/100
as rate, x.T,  (x.strike+exp((x.TBILL3M)/100*T)*(x.mbbo-x.mbbo2))
as F FROM opm.test18strike x
```

```
ORDER BY
x.date, x.diff, x.flag, x.strike;
QUIT;


*------------------------------------------*
Use R to Calculate VIX Term Structure
*------------------------------------------*;
rm(list=ls(all=TRUE))


tdata<-read.csv("zerocd_intp.csv")
tdata<-tdata[-1:-2,] # delete the first two rows
bdata<-read.csv("test1_original.csv")
date_b<-as.numeric(as.Date(as.character(bdata$date),
format='%d%b%Y'))
expiration_b<-as.numeric(as.Date(as.character
(bdata$expiration),format='%d%b%Y'))
bdata$date<-date_b
bdata$expiration<-expiration_b
date_t<-as.numeric(as.Date(tdata$date,format=
'%Y-%m-%d'))
id_b<-unique(date_b)
id_t<-unique(date_t)
#m_intp<-matrix(,nrow=length(id),ncol=length(days_intp))
#m_intp2<-matrix(,nrow=length(id_test),
ncol=length(days_intp))
# we need to calculate T=(480+510+1440*
```

```
(bdata$diff-2))/525600
T<-(480+510+1440*(bdata$diff-2))/525600
dif<-matrix(1000,dim(bdata)[1],1)
df<-data.frame(date_b,expiration_b,bdata[,
3:dim(bdata)[2]],T,dif)
df<-df[order(df$date_b,df$expiration_b,df$CP,df$strike),]
row_num<-1:dim(df)[1]
df<-data.frame(row_num,df)
row.names(df)<-NULL
# throw away the rows with bid == 0 and
next two of bid ==0
df<-data.frame(df,matrix(,dim(df)[1],1))
colnames(df)[dim(df)[2]]<-c("delete")
# first find all which bid ==0
df[df$bid==0,]$delete<-1
# find all row_num which has two consecutive
row where bid==0
sub_bid0<-subset(df,bid==0)
rn_bid0<-sub_bid0$row_num
rn_bid0.plus<-rn_bid0+1
rn_bid0.minus<-rn_bid0-1
rn_bid0.union<-union(rn_bid0.minus,rn_bid0.plus)
rn_bid0.sort<-rn_bid0.union[order(rn_bid0.union)]
sub_bid0_2<-subset(sub_bid0,row_num
%in% rn_bid0.sort)
id_bid0_date<-unique(sub_bid0_2$date_b)
```

```
for (i in 1:length(id_bid0_date))
{
  sub_bid0_date<-subset(sub_bid0_2,
  date_b==id_bid0_date[i])
  id_bid0_diff<-unique(sub_bid0_date$diff)

  for (j in 1:length(id_bid0_diff))
  {
     sub_bid0_diff<-subset(sub_bid0_date,
     diff==id_bid0_diff[j])
     sub_bid0_diff_call<-subset(sub_bid0_diff,CP==1)
     sub_bid0_diff_put<-subset(sub_bid0_diff,CP==0)

     if (dim(sub_bid0_diff_call)[1]>0)
     {
       rn_call<-sub_bid0_diff_call$row_num
       rn_call.plus<-rn_call+1
       rn_call.minus<-rn_call-1
       rn_call.union<-union(rn_call.minus,rn_call.plus)
       rn_call.sort<-rn_call.union[order(rn_call.union)]
       sub_bid0_diff_call_2<-subset(sub_bid0_diff_call,
       row_num %in% rn_call.sort)
       rn_call_max<-sub_bid0_diff_call_2[dim
       (sub_bid0_diff_call_2)[1],]$row_num
```

```
  if (dim(df[df$date_b==id_bid0_date[i]&df$diff==
  id_bid0_diff[j]&df$CP==1&df$row_num>
  rn_call_max,])[1]>0&&!is.na(rn_call_max))
  {df[df$date_b==id_bid0_date[i]&df$diff==
  id_bid0_diff[j]&df$CP==1&df$row_num>
  rn_call_max,]$delete<-1}

}

if (dim(sub_bid0_diff_put)[1]>0)
{
  rn_put<-sub_bid0_diff_put$row_num
  rn_put.plus<-rn_put+1
  rn_put.minus<-rn_put-1
  rn_put.union<-union(rn_put.minus,rn_put.plus)
  rn_put.sort<-rn_put.union[order(rn_put.union)]
  sub_bid0_diff_put_2<-subset(sub_bid0_diff_put,
  row_num %in% rn_put.sort)
  rn_put_min<-sub_bid0_diff_put_2[1,]$row_num
  if (dim(df[df$date_b==id_bid0_date[i]&df$diff==
  id_bid0_diff[j]&df$CP==0&df$row_num<
  rn_put_min,])[1]>0&&!is.na(rn_put_min))
{df[df$date_b==id_bid0_date[i]&df$diff==
id_bid0_diff[j]&df$CP==0&df$row_num<
rn_put_min,]$delete<-1}
}
```

```
   }

}

new<-matrix(,1,7)
colnames(new)<-c("date","diff","strike","CP_0",
"mbbo_0","CP_1","mbbo_1")

# we need to calculate F=strike+exp(rT)*(call-put)
if(FALSE){

for (i in 1:length(id_b))
{

 df_new<-subset(df,date_b==id_b[i])
 id_diff<-unique(df_new$diff)
 for (j in 1:length(id_diff))
 {
  df_new.d<-subset(df_new,diff==id_diff[j])
  id_s<-unique(df_new.d$strike)
  for (k in 1:length(id_s))
  {
   call<-subset(df_new.d,strike==id_s[k]&CP==1)
   put<-subset(df_new.d,strike==id_s[k]&CP==0)
   if (length(call)==0) call<-NA
```

```
   if (length(put)==0) put<-NA
    #df[row_num==rn_c,]$dif<-df[row_num==rn_c,]
    $mbbo-df[row_num==rn_p,]$mbbo
    #cp_merge<-merge(call, put
    new<-rbind(new,c(id_b[i],id_diff[j],id_s[k],0,put,1,call))

  }

 }

}

new<-new[-1,]
write.csv(new,"new_1.csv")

}

*------------------------------------------*
Empirical Tests
*------------------------------------------*;
%macro RRLOOP (indep2=dif_pc1, indep3=
dif_pc2, in_ds=mylib.all, out_ds=mylib.out_ds_sort);

%let year1=1996;
%let year2=2012;
```

```
%local date1 date2 date1f date2f yy mm;

/*Extra step to be sure to start with clean,
null datasets for appending*/
proc datasets nolist lib=work;
  delete all_ds_sort1 oreg_ds1 oreg_ds1_sort1 all_temp;
run;

data all_temp;
set &in_ds (keep= date permno exret mkt_rf dif_pc1 dif_pc2  );
run;

/*Loop for years and months*/
 %do yy = &year1 %to &year2;
   %do mm = 1 %to 12;

 /*Set date2 for mm-yy end point and date1 as 24 months prior*/
 %let date2=%sysfunc(mdy(&mm,1,&yy));
 %let date2= %sysfunc (intnx(month,
 &date2, 0,end)); *Make the DATE2 last day of the month;
 %let date1 = %sysfunc (intnx(month,
 &date2, 0, beginning)); *set DATE1 as first day of same month;

 /*FYI --- INTNX quirk in SYSFUNC:  do not
 use quotes with 'month' 'end' and 'begin'*/
```

```
/*An extra step to be sure the loop starts with
a clean (empty) dataset for combining results*/

proc datasets nolist lib=work;
  delete oreg_ds1 oreg_ds2 oreg_ds_sort1 port1 port2 port3 port4;
run;

/*Regression model estimation -- creates
output set with coefficient estimates*/
proc reg noprint data=all_temp outest=oreg_ds1 edf;
  where date between &date1 and &date2;
  *Restricted to DATE1- DATE2 data range in the loop,
  and check if there is a valid return for 1 year;
  model exret = mkt_rf &indep2 &indep3;
  by permno;
run;

/*Store DATE1 and DATE2 as dataset variables
and rename regression coefficients as ALPHA and BETA;*/
data oreg_ds1;
  set oreg_ds1;
  date1=&date1;
  date2=&date2;
  rename intercept=alpha  mkt_rf=beta_mkt  &indep2=
  beta_dv &indep3=beta_ds;
  nobs= _p_ + _edf_;
```

```
  format date1 date2 yymmdd10.;
run;

data oreg_ds2;
set oreg_ds1;
if nobs>14;
run;

**********************************************
 Form portfolio based on rank of beta(),
 here we should
 exclude the lack of observation
**********************************************;
proc sort data=oreg_ds2 out=port1; by permno; run;
proc rank data=port1 out=port2 group=3;
  var beta_mkt;
  ranks bm;
run;

proc sort data=port2; by bm; run;
proc rank data=port2 out=port3 group=3;
  by bm;
  var beta_dv;
  ranks bv;
run;
```

```
proc sort data=port3; by bm bv; run;
proc rank data=port3 out=port4 group=3;
  by bm bv;
  var beta_ds;
  ranks bs;
run;

data oreg_ds_sort1; set port4;
bm=bm+1;
bv=bv+1;
bs=bs+1;
run;

********************************************
********************************************;

/*Append loop results to dataset with all date1-
date2 observations*/
proc datasets lib=work;
  append base=all_ds_sort1 data=oreg_ds_sort1;

run;

 %end;  /*MM month loop*/

%end;  /*YY year loop*/
```

```
/*Save results in final dataset*/

data &out_ds;
  set all_ds_sort1;
run;

%mend RRLOOP;

%RRLOOP;

%MACRO TEST (b1=bm , b2=bs , beta1=beta_mkt,
beta2=beta_ds );
proc datasets nolist lib=work;
  delete out3 out3_2 out3_base out4 out5
  output _params
  _uncorr _params2 _uncorr2 ff_factors
  oreg2 oreg2_2 oreg3 corr
  oreg2_test2 oreg2_2_test2 oreg3_test2 output_test2 all ;
run;

data all;
set  mylib.all_monthly_0715 (keep=permno date_new
exret_m me mkt_rf_m hml_m smb_m mom_m);
run;
```

```
proc sql;
  create table out3;
  as select a.permno, a.date1, a.date2, a.&b1, a.&b2, a.&beta1,
  a.&beta2, b.date_new, b.me, b.exret_m, b.mkt_rf_m,
  b.hml_m, b.smb_m, b.mom_m
  from out_ds_sort1 as a, all as b
  where b.date_new=intnx('month', a.date2, 1, 'end') and
  a.permno=b.permno;
quit;

proc sort data=out3; by date_new &b1 &b2 ;
proc means data=out3 noprint;
     var exret_m &beta1 &beta2  mkt_rf_m hml_m
smb_m mom_m;
     by date_new date1 date2 ;
     output out=out3_base mean=exret_m &beta1
&beta2  mkt_rf_m hml_m smb_m mom_m;
run;

proc sort data=out3; by date_new date1 date2 &var;
run;

proc means data=out3 noprint;
     var exret_m  ;
     by date_new date1 date2 &var;
     output out=out3_2 mean=ret_&var ;
```

```
run;

proc sort data=out3_2; by date_new date1 date2;
run;

proc transpose data=out3_2 out=ff_factors;
    var ret_&var;
    by date_new date1 date2;
    id &var ;
run;

data ff_factors;
set ff_factors (drop=_NAME_);
rename _1=ret1_&var _2=ret2_&var _3=ret3_&
var _4=ret4_&var _5=ret5_&var;
F_&var=_5-_1;
run;

data out3_base;
merge ff_factors out3_base;
by date_new date1 date2;
run;

data out3_base;
set out3_base (keep= date_new date1 date2 F_&b2
mkt_rf_m hml_m smb_m mom_m);
```

```
run;

proc sort data=out3; by date_new &b1 &b2 ;
proc means data=out3 noprint;
     var exret_m &beta1 &beta2 ;
      by date_new date1 date2 &b1 &b2 ;
     output out=out4 mean=exret_m &beta1 &beta2 ;
run;

proc sort data=out3_base; by date_new date1 date2;
proc sort data=out4; by date_new date1 date2;
data out5;
merge out4 out3_base;
by date_new date1 date2;
run;

proc sort data=out5; by &b1 &b2;
/*Regression model estimation -- creates output set
with coefficient estimates*/
proc reg noprint data=out5 outest=oreg2 edf;
  model exret_m = mkt_rf_m F_&b2 hml_m smb_m
  mom_m/adjrsq;
  by &b1 &b2 ;
run;

proc sort data=oreg2; by &b1 &b2 ;
```

```
proc sort data=out4; by &b1 &b2 ;
data oreg2_2;
merge out4 (keep= date_new date1 date2 &b1 &b2 exret_m)
oreg2 (keep=&b1 &b2  mkt_rf_m f_&b2  hml_m smb_m mom_m);
by &b1 &b2 ;
run;


proc sort data=oreg2_2; by date_new date1 date2;
proc reg noprint data=oreg2_2 outest=oreg3 edf noprint;
  model exret_m = mkt_rf_m F_&b2 hml_m smb_m
  mom_m  /adjrsq;
  by date_new date1 date2;
run;


/*rename regression coefficients as ALPHA and BETA;*/
data oreg3;
  set oreg3;
  rename intercept=alpha  mkt_rf_m=lambda_mkt
  F_&b2=lambda_dskew
  hml_m=lambda_hml smb_m=lambda_smb
  mom_m=lambda_mom;
run;


** Newey-West t-stat for the time-series average of coefficients;


%let indvars= alpha lambda_mkt lambda_dskew
```

```
lambda_hml lambda_smb lambda_mom _adjrsq_;

 %do k=1 %to 7;
   %let var=%scan(&indvars,&k,%str(' '));

ods listing close;
proc means data=oreg3 mean n std t probt;
var &var;
ods output summary=_uncorr;
run;

%let lag=12;*lags for Newey-West t-stat;
proc model data=oreg3;
instruments / intonly;
&var=b01;
fit &var / gmm kernel=(bart, %eval(&lag+1), 0);
ods output parameterestimates=_params;
quit;

/*3. put the results together*/
data _params (drop=&var._n);
merge _params
_uncorr (rename=(&var._stddev=stderr_uncorr
                                 &var._t=tvalue_uncorr
                                 &var._probt=probt_uncorr)
                      );
```

```
stderr_uncorr=stderr_uncorr/&var._n**0.5;
parameter="&var";
drop esttype;
run;

proc printto log=junk;run;
proc append base=output data=_params force; run;
proc printto;run;
%end;

proc datasets nolist lib=work;
  delete _params _uncorr ;
run;

proc corr data = out3_base outp=corr;
var mkt_rf_m hml_m smb_m mom_m f_&b2 ;
run;

proc sort data=out5; by &b1 &b2;
/*Regression model estimation -- creates output set
with coefficient estimates*/
proc reg noprint data=out5 outest=oreg2_test2 edf;
  model exret_m = mkt_rf_m F_&b2  /adjrsq;
  by &b1 &b2 ;
run;
```

```
proc sort data=oreg2_test2; by &b1 &b2 ;
proc sort data=out4; by &b1 &b2 ;
data oreg2_2_test2;
merge out4 (keep= date_new date1 date2 &b1 &b2  exret_m)
oreg2_test2 (keep=&b1 &b2 mkt_rf_m f_&b2  );
by &b1 &b2 ;
run;

proc sort data=oreg2_2_test2; by date_new date1 date2;
proc reg noprint data=oreg2_2_test2 outest=
oreg3_test2 edf noprint;
  model exret_m = mkt_rf_m F_&b2  /adjrsq;
  by date_new date1 date2;
run;

/*rename regression coefficients as ALPHA and BETA;*/
data oreg3_test2;
  set oreg3_test2;
  rename intercept=alpha  mkt_rf_m=lambda_mkt
  F_&b2=lambda_dskew  ;
run;

** Newey-West t-stat for the time-series average of coefficients;

%let indvars= alpha lambda_mkt lambda_dskew _adjrsq_;
```

```
 %do k=1 %to 4;
   %let var=%scan(&indvars,&k,%str(' '));

ods listing close;
proc means data=oreg3_test2 mean n std t probt;
var &var;
ods output summary=_uncorr2;
run;

%let lag=12;*lags for Newey-West t-stat;
proc model data=oreg3_test2;
instruments / intonly;
&var=b01;
fit &var / gmm kernel=(bart, %eval(&lag+1), 0);
ods output parameterestimates=_params2;
quit;

/*3. put the results together*/
data _params2 (drop=&var._n);
merge _params2
_uncorr2 (rename=(&var._stddev=stderr_uncorr
                                 &var._t=tvalue_uncorr
                              &var._probt=probt_uncorr)
                      );
stderr_uncorr=stderr_uncorr/&var._n**0.5;
parameter="&var";
```

```
drop esttype;
run;


proc printto log=junk;run;
proc append base=output_test2 data=_params2 force; run;
proc printto;run;
%end;


%MEND;
```

Appendix C

Appendix for Chapter 3

```
*------------------------------------------*
Merge CRSP with Compustat
*------------------------------------------*;
libname mylib '/home/columbia/bgxc'; *define a home
directory on WRDS;

%let begindate='01jan1996'd;  * start calendar date of
fiscal period end;
%let enddate='31dec2013'd;    * end calendar date of
fiscal period end;

*variables to extract from Compustat;
%let comp_list= gvkey fyearq fqtr conm datadate rdq
epsfxq epspxq
prccq ajexq spiq cshoq cshprq cshfdq rdq saleq atq
fyr consol indfmt
```

```
datafmt popsrc datafqtr invtq chq cshoq rectq oancfy
actq lctq dpq
ppentq ceqq; *ceqq is book value;

*variables to extract from IBES;
%let ibes_vars= ticker value fpedats anndats revdats
measure fpi
estimator analys pdf usfirm;

*IBES filters;
%let ibes_where1=where=(measure='EPS' and fpi
in ('6','7') and
&begindate<=fpedats<=&enddate);
%let ibes_where2=where=(missing(repdats)=0 and
missing(anndats)
=0 and 0<intck('day',anndats,repdats)<=90);

*timing and primary filters for Compustat Xpressfeed;
%let comp_where=where=(fyr>0 and (saleq>0 or atq>0)
and consol='C'
 and popsrc='D' and indfmt='INDL' and datafmt='STD' and
 missing(datafqtr)=0);

*filter from LM (2006):
- earnings announcement date is reported in Compustat
- the price per share is available from Compustat as of
```

```
the end of the
fiscal quarter and is greater than $1
- the market (book) value of equity at the fiscal quarter
end is available
 and is larger than $5 mil;
%let LM_filter=(missing(rdq)=0 and prccq>1 and mcap>5.0);

*define a set of auxiliary macros;
%include '/wrds/ibes/samples/cibeslink.sas';
%include '/wrds/ibes/samples/ibes_sample.sas';
%include '/wrds/comp/samples/size_bm.sas';
%include '/wrds/ibes/samples/iclink.sas'; *build
CRSP-IBES permno-ticker
 link;

proc datasets library=work;
delete comp_final1 comp_final2 comp_final3;
run;

*CIBESLINK macro will create a linking table
CIBESLNK between IBES
ticker and Compustat GVKEY
*based on IBES ticker-CRSP permno (ICLINK)
and CCM CRSP permno
 - Compustat GVKEY (CSTLINK2) link;
%CIBESLINK (begdt=&begindate, enddt=&enddate);
```

```
*Read in IBES tickers from the specified file stored
in the user’s home
director on WRDS;
filename input ’tickers.csv’;
data tickers;
infile input;
informat ticker $6.;
input @1 ticker;
run;

* Macro IBES_SAMPLE extracts the estimates from
IBES Unadjusted
file based on the user-provided
* by adjusting for stock splits using CRSP adjustment
factor and calculates
 the median/mean/dispersion of analyst
* forecasts made in the 90 days prior to the earnings
announcement date.
Outputs file MEDEST into work directory;
%MACRO IBES_SAMPLE (infile=, ibes1_where=,
ibes2_where=, ibes_var=);

proc sql; create table ibes (drop=measure fpi)
as select *
from ibes.detu_epsus (&ibes1_where keep=&ibes_var) as a,
```

```
&infile as b
where a.ticker=b.ticker
order by a.ticker, fpedats, estimator, analys, anndats, revdats;
quit;

*Select the last estimate for a firm within broker-analyst group;
data ibes; set ibes;
by ticker fpedats estimator analys;
if last.analys;
run;

*How many estimates are reported on primary/diluted basis?;
proc sql;
create table ibes
as select a.*, sum(pdf='P') as p_count, sum(pdf='D') as d_count
from ibes as a
 group by ticker, fpedats;

* a. Link unadjusted estimates with unadjusted actuals and
 CRSP permnos;
* b. Adjust report and estimate dates to be CRSP trading days;
create table ibes1 (&ibes2_where)
as select a.*, b.anndats as repdats, b.value as act, c.permno,
case when weekday(a.anndats)=1 then intnx('day',a.anndats,-2)
when weekday(a.anndats)=7 then intnx('day',a.anndats,-1) else
a.anndats
```

```
end as estdats1,
case when weekday(b.anndats)=1 then intnx('day',b.anndats,1)
when weekday(b.anndats)=7 then intnx('day',b.anndats,2) else
b.anndats
%end as repdats1
%from ibes as a, ibes.actu_epsus as b, mylib.iclink as c
%where a.ticker=b.ticker and a.fpedats=b.pends and
a.usfirm=b.usfirm
%and b.pdicity='QTR'
and b.measure='EPS' and a.ticker=c.ticker and c.score in (0,1,2);

*   Making sure that estimates and actuals are on the same basis;

*1. retrieve CRSP cumulative adjustment factor for IBES
report and estimate dates;
create table adjfactor
as select distinct a.*
from crsp.dsf (keep=permno date cfacshr) as a, ibes1 as b
where a.permno=b.permno and (a.date=b.estdats1 or
a.date=b.repdats1);

*2.if adjustment factors are not the same, adjust the
estimate to be on the same
basis with the actual;
create table ibes1
as select distinct a.*, b.est_factor, c.rep_factor,
```

```
case when (b.est_factor ne c.rep_factor) and
missing(b.est_factor)=
0 and missing(c.rep_factor)=0
then (rep_factor/est_factor)*value else value end
as new_value
from ibes1 as a,
adjfactor (rename=(cfacshr=est_factor)) as b,
adjfactor (rename=(cfacshr=rep_factor)) as c
where (a.permno=b.permno and a.estdats1=b.date) and
(a.permno=c.permno and a.repdats1=c.date);
quit;

* Make sure the last observation per analyst is included;
proc sort data=ibes1;
by ticker fpedats estimator analys anndats revdats;
run;

data ibes1; set ibes1;
by ticker fpedats estimator analys;
if last.analys;
run;

* Compute the median forecast based on estimates in
the 90 days prior to the
 report date;
proc means data=ibes1 noprint;
```

```
by ticker fpedats;
var new_value;
* new_value is the estimate
appropriately adjusted;
output out= medest (drop=_type_ _freq_)
median=medest n=numest std=dispersion;
* SUBJECT TO
CHANGE: medest = MEDIAN or MEAN;
run;

* Merge median estimates with ancillary information
on permno, actuals
and report dates;
* Determine whether most analysts are reporting
estimates on primary

 or diluted basis;
* following the methodology outlined in Livnat and
Mendenhall (2006);
proc sql; create table medest
as select distinct a.*, b.repdats, b.act, b.permno,
case when p_count>d_count then 'P'
when p_count<=d_count then 'D'
end as basis
from medest as a left join ibes1 as b
on a.ticker=b.ticker and a.fpedats=b.fpedats;
```

```
quit;

proc sql;
drop table ibes, ibes1;
quit;
%MEND;

%IBES_SAMPLE (infile=tickers, ibes1_where=
&ibes_where1, ibes2_where
=&ibes_where2, ibes_var=&ibes_vars);

*COMPUSTAT EXTRACT;
proc sql;
create table gvkeys
as select a.*
from cibeslnk as a, tickers as b
where a.ticker=b.ticker;
*use CIBESLNK table to link IBES Ticker and GVKEY;

create table comp (drop=consol indfmt datafmt popsrc)
as select a.*, cshoq*prccq as mcap
from comp.fundq (keep=&comp_list &comp_where) as a,
gvkeys as b
where a.gvkey=b.gvkey;

create table comp
```

```
as select *
from comp a left join
(select distinct gvkey,ibtic from comp.security
(where=(missing(ibtic)=0))) b
on a.gvkey=b.gvkey;
quit;

*Create calendar date of fiscal period end in Compustat
extract;
data comp; set comp;
if (1<=fyr<=5) then date_fyend=
intnx('month',mdy(fyr,1,fyearq+1),0,'end');
else if (6<=fyr<=12) then date_fyend=
intnx('month',mdy(fyr,1,fyearq),0,'end');
fqenddt=intnx('month',date_fyend,-3*(4-fqtr),'end');
format fqenddt date9.;
drop date_fyend;
run;

* a) Link Gvkey with Lpermno;
proc sql;
create table comp1
as select a.*, b.lpermno
from comp (where=(&begindate<=fqenddt<=&enddate))
as a left join lnk as b
on a.gvkey=b.gvkey and ((b.linkdt<=a.fqenddt <=b.linkenddt) or
```

```
(b.linkdt<=a.fqenddt and b.linkenddt=.E) or
(b.linkdt=.B and a.fqenddt <=b.linkenddt));

* b) Link Gvkey with IBES Ticker;
create table comp1
as select a.*, b.ticker
from comp1 as a left join cibeslnk as b
on a.gvkey=b.gvkey and ((b.fdate<=a.fqenddt <=b.ldate) or
(b.fdate<=a.fqenddt and b.ldate=.E) or
(b.fdate=.B and a.fqenddt <=b.ldate))

* c) Link IBES analysts' expectations (MEDEST),
IBES report dates (repdats)
* and actuals (act) with Compustat data;
create table comp1
as select a.*, b.medest, b.numest, b.dispersion, b.repdats,
 b.act, b.basis
from comp1 as a left join medest as b
on a.ticker=b.ticker and
year(a.fqenddt)*100+month(a.fqenddt)=year(b.fpedats)
*100+month(b.fpedats);
quit;

*remove fully duplicate records and pre-sort;
proc sort data=comp1 noduprec; by _all_;run;
proc sort data=comp1; by gvkey fyearq fqtr;run;
```

```
proc sort data=comp1;
*descending sort is intenational to define leads;
by gvkey descending fyearq descending fqtr;
run;

* Shifting the announcement date to be a trading day;
* Defining the day after the following quarterly earnings
 announcement as
leadrdq1;
data retdates; set comp1;
by gvkey;
leadrdq=lag(rdq);
if first.gvkey then leadrdq=intnx('month',rdq,3,'sameday');
*if sunday move back by 2 days, if saturday move back by 1 day;
if weekday(rdq)=1 then rdq1=intnx('day',rdq,-2); else
f weekday(rdq)=7 then rdq1=intnx('day',rdq,-1); else rdq1=rdq;
if weekday(leadrdq)=1 then leadrdq1=intnx('day',leadrdq,2); else
if weekday(leadrdq)=7 then leadrdq1=intnx('day',leadrdq,3); else
if weekday(leadrdq)=6 then leadrdq1=intnx('day',leadrdq,3); else
leadrdq1=intnx('day',leadrdq,1);
if leadrdq=rdq then delete;
format rdq1 leadrdq1 date9.;
run;

* Extract file of raw daily returns around between
```

```
 earnings announcement dates;

proc sql;
create table dsex1
as select a.permno, a.date, a.ret, b.exchcd, b.shrcd
from crsp.msf(keep=permno ret date where=
(&begindate<=date<=&enddate))
as a
left join crsp.dseall(keep=date permno exchcd shrcd) as b
on a.permno=b.permno and a.date= b.date;
quit;

* Complete the time series for exchcd & shrcd and select
all common stocks;
proc sort data=dsex1; by permno date; run;

data dsex2;
set dsex1;
by permno date;
retain lexchcd lshrcd;
if first.permno then
do;
lexchcd = exchcd ;
lshrcd  = shrcd;
end;
else
```

```
do;
if missing(exchcd) then exchcd = lexchcd;
else lexchcd = exchcd;
if missing(shrcd)  then shrcd = lshrcd;
else lshrcd = shrcd;
end;
run;

proc sql;
create table crsprets
as select a.*, b.*
from dsex2 as a,
retdates (where=(missing(rdq1)=0 and missing(leadrdq1)=0 and
30<intck('day',rdq1,leadrdq1))) as b
where a.permno=b.lpermno and rdq1<=a.date<=leadrdq1;
quit;

proc sort data=crsprets;
by permno date fyearq fqtr;
run;

* Clean duplicates, choose exchange NYSE/Nasdaq/AMEX;
data crsprets; set crsprets;
if date ne lag(date);
if exchcd in (1,2,3); * NYSE and AMEX and Nasdaq securities only;
if shrcd in (10,11) and not missing(ret); * Common Stocks only;
```

```
run;

* Drop things not need;
data crsp_compustat;
set crsprets (keep= date ticker ret epsfxq epspxq saleq
mcap medest invtq
chq cshoq rectq oancfy actq lctq dpq ppentq permno ceqq);
bm=ceqq/mcap;
run;

*------------------------------------------*
Merge crsp_compustat with oclink
*------------------------------------------*

%OCLINK;
* Merge CRSP_Compustat with Optionmetrics
proc sql;
create table mylib.crsp_compustat_oclink
as select a.*, b.permno
from mylib.crsp_compustat as a, mylib.oclink as b
where a.secid=b.secid
and b.score in (0,1,2);
quit;

*------------------------------------------*
Prepare Macro LASTDAY to get the last date of each
```

```
month from data
*------------------------------------------*
%macro LASTDAY(in_data= , out_data= );

proc sql;
create table dtemp1
as select *
from &in_data;
quit;

proc sort data=dtemp1; by date; run;

data dtemp2;
set dtemp1;
*nwdate=mdy(month(date),24, year(date));
nwdate=intnx ('month',date,0,'E'); * mdy(month(date),24, year(date));
format nwdate yymmddn8.;
run;

*Pick the last day of the month;
proc sql;
create table mtemp_days2
as select max(date) as last_day format yymmddn8.
from dtemp2
group by nwdate;
quit;
```

```
*Pick the data which corresponds to the last day of the month;
proc sql;
create table mtemp_days3
as select *
from dtemp2 a
inner join mtemp_days2 b
on a.date=b.last_day;
quit;

data &out_data;
set mtemp_days3 (drop=date rename=(nwdate=date    ));
run;

%mend LASTDAY;

*------------------------------------------*
Get Lastday of month for data
*------------------------------------------*
%LASTDAY(in_data=crsp.msf, out_data=work.msf);

proc sql;
create table crsp_compustat_optionm
as select a.*, b.ret, b.last_day as date_crsp
from mylib.crsp_compustat_oclink (drop=return) as a,msf as b
where a.permno=b.permno and a.date=b.date;
```

```
*-----------------------------------------*
Get weekly_var for crsp returns
*-----------------------------------------*;
%let begindate='01jan1996'd;
 * start calendar date of fiscal period end;
%let enddate='31dec2013'd;

proc sql;
create table crsprets
as select a.permno, a.date, a.ret, b.exchcd, b.shrcd
from crsp.dsf(keep=permno ret date where=
(&begindate<=date<=&enddate))
as a
left join crsp.dseall(keep=date permno exchcd shrcd) as b
on a.permno=b.permno and a.date= b.date;
quit;

proc sql;
create table crsprets_index
as select a.*, b.vwretd
from crsprets as a inner join crsp.dsi as b
on a.date= b.date;
quit;

%macro RRLOOP (in_ds = crsprets_index, out_ds=mylib.out_ds);
```

```
%let year1=1996;
%let year2=2013;

%local date1 date2 date1f date2f yy mm;

/*Extra step to be sure to start with clean, null
 datasets for appending*/
proc datasets nolist lib=work;
delete all_ds_sort1 oreg_ds1 oreg_ds1_sort1 all_temp;
run;

data all_temp;
set &in_ds;
run;

/*Loop for years and months*/
%do yy = &year1 %to &year2;
%do mm = 1 %to 12;

 /*Set date2 for mm-yy end point and date1 as 24 months prior*/
 %let date1=%sysfunc(mdy(&mm,1,&yy));
 %let date1= %sysfunc (intnx(month, &date1, 0,beginning)); *set
 DATE1 as first day of same month;
 %let date2 = %sysfunc (intnx(month, &date1, 11,end)); *Make the
  DATE2 last day of 12 month;
```

```
 /*FYI --- INTNX quirk in SYSFUNC:  do not use quotes with 'month'
  'end' and 'begin'*/

/*An extra step to be sure the loop starts with a clean (empty)
dataset for combining results*/

proc datasets nolist lib=work;
  delete oreg_ds1 oreg_ds2 oreg_ds_sort1 port1 port2 port3 port4;
run;

/*Regression model estimation -- creates output set with coefficient
 estimates*/
proc reg noprint data=all_temp outest=oreg_ds1 edf;
  where date between &date1 and &date2;  *Restricted to DATE1-
  DATE2 data range in the loop, and check if there is
  a valid return for 1 year;
  model ret = vwretd;
  by permno;
run;

/*Store DATE1 and DATE2 as dataset variables
and rename regression coefficients as ALPHA and BETA;*/
data oreg_ds1;
  set oreg_ds1;
  date1=&date1;
```

```
  date2=&date2;
  rename intercept=alpha  vwretd=beta_mkt ;
  nobs= _p_ + _edf_;
  format date1 date2 yymmdd10.;
run;

data oreg_ds2;
set oreg_ds1;
if nobs>220;
run;

/*Append loop results to dataset with all date1-date2 observations*/
proc datasets lib=work;
  append base=all_ds_sort1 data=oreg_ds2;

run;

 %end;  /*MM month loop*/

%end;  /*YY year loop*/

/*Save results in final dataset*/

data &out_ds;
  set all_ds_sort1;
run;
```

```
%mend RRLOOP;

%RRLOOP;

* Merge out_ds with crsp_daily

%let begindate='01jan1996'd;         * start calendar date of fiscal
period end;
%let enddate='31dec2013'd;

proc sql;
create table crsprets
as select a.permno, a.date, a.ret, b.exchcd, b.shrcd
from crsp.dsf(keep=permno ret date where=(&begindate<=date
<=&enddate)) as a
left join crsp.dseall(keep=date permno exchcd shrcd) as b
on a.permno=b.permno and a.date= b.date;
quit;

proc sql;
create table crsprets_index
as select a.*, b.vwretd
from crsprets as a inner join crsp.dsi as b
on a.date= b.date;
quit;
```

```
proc sql;
create table mylib.crsprets_beta as
select a.*, b.alpha, b.beta_mkt, b.date2
from crsprets_index as a, mylib.out_ds as b
where INTCK('MONTH', a.date, b.date2) = 0
and a.permno = b.permno
order by permno, date;
quit;

proc sql;
create table new as
select *, ret - alpha - beta_mkt*vwretd as epsilon
from mylib.crsprets_beta;
quit;

data new2;
set new;
year = YEAR(date);
month = MONTH(date);
week = WEEK(date);
wdate=1000*YEAR(date)+10*WEEK(date)+WEEKDAY(date);
wweek=100*YEAR(date)+WEEK(date);
run;

proc summary
```

```
data=new2 nway;
*class permno year month;
class permno wweek;
var epsilon;
*output out=month_var var=;
output out=week_var var=;
run;

proc sort data = week_var;
by permno wweek;
run;

*data month_var2;
data week_var2;
*set month_var;
set week_var;
by permno;
epslag1 = lag1(epsilon);
epslag2 = lag2(epsilon);
epslag3 = lag3(epsilon);
epslag4 = lag4(epsilon);
epslag5 = lag5(epsilon);
epslag6 = lag6(epsilon);
epslag7 = lag7(epsilon);
epslag8 = lag8(epsilon);
epslag9 = lag9(epsilon);
```

```
epslag10 = lag10(epsilon);
epslag11 = lag11(epsilon);
epslag12 = lag12(epsilon);
epslag13 = lag13(epsilon);
epslag14 = lag14(epsilon);
epslag15 = lag15(epsilon);
epslag16 = lag16(epsilon);
epslag17 = lag17(epsilon);
epslag18 = lag18(epsilon);
epslag19 = lag19(epsilon);
epslag20 = lag20(epsilon);
epslag21 = lag21(epsilon);
epslag22 = lag22(epsilon);
epslag23 = lag23(epsilon);
epslag24 = lag24(epsilon);
run;

*--------------------------------------------*
Run R with week_var2 dataset
*--------------------------------------------*;
library(foreign)
rm(list=ls(all=TRUE))
#setwd("~/Desktop")
#data<-read.csv("month_var2.csv")
data<-read.csv("week2_var.csv")
data<-data.frame(data,matrix(,nrow=dim(data)[1],ncol=3))
```

```
colnames(data)[(length(colnames(data))-1):length(colnames(data))]
<-c('max','max_2nd','is_event')
data$is_event=0
permno<-unique(data$PERMNO)
for (i in 1:length(permno))
{
df2<-subset(data,PERMNO==permno[i])
for (j in 1:dim(df2)[1])
{
if(!is.na(df2[j,6]))
{
      max = df2[j,6]
    }
    else
    {
      max = 0
    }
    max_2nd = 0
    for (k in 1:23)
    {
      if(!is.na(df2[j,6+k]))
      {
        if(df2[j,6+k] > max)
        {
          max_2nd = max
          max = df2[j,6+k]
```

```
        }
        else if(df2[j,6+k] > max_2nd)
        {
          max_2nd = df2[j,6+k]
        }
      }
    }
    df2[j,]$max = max
    df2[j,]$max_2nd = max_2nd
    if(!is.na(df2[j,]$epsilon))
    {
      if(df2[j,]$max_2nd <= df2[j,]$epsilon)
      {
        df2[j,]$is_event = 1
      }
    }

  }
  data[data$PERMNO==permno[i],] = df2
}
write.dbf(data,"weekevent.dbf")

*------------------------------------------*
Merge weekevent.dbf with crsp_compustat_optionm
*------------------------------------------*;
```

```
*-----------------------------------------*
Sort crsp_compustat_optionm_weekevent
*-----------------------------------------*;
%macro Sortdifimpl (in_ds=
crsp_compustat_optionm_weekevent);

%let year1=1996;
%let year2=2013;

%local date1 date2 yy mm k;

/*Extra step to be sure to start with clean, null datasets
 for appending*/
proc datasets nolist lib=work;
delete all;
run;

/*Loop for years and months*/
 %do yy = &year1 %to &year2;
   %do mm = 1 %to 12;

 /*Set date2 for mm-yy end point and date1 as 24 months prior*/
 %let date2=%sysfunc(mdy(&mm,1,&yy));
 %let date2= %sysfunc (intnx(month, &date2, 0,end)); *Make the
 DATE2 last day of the month;
 %let date1 = %sysfunc (intnx(month, &date2, 0, beginning)); *set
```

```
 DATE1 as first day of same month;
 /*FYI --- INTNX quirk in SYSFUNC:  do not use quotes with 'month'
 'end' and 'begin'*/

/*An extra step to be sure the loop starts with a clean (empty) dataset
 for combining results*/
proc datasets nolist lib=work;
  delete temp1 temp2 temp3;
run;

proc sql;
create table temp1 as
select * from &in_ds
where date between &date1 and &date2;
run;

proc sort data=temp1 out=temp2; by difimpl; run;
proc rank data=temp2 out=temp3 group=5;
  var difimpl;
  ranks rnk_difimpl;
run;

data temp3; set temp3;
rnk_difimpl=rnk_difimpl+1;
run;
```

```
/*Append loop results to dataset with all date1-date2
observations*/
proc datasets lib=work;
  append base=all data=temp3;
run;

 %end;  /*MM month loop*/

%end;  /*YY year loop*/

/*Save results in final dataset*/
data mylib.all_sorted;
  set all;
run;

%mend Sortdifimpl;
%Sortdifimpl;

*------------------------------------------*
Summary Stat
*------------------------------------------*;

%let T=1;
proc datasets nolist lib=work;
  delete out1 out2 out3 out4 out5 out6;
run;
```

```
*match the next month return with this month difimpl;
proc sql;
create table out1
as select a.permno, a.date_end as date1, a.difimpl,
a.impl, a.skew,
a.permno, a.rnk_cumret, a.rnk_skew, a.mcap, a.cum_return,
a.delta_difimpl, b.date_end as date2, b.ret, b.impl as
 impl_new, b.difimpl
as difimpl_new, b.mcap as mcap_new, b.skew as skew_new,
b.cum_return as cum_return_new, b.delta_difimpl as
delta_difimpl_new
from mylib.all as a, mylib.all
where b.date_end=intnx('month', a.date_end, &T, 'end')
and a.permno=
b.permno;
quit;

proc sort data=out1; by permno date1;

data out1;
set out1;
if mcap="." & permno=lag(permno) then mcap=lag(mcap);
if mcap="." & permno ne lag(permno) then mcap=0;
run;
```

```
proc sort data=out1; by date1 rnk_difimpl ;


proc means data=out1 noprint;
var ret impl impl_new difimpl difimpl_new mcap
mcap_new skew
skew_new cum_return cum_return_new delta_difimpl
delta_difimpl_new;
weight mcap;
by date1 rnk_difimpl;
output out=out2 mean=ret impl impl_new difimpl
difimpl_new mcap
mcap_new skew skew_new cum_return cum_return_new
delta_difimpl
delta_difimpl_new;
run;


proc sort data=out2; by rnk_difimpl


proc means data=out2 noprint;
var ret impl impl_new difimpl difimpl_new mcap
mcap_new skew
skew_new cum_return cum_return_new delta_difimpl
delta_difimpl_new;
by rnk_difimpl;
output out=out4 mean=ret impl impl_new difimpl
difimpl_new mcap
```

```
mcap_new skew skew_new cum_return cum_return_new
delta_difimpl
delta_difimpl_new;
run;

*------------------------------------------*
Industry
*------------------------------------------*;
%include '/user/user2/cxie15/ff12.sas';

data new;
set crsp_compustat_optionm;
 if missing(ffi12)=1 and missing(hsiccd)=0 then
 %FFI12(hsiccd);
 run;

proc sort data=new;
by date ffi12;
run;

proc means data=new noprint;
var ret impl difimpl mcap skew delta_difimpl;
by date ffi12;
output out=out2 mean=ret impl difimpl mcap skew
delta_difimpl;
run;
```

```
proc sort data=out2;
by ffi12;
run;
proc means data=out2 noprint;
var ret impl difimpl mcap skew delta_difimpl;
by ffi12;
output out=out3 mean=ret impl difimpl mcap skew
delta_difimpl;
run;

proc sort data=out3;
by difimpl;
run;

proc sort data=out3 nodup out=new2;
by ffi12;
quit;

proc sort data=new2;
by difimpl;
run;

*-------------------------------------------*
Sorted by IV, Slope
*-------------------------------------------*;
```

```
%macro Sortdelta_rvts (in_ds=
crsp_compustat_optionm_weekevent);

%let year1=1996;
%let year2=2013;

%local date1 date2 yy mm k;

/*Extra step to be sure to start with clean,
null datasets for appending*/
proc datasets nolist lib=work;
delete all;
run;

/*Loop for years and months*/
 %do yy = &year1 %to &year2;
   %do mm = 1 %to 12;

 /*Set date2 for mm-yy end point and date1
 as 24 months prior*/
 %let date2=%sysfunc(mdy(&mm,1,&yy));
 %let date2= %sysfunc (intnx(month, &date2,
 0,end)); *Make the DATE2
  last day of the month;
 %let date1 = %sysfunc (intnx(month, &date2,
```

```
 0, beginning)); *set DATE1
  as first day of same month;
 /*FYI --- INTNX quirk in SYSFUNC:  do not
 use quotes with 'month'
 'end' and 'begin'*/

/*An extra step to be sure the loop starts with
a clean (empty) dataset
for combining results*/
proc datasets nolist lib=work;
  delete temp1 temp2 temp3;
run;

proc sql;
create table temp1 as
select * from &in_ds
where date_end between &date1 and &date2;
run;

proc sort data=temp1 out=temp2; by impl; run;
proc rank data=temp2 out=temp3 group=5;
  var impl;
  ranks rnk_impl;
run;
proc sort data=temp3 out=temp4; by difimpl; run;
proc rank data=temp4 out=temp5 group=5;
```

```
  var difimpl;
  ranks rnk_difimpl;
run;

data temp5; set temp5;
rnk_difimpl=rnk_difimpl+1;
rnk_impl=rnk_impl+1;
run;

/*Append loop results to dataset with all
date1-date2 observations*/
proc datasets lib=work;
  append base=all data=temp5;
run;

 %end;  /*MM month loop*/

%end;  /*YY year loop*/

/*Save results in final dataset*/
data mylib.all_2;
  set all;
run;

%mend Sortdelta_rvts;
%Sortdelta_rvts;
```

```
data optionm_crsp_1208_rdq;
set mylib.optionm_crsp_1208;
if  date ne intnx('month', rdq, 0, 'end');
run;

%macro Sortdelta_difimpl (in_ds=
optionm_crsp_1208_rdq);

%let year1=1996;
%let year2=2013;

%local date1 date2 yy mm k;

/*Extra step to be sure to start with clean, null datasets
for appending*/
proc datasets nolist lib=work;
delete all;
run;

/*Loop for years and months*/
 %do yy = &year1 %to &year2;
   %do mm = 1 %to 12;

 /*Set date2 for mm-yy end point and date1
 as 24 months prior*/
```

```
 %let date2=%sysfunc(mdy(&mm,1,&yy));
 %let date2= %sysfunc (intnx(month, &date2
 , 0,end)); *Make the
 DATE2 last day of the month;
 %let date1 = %sysfunc (intnx(month, &date2
 , 0, beginning)); *set
 DATE1 as first day of same month;
 /*FYI --- INTNX quirk in SYSFUNC:  do not
 use quotes with 'month'
  'end' and 'begin'*/

/*An extra step to be sure the loop starts with a
clean (empty) dataset
 for combining results*/
proc datasets nolist lib=work;
  delete temp1 temp2 temp3;
run;

proc sql;
create table temp1 as
select * from &in_ds
where date_end between &date1 and &date2;
run;

proc sort data=temp1 out=temp2; by difimpl; run;
proc rank data=temp2 out=temp3 group=5;
```

```
  var difimpl;
  ranks rnk_difimpl;
run;

data temp3; set temp3;
rnk_difimpl=rnk_difimpl+1;
run;

/*Append loop results to dataset with all date1-date2
 observations*/
proc datasets lib=work;
  append base=all data=temp3;
run;

 %end;  /*MM month loop*/

%end;  /*YY year loop*/

/*Save results in final dataset*/
data mylib.all_1208_rdq;
  set all;
run;

%mend Sortdelta_difimpl;
%Sortdelta_difimpl;
```

```
*-----------------------------------------*
Phase III
*-----------------------------------------*;
proc sql;
create table crsp_fda as select
a.*, b.date as event_date from
crsp_compustat_optionm_weekevent
as a, fda as b
where a.ticker=b.ticker;
quit;

data crsp_fda2;
set crsp_fda;
if INTCK('MONTH', date, event_date) = 0;
run;

proc sort data=crsp_fda; by date; run;

proc means data=crsp_fda noprint;
        var ret;
        by date;
        output out=out1 mean=ret;
run;

proc means data=out1 noprint;
        var ret;
```

```
        output out=out2 mean=ret;
run;

proc sort data=crsp_fda2; by date; run;

proc means data=crsp_fda2 noprint;
        var ret;
        by date;
        output out=out3 mean=ret;
run;

proc means data=out3 noprint;
        var ret;
        output out=out4 mean=ret;
run;

*-------------------------------------------*
Volume
*-------------------------------------------*;
data test;
set mylib.all;
vol_new=vol/crshoq;
run;

ods listing close;
proc means data=out1 mean n std t probt median p5 p95 ;
```

```
var difimpl skew ret impl mcap vol_new vol;
ods output summary=Portf_Stats_ew3;
run;
```