# A Telltale About Asset Prices

# *A Telltale About Asset Prices: An Options Perspective*

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# *A Telltale About Asset Prices: An Options Perspective*

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# Acknowledgments

I remember my first day of school, when I was only six years old, September 8th, 1994. Excited about the new adventure but nervous of not knowing anyone there, I was going to the school with my parents. Just before saying goodbye and leaving me with my new friends, my father gave me an unforgettable piece of advice:

***"The first step in order to become a great man is to hang out with great people; their good traits will teach you how to become great."***

Today, looking back at my father's advice 23 years later, I am very happy that I have always been surrounded by great people. I would like to use the next few paragraphs to express my heartiest gratitude to those who supported me over the past four years.

It was June 15th, 2013 when I first came to Maastricht University to meet my supervisor, Dennis Bams. That day, I got to know not only my supervisor but also the type of man I would like to be. Dennis is the ultimate man of balance in life: he is a great researcher, an outstanding businessman and a fantastic man-of-family. I am heartily grateful to him for his patient guidance, excellent support and brilliant advice in every stage of my PhD. Besides his friendliness, his creativity in conceptual development and exactitude in writing are admirable.

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When in December 2011, I went to FinLab for my six-month internship interview, I could not imagine that our collaboration will last for more than six years. Over this relatively long time, I learned many new things from my incredibly friendly colleagues. I am thankful to Denis de Pentheny O'Kelly for his fatherly advise in different occasions and Arnaud Baiges for trusting me with challenging tasks. I am also grateful to Amirhossein Farman-Farmaian, my fellow Iranian colleague, for teaching me VBA and the good memories of playing golf in the office.

I am grateful to the best family in the world; to my mother and my father, who do not wish anything but the success of their children. I do not want anything but their health and happiness. Being away from you is really hard. As the last kid of a four-kid family, I was always inspired by two fantastic brothers and the best sister anyone could wish for. I miss you, every moment of being away from you.

And finally, I would like to thank the person who was with me day and night over the past four years. The person with whom, I feel happy and proud. The person whose smile makes me happy. The person that I love. I am thankful to Iulia Elena Falcan for her kindness, sweetness and love.

I believe just like a portfolio, a person's assets, skills and interests must be diversified. It is nice to have a good house and a good job. It is nice to have a beautiful mind and a healthy body. It is nice to be able to play a musical instrument well and to perform in a sport professionally. In this "personality portfolio", the family and good friends are the heavenly safe haven assets; when things go wrong, they do not let you down. They have positive "Co-skewness". They are very precious!

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# Chapter 1

# Introduction

## 1.1 Derivative Markets

Today, derivative assets have become one of the most important members of the assets family, and they have been cherished or blamed as the origin of many good and bad events in the history of finance. While they are extremely useful instruments for transferring risk from someone who does not want to take it to someone who want to manage it, derivative assets have been regarded as the starting point of the recent financial and credit crisis in 2007 to 2009.

As the name suggests, the payoff of a derivative contract is derived from (depends on) certain underlying variables. For instance, for a weather derivative the underlying variable can be the average temperature or the amount of rainfall over a month in a specific place, and for a forward contract the underlying variable might be the price of a particular stock.

While evidence of trade with money goes back to the Sumerians (between 4500 BC and 4000 BC), the records of the first derivative contracts were found in the Code of Hammurabi, dating back to 1754 BC. Hammurabi, who lived from 1810 BC to 1750 BC, was the sixth king of the first Babylonian Dynasty in Mesopotamia. In article 100 of the Code of Hammurabi, he rules that a merchant, who borrows money, must return it with interest. Articles 101 and 102 emphasize that money must be paid back, no matter the merchant's trade is successful or not. Up until here, these definitions recall the terms of a zero-coupon bond. However in article 103, a contingency is added to these terms of repayment: "*If, while on the journey, an enemy take away from him anything that he had, the broker shall swear by God and be free of obligation.*" (This phrase is borrowed from the translation of King (1910).) According to article 103, the amount of money that the lender receives depends on an incident; if the merchant has not been robbed, the lender gets his full money and its interest back, but if the merchant has been robbed the lender gets nothing. Interestingly, these contracts were tradable and credit could transfer from one person to another. Geoffrey Parker, a British historian from the Ohio State University, recounts other evidence for commodity derivatives trading by the Mesopotamians as the earliest recorded uses of derivatives in human societies.

Historical studies show that derivative contrasts have been further developed and used by various ancient nations. From Thales of Miletus (624 BC – 546 BC), who invented and traded the first call option on the use of olive presses, to the Romans (from 27 BC), who engaged in trading commodities with delivery in the future, derivatives became an important tool for hedging and speculation on asset prices. In modern history the trade of derivatives continued with the permission of Charles V (24 February 1500 - 21 September 1558) to trade commodity contracts with delivery in the future, and it flourished with the trade of tulips futures during the tulip mania of the seventeenth century in The Netherlands.

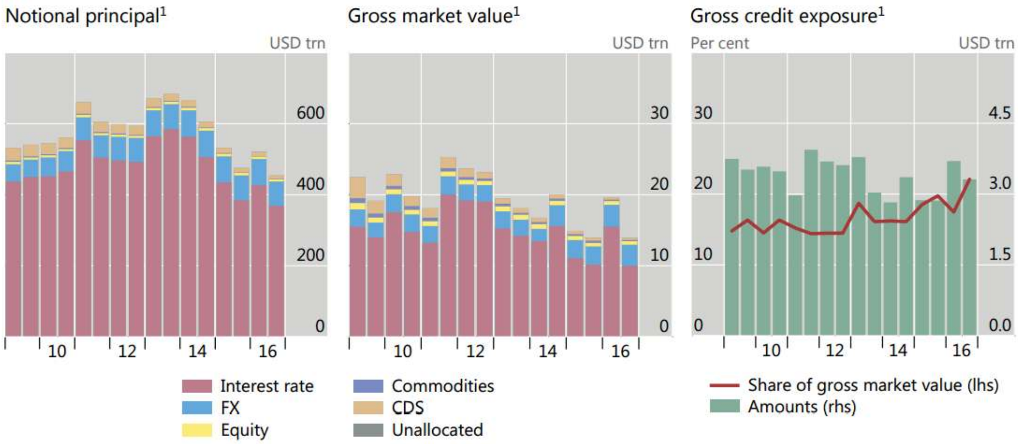
Throughout the recent centuries, the size and the diversity of derivative markets grew substantially. But perhaps one major development was the openings of the Chicago Board of Trade, in 1848, and the Chicago Mercantile Exchange, in 1898. In 2007, these two markets merged to form the world's largest options and futures exchange, named as the Chicago Mercantile Exchange Group or shortly the CME Group.

According to the Bank of International Settlement (BIS), in December 2016, the notional amount of outstanding OTC derivatives contracts, which determines contractual payments, stood at 483 trillion dollars. (See Bank of International Settlement (2017).) Comparing this number with an estimation of the International Monetary Fund on the world GDP at 2016, that is just over 75 trillion dollars, reveals the overwhelmingly large size of the derivatives markets. (See International Monetary Fund (2017).) Also the BIS reports that, at the same time, the gross market value of outstanding derivatives contracts, which provides a more meaningful measure of amounts at risk, was over 15 trillion dollars and the gross credit exposures, which adjust gross market values for legally enforceable bilateral netting agreements, amounted to 3.3 trillion dollars. Figure (1.1), from the BIS website, displays the size of the Global OTC derivatives markets over the past few years. In this figure, each bar represents one half of a calendar year.

## 1.2 Derivative-Implied Information

As already mentioned the payoff of a derivative contract is derived from certain underlying variables. For instance, let's have a closer look at Heating Degree Days (HDD) futures, traded on the CME. These contracts are written on the temperature of a specified city over each month. For these contracts, the underlying variable is the HDD

Figure 1.1: Size of Global OTC Derivatives Markets




Further information on the BIS derivatives statistics is available at www.bis.org/statistics/derstats.htm.

[1] At half-year end (end-June and end-December). Amounts denominated in currencies other than the US dollar are converted to US dollars at the exchange rate prevailing on the reference date.

index that is the sum of the average degrees that the outside air temperature drops below the base of 65 degrees of Fahrenheit.[1] Over a cold month, the HDD index is high. In summers, electricity companies can smoothen (hedge) their revenue by buying some HDD futures. Then if the weather gets colder and the use of electricity for air conditioning declines, the HDD futures expire in-the-money, and thus, their positive payoff compensates for the reduced sale of electricity.

If the electricity companies expect a cool upcoming summer, buying HDD futures is even more desirable. Hence, the expectation of a cold summer leads to higher prices for these futures contracts. The link between investors' weather expectation and the price of HDD futures is just one example that shows the impact of investors' expectation about the future value of the underlying variable and the derivative price.

Financial markets are constituted of heterogeneous investors with different expectations and objective functions. Observing and measuring the expectation of every investor is virtually impossible. In an arbitrage-free market, every asset has only one observable trading price at any point in time. All the information on investors' expectations about the underlying variable is summarized in a unique derivative price. Or saying it differently, this derivative price hints about the overall expectation of investors' on the future value of the underlying variable. Hence, derivative prices can be used to exploit valuable

[1] For further details, please see the website of the CME Group at: http://www.cmegroup.com/trading/weather/temperature/us-monthly-weather-heating_contract_specifications.html.

information about investors' believes on important market variables.

Remember the first derivatives, invented by the Mesopotamians. According to these contracts, if the merchant was robbed during his journey, the lender would lose his principal and interest. Imagine that a lender wants to sell his contract to another person. Rationally, a new lender must be compensated for the risk of robbery. The higher the risk of robbery, the lower the price of the contract should be. While measuring the risk of robbery is relatively complicated, the transaction price of the derivative hints about lenders' expectation on the risk of robbery.

Similarly, a higher price of HDD futures contracts implies an expectation of a cooler upcoming summer, and a more expensive credit default swap contracts suggests a higher probability of default for the corresponding debtors. These precious information that can be exploited from derivative prices is called derivative-implied information. One of the most well-known derivative-implied information is the VIX index.

## 1.3 VIX Index

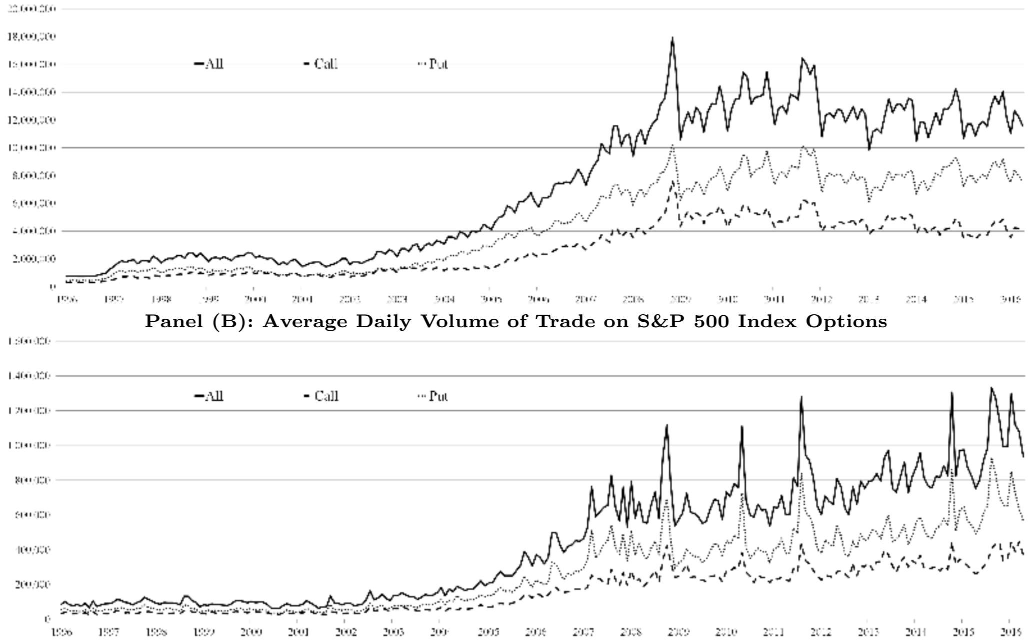
The idea of having an index for the market volatility and trading hedging instruments on that was first brought up by Brenner and Galai (1989). This idea was further developed by Whaley (1993) and finally in January 1993, the Chicago Board of Option Exchange (CBOT) announced the launch of reporting the VIX index. Whaley (2009) explains that: "*Conceptually, VIX is like a bond's yield to maturity. Yield to maturity is the discount rate that equates a bond's price to the present value of its promised payments. As such, a bond's yield is implied by its current price and represents the expected future return of the bond over its remaining life. In the same manner, VIX is implied by the current prices of S&P 500 index options and represents expected future market volatility over the next 30 calendar days.*"

At any point in time, the VIX index reflects investors' aggregate expectation about the market volatility over the next 30 days. Since the VIX index is extracted from price of the options, written on the S&P 500, the VIX is also referred to as the option-implied volatility of the market. The large number of open interest and huge volume of trade on S&P 500 index options are ideal for an accurate computation of the VIX. Panel (A) in figure (1.2) shows the average number of open interest of the options on the S&P 500 index for each month, from January 1996 to April 2016. Moreover, Panel (B) in the same figure displays the average daily volume of trade on the S&P 500 index options in each month.

Today, the VIX index is the most important and well-known derivative-implied information among both academics and practitioners. Academics refer to this index with different names such as the risk-neutral volatility of the market or the second-moment

Figure 1.2: Average Number of Open Interest and Trade Volume on S&P 500 Index Options

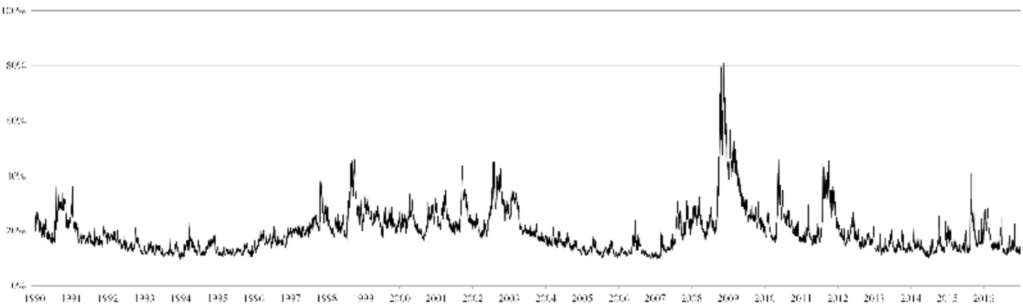
**Panel (A): Average Number of Open Interest on S&P 500 Index Options**




**Source: OptionMetrics Database**

of the market, and practitioners label it as the fear index or the uncertainty index of the market. Figure (1.3) displays the time series of the VIX index from January 1990 to December 2016.

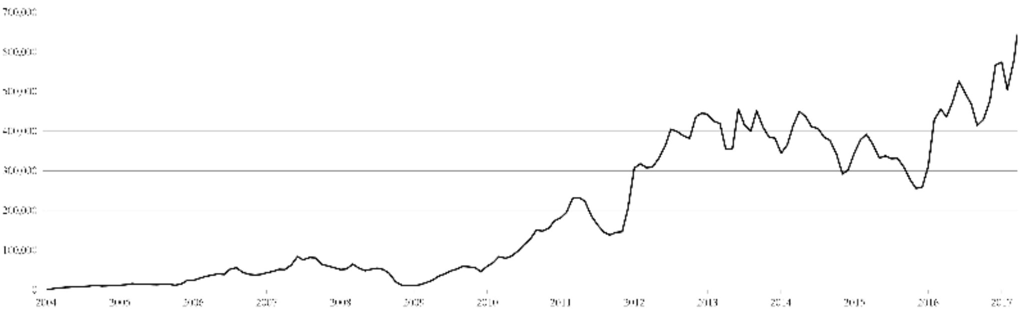
Figure 1.3: VIX Index



**Source: CBOE Website**

Hedging against market volatility risk started with the first trades on VIX futures in 2004. Later in 2006, the CBOE also launched a platform for the trade of options on the VIX index. Figure (1.4) and (1.5), respectively, show the average number of open interest on the VIX futures and VIX options for each month.

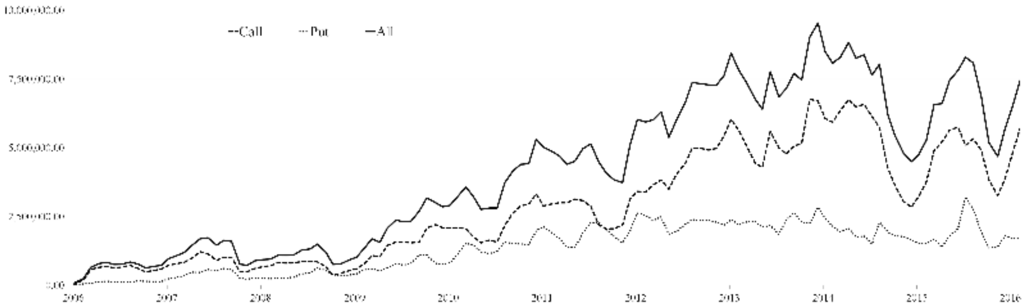
Figure 1.4: Average Number of Open Interest on VIX Futures



**Source: CBOE Website**

Since the VIX index is the option-implied volatility of the S&P 500 index, it reflects investors' overall expectation about the market volatility under the risk-neutral measure. If investors have aversion to certain states of the economy, then the risk-neutral probability density function gives a higher weight to those states, compared to the physical measure. Since investors generally dislike the states of the economy with high levels of volatility, the risk-neutral volatility of the S&P 500 index i.e. the VIX index, is typically larger than what investors actually expect about the future value of the market

Figure 1.5: Average Number of Open Interest on VIX Options




**Source: OptionMetrics Website**

volatility. This wedge is called the volatility risk premium. If investors have higher aversion to volatile states of the market and thus they overweight those states, then the estimated value of the VIX will be higher. Therefore the VIX index is also an increasing function of investors' risk aversion [about the volatility of the market portfolio and their consumption].

Moreover as already mentioned the VIX reflects investors' overall expectation about the market volatility. Since the market volatility is an increasing function of the variance of its individual constituent stocks and their pairwise correlations, one can argue that the VIX ix also an increasing function of individual stock variances and correlations.

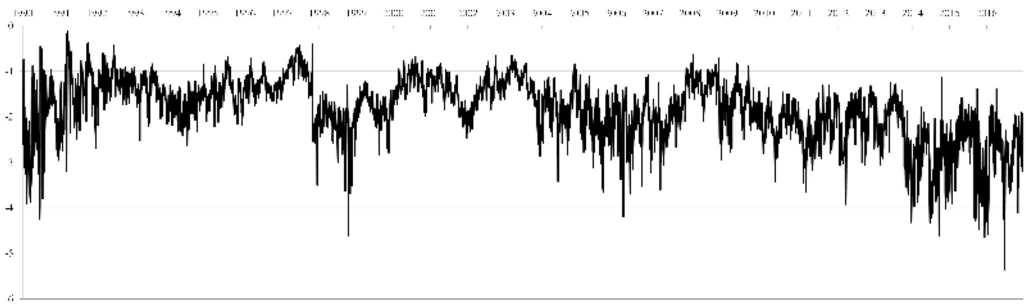
Since February 2011, the CBOE also began publishing values for the Skew Index. While the VIX index is a proxy for the market expected volatility, the SKEW index of the CBOE reveals investors' expectation about the market return skewness. Just like the VIX index, the SKEW index is also exploited from the price of options on the S&P 500 index and therefore it is computed under the risk-neutral measure. Figure (1.6) displays the time series of the VIX index from January 1990 to December 2016.[2]

## 1.4 This Dissertation

As the VIX encapsulates precious information on investors' risk aversion, asset variances and asset correlations, it also carries decisive information for asset pricing; For example, Ang, Hodrick, Xing and Zhang (2006) show that stocks which are negatively affected by a shock in the VIX index are compensated with higher expected returns; in other words

[2]It is important to note that over the past 20 years, in a few occasions, the CBOE has modified its methodology to compute the VIX index. For example while in early years, the VIX was exploited from the S&P 100 options, since September 2003, the CBOE computes the VIX using the price of options in the S&P 500 index.

Figure 1.6: SKEW Index



**Source: CBOE Website**

the market volatility (the VIX) is negatively priced in the cross section of expected stock returns. Furthermore, Bollerslev, Marrone, Xu and Zhou (2014) and Bali and Zhou (2016) find that the wedge between the VIX index and the physical expected volatility, i.e. the volatility risk premium, is priced in the time series and the cross section of stock returns. And Nagel (2012) shows that when the VIX is high the liquidity premium becomes more expensive.

This dissertation is constituted of three academic papers.

### 1.4.1 From Time Varying Risk-Aversion to Anomalies in Market Moments' Risk Premia

By extending the work of Ang, Hodrick, Xing and Zhang (2006) to higher market moments i.e. market skewness and market kurtosis, Chang, Christoffersen and Jacobs (2013) find that stocks that have positive beta on market skewness shocks are compensated with lower returns. Although this finding is empirically robust, it is against the intuition of the inter-temporal capital asset pricing model of Merton (1973). We call this phenomenon the market skewness anomaly.

Rationally, positive skewness is always more desirable. That is why people bet. According to the ICAPM, if a positive shock in a risk factor is associated with an improvement in the investment opportunity set, then stocks with *negative* loadings on this risk factor must be compensated with lower expected returns. Because then if, with a negative shock in this risk factor, the investment opportunity set deteriorates, stocks with negative beta tend to have positive returns and thus they smoothen investors' consumption. This desirability of negative-beta assets increases their prices and decreases their expected returns. In chapter 2, we show that the market skewness anomaly, discovered by Chang, Christoffersen and Jacobs (2013), is stronger when investors' risk aversion is lower or when their sentiment is higher. When investors' become sufficiently risk averse, this anomaly shrink in magnitude.

Furthermore, we find that when investors are more risk averse, the market volatility premium, found by Ang, Hodrick, Xing and Zhang (2006), becomes more expensive. [3]

### 1.4.2 Does Oil and Gold Price Uncertainty Matter for the Stock Market?

The difference between the VIX-squared and the physical expected variance of the market is called the market variance risk premium. Following the works of Bansal and Yaron (2004), Buraschi, Trojani and Vedolin (2014), Bollerslev, Marrone, Xu and Zhou (2014), the variance risk premium is considered as a proxy for the level of uncertainty in the market. Bali and Zhou (2016) show that the variance risk premium of the S&P 500 index is priced in the cross section of expected stock returns, as rising uncertainty is associated with a deterioration in the investment opportunity set.

Following Bali and Zhou (2016), we estimate the level of uncertainty in the stock, oil and gold markets, using the price of options and futures written on each of these asset classes and find that only the stock market uncertainty is a *systematic* priced factor in the entire cross section of expected stock returns. The oil price uncertainty is a *sector-specific* factor, and due to the industry segmentation of the market, it is only a priced factor within oil-relevant industries. Gold price uncertainty is an *asset-specific* factor that is neither priced across nor within industries.[4]

### 1.4.3 Why is the VIX index related to the liquidity premium?

Compensation for liquidity provision depends on short-term price reversal. In an empirical study, Nagel (2012) shows that when the VIX is high the intensity of the short-term price reversal effect is stronger, as liquidity providers charge a higher premium for their service. He argues that when the VIX is high financial constraints are tighter and thus market makers, who face higher borrowing costs, charge a higher premium for liquidity provision. This higher price of liquidity, in turn, increases the magnitude of the short-term price reversal effect.

In this chapter, we provide further explanations for the positive relationship between the VIX index and liquidity providers' compensation. For this purpose, we extend the theoretical framework of Vayanos and Wang (2012) and show that even in a perfect market with no financial constraints, higher investors' risk aversion, asset variances and

[3] This chapter is co-authored with Prof. Dr. Dennis Bams and Prof. Dr. Thorsten Lehnert.

[4] This chapter, which is co-authored with Prof. Dr. Dennis Bams, Dr. Gildas Blanchard and Prof. Dr. Thorsten Lehnert, is published in Journal of Empirical Finance.

asset correlations lead to a larger expected return and Sharpe ratio for liquidity providers. On the other hand, the VIX index also encapsulates investors' risk aversion, stocks' average variance and stocks' average correlation. Therefore, we argue that the VIX index and liquidity providers' compensation are correlated, as they both depend on the same fundamentals.[5]

[5] This chapter is co-authored with Prof. Dr. Dennis Bams.

# Chapter 2

# From Time Varying Risk-Aversion to Anomalies in Market Moments' Risk Premia

## 2.1 Introduction

We empirically investigate the impact of time variation in risk-aversion on the higher market moments' (volatility, skewness and kurtosis) risk premia, and observe that the compensations for exposure to the risk of the market volatility, skewness and kurtosis are significantly affected by investors' risk-aversion. The impact of risk-aversion is substantial, such that in low risk-aversion periods, investors price these risk factors against the prediction of the intertemporal capital asset pricing model (hereinafter ICAPM). Hence, our research highlights the importance of considering investor risk-aversion while studying market anomalies.

Even at a constant level of wealth, current consumption is negatively affected by uncertainty about the future investment opportunities. Merton (1973) introduced the ICAPM to address the static drawback in the CAPM (e.g. Sharpe (1964), and Lintner (1965)) and argued that the pricing kernel should be adjusted to allow for continuous improvement or deterioration in the investment opportunity set. Therefore, more elaborate asset pricing models, with state variables that project future investment opportunity sets, have been developed. Especially as market volatility, skewness and kurtosis are crucial indicators of market-wide risk, researchers have formulated various pricing kernels that compensate investors for bearing the risk of higher market moments.[1] Market-wide

[1]See for example Kraus and Litzenberger (1976), Campbell (1996), Fang and Lai (1997) Bollerslev,

risk matters for the cross-section of expected stock returns, because it allows risk-averse investors to hedge themselves against adverse changes in future investment opportunities.

The price of a risk factor is either positive or negative, depending on whether its variation reflect improvement or deterioration in the economy's future opportunity set. If the price of a risk factor is positive (negative), stocks with higher exposure to that risk factor are expected to have higher (lower) returns over the subsequent periods. Based on the ICAPM, when investors are risk-averse:

1. The price of market volatility risk should be negative, because higher market volatility today is associated with a deterioration of the future investment opportunity set. Stocks, whose returns are positively exposed to (correlated with) changes in market volatility, offer higher returns when the market volatility is rising, and therefore, they provide a desirable hedge when the investment opportunity set is shrinking. This attractive property raises their current prices and reduces their future expected returns. Hence, the difference between the expected return of a high volatility exposure portfolio and a low volatility exposure portfolio should be negative.

2. Negative skewness reflects market participants' fear about a negative jump in the stock market. (See e.g. Bates (2000).) The price of market skewness risk should be positive, because lower (more negative) market skewness today is associated with an increase in the negative jump risk, and therefore a deterioration of the future investment opportunity set. Stocks, whose returns are negatively correlated with changes in market skewness, provide a hedge against this unfavorable scenario. Because of this attractive feature, risk-averse investors would expect lower returns on these stocks over the next periods. Hence the difference between the expected return of a high (positive) skewness exposure portfolio and a low (negative) skewness exposure portfolio should be positive.

3. The prices of market kurtosis and volatility risk are related. The price of market kurtosis risk should be negative, because higher market kurtosis today can be associated with a deterioration of the future investment opportunity set. Stocks, whose returns are positively correlated with changes in market kurtosis, provide a hedge against this unfavorable scenario. Because of this desirable feature, risk-averse investors would require lower returns on these stocks over the next periods. Hence the difference between the expected return of a high kurtosis exposure portfolio and a low kurtosis exposure portfolio should be negative.

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Engle and Wooldridge (1988) Harvey and Siddique (1999), Dittmar (2002), Bakshi and Madan (2006), Ang, Hodrick, Xing and Zhang (2006), Adrian and Rosenberg (2008), Li (2012), Chabi-Yo (2012), Kostakis, Muhammad and Siganos (2012) Chang, Christoffersen and Jacobs (2013) etc.

Empirically, researchers find negative prices of risk for market volatility and market skewness in the cross-section of stocks. For example,Ang, Hodrick, Xing and Zhang (2006) take the innovation of the market volatility index (VIX), as a state variable and find that on average stocks with positive correlation with the innovations in the VIX have lower expected returns. Adrian and Rosenberg (2008) decompose the market volatility into short-term and long-term components, and observe that they are both priced negatively. They argue that the short-term volatility captures the skewness risk of the market. In a special theoretical setup, Chabi-Yo (2012) shows that the signs of the market volatility and the market skewness risk premia depend on investors' risk-aversion and skewness and kurtosis preferences. Chang, Christoffersen and Jacobs (2013) extend the analysis of Ang, Hodrick, Xing and Zhang (2006) by including the skewness and kurtosis of the market return, and show that assets with higher exposure to innovations in the market skewness have significantly lower expected returns. Obviously, the findings about the price of market skewness risk are in contradiction to the economic intuition that we developed earlier, assuming risk-averse investors.

It is broadly believed that risk-aversion fluctuates over the business cycle, rising in recessions and dropping in expansions (e.g. Campbell and Cochrane (1999) and Rosenberg and Engle (2002)). We argue that the compensation of higher moments' risks in the cross-section of stocks also depends on market conditions. As in up-markets risk-aversion is low, we do not detect a significant mean-variance relationship in such periods, however, in down-markets, risk-aversion is high and the mean-variance relationship is significant (e.g. Campbell and Hentschel (1992) and Yu and Yuan (2011)). Similarly, we believe that fluctuation in investors' risk-aversion affects the exposure of stock returns to market risks captured by higher risk-neutral moments. Therefore, we expect the market moments' risk premia to be different in up- and down-markets, which is a potential explanation for the counterintuitive results previously found for market skewness.

Our results over the full data sample show that the market volatility and the market skewness premia are negative and the market kurtosis premium is slightly positive. These findings are in line with Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013). Nevertheless the results for market skewness and kurtosis are against the ICAPM predictions, as we expected the opposite signs for both of them. To investigate the impact of risk-aversion on the cross-sectional market moments' risk premia, we look at periods of high and low risk-aversion, separately. For this purpose we compute the time series of investor's relative risk-aversion, using the methodology of Campbell and Cochrane (1999) and Brandt and Wang (2003), and observe that:

1. The price of market volatility risk is significantly negative in down-markets, periods of high risk-aversion. However, in low risk-aversion periods, it is neither statistically

nor economically significant. In other words, lower risk-aversion in up-markets undermines the otherwise significantly negative price of market volatility risk in the cross-section of stock returns. This result extends the analysis of Yu and Yuan (2011), who investigate the strength of mean-variance relationship from a time series perspective.

2. The price of market skewness risk is found to be insignificant in down-markets, but significantly negative in up-markets, while according to the ICAPM intuition, we would expect it to be positive. We explain this finding as the result of the substantially lower risk-aversion in up-markets. When investors are more risk-seeking, the hedge against the negative skewness scenario, provided by stocks, is not necessarily desirable.

3. The price of market kurtosis risk is insignificant in periods of high risk-aversion, and partly significantly positive in low risk-aversion periods, while according to the ICAPM intuition, we would expect it to be negative. This finding is in line with the results for market skewness. In low risk-aversion periods, more risk-seeking investors do not find the hedge, provided by stocks against the market kurtosis risk, desirable.

There is a separate strand in the literature that investigates the impact of investors' sentiment on future expected stock returns. Previous empirical results in this area (e.g. Brown and Cliff (2004), Brown and Cliff (2005), Baker and Wurgler (2006), Yu and Yuan (2011), Stambaugh, Yu and Yuan (2012), Stambaugh, Yu and Yuan (2014) and Mian and Sankaraguruswamy (2012)) suggest that high sentiment periods are characterized as periods where stocks are overvalued, investors are optimistic about the market prospect and stocks' expected returns are low. As a result of this optimism in high sentiment periods, noise traders turn out to be more active in such periods. In contrast, in low sentiment periods the future of the market is gloomy and stocks are undervalued. Investors are skeptical about the future of the market and noise traders are less active. Yu and Yuan (2011) show that in high sentiment periods the active participation of sentiment (noise) traders weakens the otherwise significant mean-variance tradeoff. Also, Stambaugh, Yu and Yuan (2012) and Stambaugh, Yu and Yuan (2014) identify the waves of investors' sentiment as the main reason of many anomalies in cross-sectional stock returns.

To test the validity of these arguments, we investigate the relationship between investors' risk-aversion and investors' sentiment. For this purpose, we use the Baker and Wurgler (2006) investor sentiment index, and find that sentiment is strongly negatively affected by past realizations (3-12 months) in the relative risk-aversion. In other words, periods of low (high) sentiment are typically preceded by periods of increased (decreased) risk-aversion in the market. Hence, our findings further suggest that our previous results can also be replicated by analyzing periods of high and low sentiment, such that the anomalies in the market moments' risk premia only appear in high sentiment periods, and they vanish, once the investor sentiment declines.

The rest of this paper is structured as follows: In section 2, we discuss our methodology for computing the market moments' risk premia and the relative risk-aversion time series. In section 3, we investigate the impact of time variation in risk-aversion on the market moments' risk premia. Section 4 explores the relation between sentiment and risk-aversion and tests whether the time variation in sentiment can also explain the anomalies in the market moments' risk premia. Section 5 provides robustness tests, and finally in section 6, we draw our conclusion.

## 2.2 Data and Methodology

### 2.2.1 Risk-Neutral Market Moments

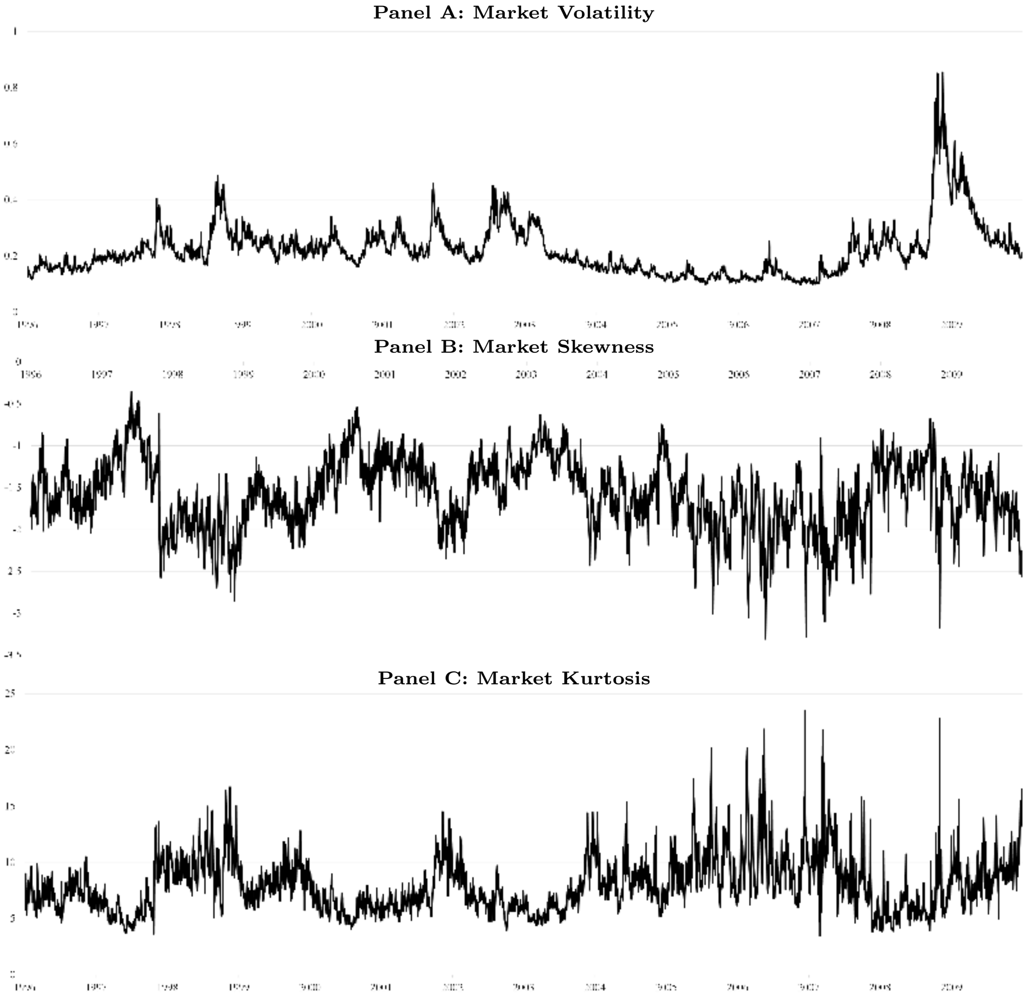
We use the methodology of Bakshi, Kapadia and Madan (2003) (hereinafter BKM) to calculate the risk-neutral market moments time series. Bakshi and Madan (2000) show that any claim payoff with finite expectation can be spanned by a continuum of out-of-the-money (OTM) European call and put options. Accordingly, Bakshi, Kapadia and Madan (2003) set up a model free framework to extract the conditional time series of the risk-neutral moments.

The BKM method enables us to calculate the risk-neutral moments for each day by only using the options traded on that specific day. Therefore, the computed moments are strictly conditional, as opposed to the traditional techniques such as using a rolling-window of daily returns. Alternatively, one could use high-frequency returns of a single day to compute the moments in that particular day (see e.g. Bollerslev, Tauchen and Zhou (2009) and Amaya, Christoffersen, Jacobs and Vasquez (2015)). However, since high-frequency returns are affiliated with microstructural frictions and the sampling properties of high-frequency returns do not necessarily reflect the statistical characteristics of daily returns (Brenner, Pasquariello and Subrahmanyam (2009)), using intraday data may not be the best choice for estimating the higher moments. Moreover in contrast to the moments computed using rolling-windows or high-frequency data, since investors' expectations about the future market condition impact option prices, the option implied moments are strictly forward-looking, and therefore, they can predict the improvement or deterioration of the investment opportunity set, efficiently.

As near-to-maturity options reflect investors' short-term expectations more clearly, for each day we calculate the risk-neutral moments for the horizon of the next 30 days.

We obtain the daily prices of the European options written on the S&P 500 index, starting in January 1996 to June 2010, from the OptionMetrics database. This interval covers mild and harsh, expansion and recession periods. A detailed explanation about our implementation is provided in the appendix. Figure (2.1) exhibits the resulting time series of the daily risk-neutral market volatility, market skewness and market kurtosis.

Figure 2.1: Market Moments Time Series




*Note:* This figure reports the daily time series of the market volatility, skewness and kurtosis. We implement the methodology of Bakshi, Kapadia and Madan (2003) to compute the risk-neutral market moments using out-of-the-money options written on the S&P 500 index.

Figure (2.1) reveals many stylized facts about the market moments. Panel (A) shows that the market volatility varies over time and big sudden spikes in the market volatility decline slowly. Panel (B) demonstrates that market skewness is always negative, meaning investors perceive significant negative shocks more likely than the same-size positive shocks. And finally as displayed in panel (C), the market kurtosis is always more than 3, showing that the investors' risk-neutral expectation about the market return distribution is more fat-tailed than implied by a normal distribution.

Since we want to investigate the comovement of cross-sectional stock returns with deterioration or improvement of the future investment opportunity set, following Chang, Christoffersen and Jacobs (2013), we proxy the innovations in the market moments with the residuals of the three ARMA (1, 1) processes fitted to the market volatility, skewness and kurtosis, respectively. The dynamics of the innovations in the market moments, referred to as $\Delta Vol$, $\Delta Skew$ and $\Delta Kurt$, follow from equations (2.1) to (2.3). As it does not change our interpretations but simplifies our notations, we divide $\Delta Skew$ and $\Delta Kurt$ time series by 100.

$$Vol_t = 0.9856 \times Vol_{t-1} - 0.1261 \times \Delta Vol_{t-1} + \Delta Vol_t, \tag{2.1}$$

$$Skew_t = 0.9614 \times Skew_{t-1} - 0.4043 \times \Delta Skew_{t-1} + \Delta Skew_t, \tag{2.2}$$

$$Kurt_t = 0.9458 \times Kurt_{t-1} - 0.4280 \times \Delta Kurt_{t-1} + \Delta Kurt_t. \tag{2.3}$$

Obviously the three AR (1) coefficients are close to one, showing that the moment processes exhibit an autoregressive component. Table (2.1) and (2.2) provide descriptive statistics for these time series.

Table 2.1: Factors Dynamics

| | | | Correlation | | ARMA (1, 1) Parameters | |
|---|---|---|---|---|---|---|
| | Mean | Standard Deviation | Skewness | Kurtosis | AR(1) | MA(1) |
| Volatility | 0.22 | 0.09 | 0.093 | -0.162 | 0.9856 | -0.1261 |
| Skewness | -1.6 | 0.43 | | -0.93 | 0.9614 | -0.4043 |
| Kurtosis | 8.11 | 2.6 | | | 0.9458 | -0.4280 |

*Note:* This table reports the correlations and the parameters of the ARMA (1, 1) process fitted to the daily time series of the volatility, skewness and kurtosis of the S&P500 index return.

The results presented in (2.2) reveal that there exists a strong negative correlation of -0.78, between $\Delta Vol_t$ and the concurrent market excess return. This suggests that a positive shock in the market volatility, which we interpret as a deterioration of the investment opportunity set, is contemporaneously accompanied by negative market excess return. The interpretation of the correlation coefficients between the market excess return and $\Delta Skew_t$ and $\Delta Kurt_t$ is not as straightforward, because the magnitude of these coefficients are much smaller.

Table 2.2: Factors Correlations

| | $\Delta Vol_t$ | $\Delta Skew_t$ | $\Delta Kurt_t$ |
|---|---|---|---|
| $\Delta Vol_t$ | | 0.10 | -0.17 |
| $\Delta Skew_t$ | | | -0.87 |
| $R_M - R_F$ | -0.78 | -0.26 | 0.12 |
| $SMB$ | 0.09 | 0.02 | -0.04 |
| $HML$ | 0.06 | 0.02 | -0.04 |
| $MOM$ | 0.19 | 0.06 | 0.02 |

*Note:* This table reports the correlation coefficients of the market moments' innovations and the Fama-French and the Carhart factors.

The correlation coefficient between $\Delta Skew_t$ and $\Delta Kurt_t$ is strongly negative. A growing risk of a negative jump will substantially decrease market skewness and increase market kurtosis, and thus results in negative and positive values for $\Delta Skew_t$ and $\Delta Kurt_t$, respectively. In order to avoid multicollinearity and to be able to disentangle the impact of $\Delta Skew_t$ from $\Delta Kurt_t$, following Chang, Christoffersen and Jacobs (2013), we regress $\Delta Kurt_t$ on $\Delta Skew_t$ and for the remainder of this paper, we take the corresponding residual time series as $\Delta Kurt_t$.

### 2.2.2 Market Moments' Risk Premia

Ang, Hodrick, Xing and Zhang (2006) argue that based on arbitrage pricing theory, if market volatility is a priced risk factor, it should also be priced in the cross-section of stock returns, and thereby, assets with different sensitivities to the market volatility innovations ($\Delta Vol_t$) should have different expected returns in the subsequent periods. Motivated by this fact, they measure and compare the cross-sectional exposure of returns to the market volatility innovations, using the market volatility index (VIX) of the Chicago Board of Options Exchange (CBOE). Chang, Christoffersen and Jacobs (2013) extend this analysis for the market skewness innovations ($\Delta Skew_t$) and the market kurtosis innovations ($\Delta Kurt_t$). We carry out the same analysis for a longer time interval, and indeed, we are able to replicate their results, which also remain to hold for the longer time period.

We obtain the daily return time series of all actively traded ordinary common shares, traded on NYSE, AMEX and NASDAQ, from the database of the Center for Research in Security Prices (CRSP). In addition, to calculate the market capitalization of each stock at the end of each month, we obtain the monthly time series of stock prices and numbers of shares outstanding from the CRSP database. In each month, we omit the stocks with missing observations.

In order to capture the stock's conditional exposure to the market moments' innovations, starting from January 1996, for each stock in each month, we run the following regressions:

$$R_t^{i,j} - R_{F,t}^j = \alpha^{i,j} + \beta_{Mrkt}^{i,j}(R_{M,t}^j - R_{F,t}^j) + \beta_{Vol}^{i,j}\Delta Vol_t^j + \beta_{Skew}^{i,j}\Delta Skew_t^j + \beta_{Kurt}^{i,j}\Delta Kurt_t^j + \varepsilon_t^{i,j}. \tag{2.4}$$

Where $R_t^{i,j}$ represents the return of stock $i$ in day $t$ of month $j$ and $R_{M,t}^j - R_{F,t}^j$ denotes the excess return of the market over the risk-free rate. Hence for each stock $i$ in each month $j$, we obtain a set of estimated exposure parameters, denoted as $\beta_{Mrkt}^{i,j}$, $\beta_{Vol}^{i,j}$, $\beta_{Skew}^{i,j}$ and $\beta_{Kurt}^{i,j}$. Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) also use one-month daily returns in the same setup, as it creates a good balance between the precision and the conditionality of the estimated betas.

A positive $\beta_{Vol}^{i,j}$ suggests that the daily excess returns of stock $i$ typically changes in the same direction as the innovations in the market volatility. This feature makes stock $i$ an attractive asset that pays off well when the market volatility is rising and the investment opportunity set is shrinking. Therefore, risk-averse investors will pay higher prices for this stock, and consequently, the expected return of stock $i$ over the next month will diminish. Similarly, a negative $\beta_{Skew}^{i,j}$ and a positive $\beta_{Kurt}^{i,j}$ will respectively suggest that stock $i$ provides attractive hedges against the risk of market skewness decline and the risk of market kurtosis increase.

In order to evaluate the tradeoff between the stocks exposure to the market moments innovations and their future expected return, at the end of each month $j$, we sort all the stocks three times independently based on their $\beta_{Vol}^{i,j}$, $\beta_{Skew}^{i,j}$ and $\beta_{Kurt}^{i,j}$, and each time we form five value-weighted exposure portfolios such that the first portfolio is composed of one-fifth of the stocks with the lowest exposures to each moment's innovations (the stocks with the smallest $\beta_{Vol}^{i,j}$, $\beta_{Skew}^{i,j}$ and $\beta_{Kurt}^{i,j}$) and the last portfolio includes one-fifth of the stocks with the highest loadings on each moment's innovations (the stocks with the largest $\beta_{Vol}^{i,j}$, $\beta_{Skew}^{i,j}$ and $\beta_{Kurt}^{i,j}$). Then we record the daily returns of these five portfolios over the month after the beta-calculation period ($j+1$), to construct the post-ranking return time series.[2]

We continue by rolling the window one month forward and repeat the same procedure, up until the end of our data sample in June 2010. As a result, we will obtain the daily time series of five volatility exposure portfolios (VEP1 to VEP5), five skewness exposure portfolios (SEP1 to SEP5) and five kurtosis exposure portfolios (KEP1 to KEP5), from January 1996 to June 2010. By construction, VEP1, SEP1 and KEP1 are the post-ranking daily time series of the most negatively exposed portfolios to $\Delta Vol_t$, $\Delta Skew_t$ and

[2]To control for outliers in the estimated betas ($\beta_{Vol}^{i,j}$, $\beta_{Skew}^{i,j}$ and $\beta_{Kurt}^{i,j}$), we also construct the moment exposure portfolios, based on the t-statistics of stocks exposure to the market moments innovations. Our results (not reported) are qualitatively and quantitatively similar.

$\Delta Kurt_t$, respectively, and VEP5, SEP5 and KEP5 are the post-ranking daily time series of the most positively exposed portfolios to $\Delta Vol_t$, $\Delta Skew_t$ and $\Delta Kurt_t$ respectively. Table (2.3) displays the average monthly returns and the alpha values of each exposure portfolio based on the CAPM, the Fama-French and the Carhart models.

Panel (A) is dedicated to the volatility exposure portfolios. In this panel, VEP5-1 represents a self-financing portfolio that goes long in VEP5 and short sells VEP1. Panel (B) and panel (C) are dedicated to the skewness and kurtosis exposure portfolios and SEP5-1 and KEP5-1 in these panels, represent similar portfolios as VEP5-1.[3]

As shown in panel (A), the average monthly returns and the alpha values of the volatility exposure portfolios follow a declining pattern. In fact, when we move from VEP1 towards VEP5, by construction the average beta of the exposure portfolios increase, and as the ICAPM suggests, their average monthly returns and the alpha values decline. This result is in line with the findings of Ang, Hodrick, Xing and Zhang (2006). However it is important to mention that the average monthly return of VEP5-1 is neither statistically nor economically significant. This can be inferred from the t-statistics, adjusted with the Newey and West (1987) technique.

Similarly in panel (B), we observe strictly declining patterns for the average monthly returns and the alpha values of the skewness exposure portfolios. This finding is exactly in line with the results of Chang, Christoffersen and Jacobs (2013). Stocks with positive exposure to the market skewness innovations, i.e. a stock with positive $\beta^{i,j}_{Skew}$, have lower returns and alphas over the subsequent period. Even though the average monthly return and the alpha values of SEP5-1 are statistically significant, this result moves against the ICAPM intuition. Particularly, stocks with positive exposure to the market skewness pay off poorly when the market skewness decreases and the negative jump risk increases. Thus, since they cannot provide a good hedge when the investment opportunities are shrinking, they should be cheaper and have higher expected return over the subsequent periods.

Also when we move from KEP1 toward KEP5, panel (C) shows mildly increasing patterns for the average monthly returns and the alpha values of the kurtosis exposure portfolios. The patterns are not monotonically increasing, and the average monthly returns and the different alpha values of KEP5-1 are not statistically significant. Nevertheless, with a similar line of reasoning as what we had for the exposure to the market skewness risk, this result is against the ICAPM intuition, since we would expect downward sloping patterns.[4]

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[3]Thus in our notations, VEP5-1 = VEP5 - VEP1, SEP5-1 = SEP5 - SEP1 and KEP5-1 = KEP5 - KEP1.

[4]Here, we focus on standard portfolio sorts on exposure to market moments. We also conduct the sorting approach used in e.g. Chang, Christoffersen and Jacobs (2013) to overcome the problem of correlation between different market moments (results not reported). We find that our results are robust

Table 2.3: Moments' Exposure Portfolios

Panel (A): Volatility Exposure Portfolios

| | Average Monthly Return | Alpha | | |
|---|---|---|---|---|
| | | CAPM | Fama-French | Carhart |
| VEP1 | 0.67 | 0.21 | 0.15 | 0.31 |
| | (1.18) | (0.81) | (0.58) | (1.25) |
| VEP2 | 0.56 | 0.19 | 0.19 | 0.20 |
| | (1.40) | (1.56) | (1.64) | (1.73) |
| VEP3 | 0.51 | 0.17 | 0.17 | 0.15 |
| | (1.41) | (2.17) | (2.34) | (2.02) |
| VEP4 | 0.49 | 0.12 | 0.09 | 0.06 |
| | (1.17) | (1.07) | (0.80) | (0.49) |
| VEP5 | 0.16 | -0.31 | -0.40 | -0.34 |
| | (0.26) | (-1.17) | (-1.81) | (-1.51) |
| VEP5-1 | -0.51 | -0.52 | -0.55 | -0.65 |
| | (-1.25) | (-1.27) | (-1.41) | (-1.63) |

Panel (B): Skewness Exposure Portfolios

| | Average Monthly Return | Alpha | | |
|---|---|---|---|---|
| | | CAPM | Fama-French | Carhart |
| SEP1 | 1.05 | 0.61 | 0.64 | 0.80 |
| | (1.88) | (2.53) | (2.69) | (3.31) |
| SEP2 | 0.58 | 0.22 | 0.23 | 0.25 |
| | (1.45) | (1.94) | (2.21) | (2.22) |
| SEP3 | 0.52 | 0.17 | 0.15 | 0.12 |
| | (1.37) | (2.12) | (1.92) | (1.60) |
| SEP4 | 0.27 | -0.10 | -0.16 | -0.19 |
| | (0.66) | (-0.86) | (-1.36) | (-1.50) |
| SEP5 | 0.24 | -0.23 | -0.36 | -0.30 |
| | (0.41) | (-0.96) | (-1.73) | (-1.41) |
| SEP5-1 | -0.81 | -0.84 | -1.00 | -1.10 |
| | (-2.32) | (-2.42) | (-2.88) | (-2.97) |

Panel (C): Kurtosis Exposure Portfolios

| | Average Monthly Return | Alpha | | |
|---|---|---|---|---|
| | | CAPM | Fama-French | Carhart |
| KEP1 | 0.32 | -0.13 | -0.22 | -0.15 |
| | (0.56) | (-0.57) | (-1.01) | (-0.72) |
| KEP2 | 0.56 | 0.20 | 0.19 | 0.16 |
| | (1.45) | (1.84) | (1.71) | (1.38) |
| KEP3 | 0.47 | 0.12 | 0.12 | 0.09 |
| | (1.26) | (1.30) | (1.50) | (1.03) |
| KEP4 | 0.48 | 0.10 | 0.07 | 0.09 |
| | (1.11) | (0.86) | (0.61) | (0.82) |
| KEP5 | 0.71 | 0.24 | 0.17 | 0.32 |
| | (1.23) | (0.98) | (0.73) | (1.35) |
| KEP5-1 | 0.40 | 0.38 | 0.39 | 0.47 |
| | (1.12) | (1.08) | (1.12) | (1.30) |

*Note:* This table reports the average monthly returns and the alpha values of the volatility, skewness and kurtosis exposure portfolios over the whole data sample from January 1996 to June 2010.

### 2.2.3 Relative Risk-Aversion

Based on the habit formation idea, Campbell and Cochrane (1999) setup a framework to compute the time variation in investors' risk-aversion. Brandt and Wang (2003) extend this model by adding the impact of inflation news, and find that risk-aversion is affected by release of bad news in consumption growth and inflation. We mainly focus on the implementation of Brandt and Wang (2003) to extract the time variation in investors' relative risk-aversion. However, since we work with real (inflation-adjusted) consumption growth and real stock prices (as opposed to their nominal values), we omit the impact of inflation and assume that risk-aversion is only influenced by news in real consumption growth.

According to the fundamental equation of asset pricing for every asset with a real payoff of $P_{t+1}$ and a real standardized payoff of $R_{t+1} = \frac{P_{t+1}}{P_t}$, we have

$$E_t\big[m_{t+1}R_{t+1}\big] = 1. \tag{2.5}$$

where $m_{t+1} = \delta\frac{U'(C_{t+1})}{U'(C_t)}$ is the intertemporal marginal rate of substitution or the pricing kernel between time $t$ and $t+1$. Following Brandt and Wang (2003), we assume a representative investor maximizes her life-time utility function:

$$\sum_{t=0}^{\infty} \delta^t \ \frac{(C_t - X_t)^{1-\alpha} - 1}{1-\alpha} \tag{2.6}$$

Here $\delta$ is a subjective discount factor, $\alpha$ is a measure of risk-aversion, and $C_t$ and $X_t$ are the levels of consumption and habit at time $t$. A few points are relevant here. Firstly, at any point in time the consumption must be more than the habit, so that $C_t - X_t > 0$ and the utility function is measurable. And secondly, habit should be formed externally and thereby it must not be affected by contemporaneous changes in consumption ($\frac{dX_t}{dC_t} = 0$). The resulting real pricing kernel follows as:

$$m_{t+1} = \delta \ exp\big(\alpha(\gamma_{t+1} - \gamma_t - g_{t+1})\big) \tag{2.7}$$

where $\gamma_t$ is the logarithm of relative risk-aversion at time $t$ and we assume its dynamics is given by

$$\gamma_{t+1} = \bar{\gamma} + \Phi(\gamma_t - \bar{\gamma}) - \lambda(\gamma_t)(g_{t+1} - E_t[g_{t+1}]) \tag{2.8}$$

It holds that $g_{t+1} = \ln(C_{t+1}) - \ln(C_t) - \pi_{t+1}$, which is the real consumption growth rate between time $t$ and $t+1$, $\pi_{t+1}$ represents the inflation rate between time $t$ and $t+1$,

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to variations in the empirical setup.

and $\lambda(\gamma_t)$ is the sensitivity of relative risk-aversion to news about consumption growth, and following Brandt and Wang (2003) we set it equal to

$$\lambda(\gamma_t) = \frac{1}{\alpha} exp(\gamma_t) - 1. \tag{2.9}$$

Clearly, once risk-aversion increases, the representative investor becomes more sensitive to news in consumption growth. Moreover since $\lambda(\gamma_t)$ is always positive, according to equation (2.8), if the real consumption growth in a period is less than its expected value, the relative risk-aversion will rise.

In order to estimate the values of the unknown parameters $\theta = \{\alpha, \delta, \bar{\gamma}, \Phi\}$, we use the Generalized Method of Moments (GMM). For this purpose, we first fit an ARMA (1, 1) process to the real consumption growth time series,[5] and take the fitted value of $t+1$ as our estimation for $E_t[g_{t+1}]$ in equation (2.8). Then we minimize the sum of squares of deviations from equation (2.5) using certain conditioning variables ($Z_t$). Thus we define $h_{t+1}$ as

$$h_{t+1} = (m_{t+1} R_{t+1} - 1) \bigotimes Z_t. \tag{2.10}$$

Obviously $E_t[h_{t+1}] = 0$. Hence, using the GMM and the law of iterated expectations, we find the value for $\theta$ that minimizes

$$\Big[\frac{1}{T}\sum_{t=1}^{T} h_{t+1}(\theta)\Big] W_T \Big[\frac{1}{T}\sum_{t=1}^{T} h_{t+1}(\theta)\Big] \tag{2.11}$$

where $W_T$ is the optimal weighting matrix that is updated in each iteration of the optimization process, based on Hansen (1982).

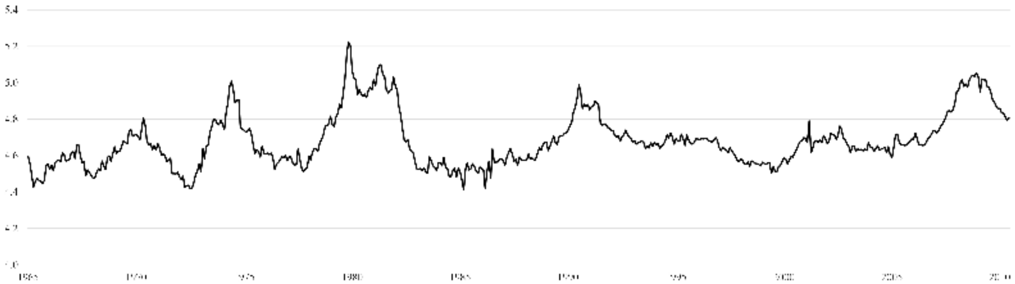
We obtain the monthly time series of Personal Consumption Expenditure of the US from the website of the Federal Reserve Bank of Saint Louis. We also set the dividend yield, term spread and 1-month US Treasury yield, from the Factset database, as the conditioning variables and fit the model to the monthly time series of 25 Fama and French stock portfolios. We calculate the monthly time series of risk-aversion for the period from 1965 to 2010. The broad dispersion between the 25 Fama and French stock portfolios and our long analysis period, with several economic expansions and recessions, enable us to compute the relative risk-aversion time series accurately. Figure (2.2) shows the relative risk-aversion time series from 1965 to 2010.

As can be seen from the figure, the relative risk-aversion fluctuates counter-cyclically, rising in recessions and declining in expansions (e.g. Campbell and Cochrane (1999) and Rosenberg and Engle (2002). Table (2.4) provides summary statistics for the relative

[5] Although our result is not sensitive to the choice of p and q in ARMA (p, q) model, an ARMA (1, 1) process provides us the best Akaike Information Criterion (AIC) among the models that we tested. The detailed analysis is available upon request.

risk-aversion time series. The parameter estimates of our model ($\theta = \{\alpha, \delta, \bar{\gamma}, \Phi\}$) are also reported in this table.

Figure 2.2: Relative Risk-Aversion



*Note:* This figure shows the monthly time series of the relative risk-aversion from 1965 to 2010. We compute the investor relative risk-aversion time series, using the methodology of Brandt and Wang (2003).

The relative risk-aversion time series ranges from 4.411 to 5.224, which is also consistent with the previous findings in the literature. (See e.g. Mehra and Prescott (1985), Constantinides (1990), Campbell and Cochrane (1999), Brandt and Wang (2003), Bansal and Yaron (2004) and Bliss and Panigirtzoglou (2004).)

## 2.3 Risk-Aversion and Risk Premia

In this section, we investigate and compare the prices of the market moments' risk, in up- and down-markets. Our conjecture is that due to lower risk-aversion, up-markets are characterized by overvaluation in the market, when investors are more risk-seeking, and therefore risk premia are assumed to be low. Conversely, in down-markets, due to higher levels of risk-aversion, stocks are undervalued, investors are more risk-averse and market risk is priced. In order to identify up- and down-markets, we use the estimated relative risk-aversion time series. We refer to the months with the relative risk-aversion above its median as the high risk-aversion periods and the months with the relative risk-aversion below its median as the low risk-aversion periods.[6] Table (2.5) summarizes our results for the market moments' risk premia, under the different market conditions.

Looking at panel (A.L) in table (2.5), we cannot observe a strictly increasing or decreasing pattern in the average monthly returns of the volatility exposure portfolios or their corresponding alpha values. In other words in low risk-aversion periods, market

[6] We repeat all the analysis of this paper, also, by segregating the high and low risk-aversion periods with the mean of the relative risk-aversion time series. For the sake of brevity, the results are not reported, but they are qualitatively and quantitatively similar. These results are available upon request.

Table 2.4: Relative Risk-Aversion

| Statistics | |
|---|---|
| Mean | 4.68 |
| Standard Deviation | 0.148 |
| Percentiles | |
| Minimum | 4.411 |
| 5th Percentile | 4.489 |
| 25th Percentile | 4.573 |
| Median | 4.656 |
| 75th Percentile | 4.738 |
| 95 Percentile | 4.992 |
| Maximum | 5.224 |
| Model Calibration | |
| $\alpha$ | 1.954 |
| $\bar{\gamma}$ | 1.532 |
| $\Phi$ | 0.938 |
| $\delta$ | 0.991 |

*Note:* This table provide descriptive statistics on the relative risk-aversion time series from 1967 to 2010. We compute the monthly time series of investor relative risk-aversion, using the methodology of Brandt and Wang (2003).

volatility is not priced in the cross-section of stocks and higher or lower exposure to the market volatility innovations does not result in significantly higher or lower expected returns. This result seems counterintuitive, because a stock with positive exposure to the market volatility innovations, i.e. a stock with positive $\beta_{Vol}$, pays off well when the investment opportunities are shrinking. Hence, compared to a stock with negative exposure to the market volatility innovations, this stock should be more expensive and have a higher price and smaller expected return. In conclusion, the absence of a downward sloping pattern in panel (A.L) of table (2.5) indicates that in low risk-aversion periods, when the market is overvalued, the market volatility risk is not priced in the cross-section of stocks.

Likewise, the monotonically downward slopping patterns of the average monthly returns and the different alpha values of the five skewness exposure portfolios, displayed in panel (B.L), are a sign of investors' increased risk-seeking behavior in low risk-aversion periods. Economic intuition would tell us that for risk-averse investors, a stock with low exposure to market skewness innovations, i.e. a stock with negative $\beta_{Skew}$, provides a good hedge when the market skewness is becoming more negative and the investment opportunities are shrinking. Thus, this stock should be more expensive and have a lower expected return. With a similar line of reasoning, a stock with positive exposure to the market skewness innovations should have a higher expected return. Hence, we should

Table 2.5: Exposure Portfolios over Low Risk-Aversion and High Risk-Aversion Periods

| | Low Risk-Aversion Periods | | | | | High Risk-Aversion Periods | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (A.L): Volatility Exposure Portfolios | | | | | (A.H): Volatility Exposure Portfolios | | | |
| | Average Monthly Return | CAPM | Alpha Fama-French | Carhart | | Average Monthly Return | CAPM | Alpha Fama-French | Carhart |
| VEP1 | 0.99 | 0.12 | 0.24 | 0.43 | VEP1 | 0.35 | 0.35 | 0.31 | 0.34 |
| | (1.34) | (0.28) | (0.57) | (1.06) | | (0.40) | (1.11) | (0.96) | (1.07) |
| VEP2 | 0.85 | 0.14 | 0.06 | 0.12 | VEP2 | 0.25 | 0.26 | 0.27 | 0.27 |
| | (1.82) | (0.73) | (0.34) | (0.67) | | (0.39) | (1.83) | (1.96) | (1.91) |
| VEP3 | 0.86 | 0.20 | 0.10 | 0.09 | VEP3 | 0.16 | 0.17 | 0.18 | 0.17 |
| | (2.11) | (1.64) | (0.98) | (0.90) | | (0.27) | (1.74) | (1.84) | (1.78) |
| VEP4 | 0.92 | 0.18 | 0.16 | 0.10 | VEP4 | 0.06 | 0.06 | 0.03 | 0.03 |
| | (1.81) | (1.01) | (0.89) | (0.56) | | (0.09) | (0.45) | (0.24) | (0.22) |
| VEP5 | 0.73 | -0.26 | -0.03 | -0.10 | VEP5 | -0.41 | -0.41 | -0.51 | -0.48 |
| | (0.92) | (-0.65) | (-0.11) | (-0.29) | | (-0.43) | (-1.11) | (-1.55) | (-1.62) |
| VEP5-1 | -0.26 | -0.37 | -0.27 | -0.52 | VEP5-1 | -0.76 | -0.76 | -0.83 | -0.82 |
| | (-0.40) | (-0.56) | (-0.45) | (-0.82) | | (-1.54) | (-1.52) | (-1.70) | (-1.69) |
| | (B.L): Skewness Exposure Portfolios | | | | | (B.H): Skewness Exposure Portfolios | | | |
| | Average Monthly Return | CAPM | Alpha Fama-French | Carhart | | Average Monthly Return | CAPM | Alpha Fama-French | Carhart |
| SEP1 | 1.70 | 0.75 | 1.09 | 1.32 | SEP1 | 0.39 | 0.40 | 0.37 | 0.38 |
| | (2.36) | (1.98) | (2.53) | (3.40) | | (0.46) | (1.36) | (1.31) | (1.43) |
| SEP2 | 1.04 | 0.33 | 0.37 | 0.41 | SEP2 | 0.12 | 0.12 | 0.14 | 0.14 |
| | (2.13) | (1.88) | (2.29) | (2.66) | | (0.18) | (0.86) | (1.00) | (1.00) |
| SEP3 | 0.81 | 0.15 | 0.01 | -0.00 | SEP3 | 0.23 | 0.24 | 0.24 | 0.23 |
| | (1.88) | (1.13) | (0.11) | (-0.02) | | (0.37) | (2.63) | (2.68) | (2.62) |
| SEP4 | 0.58 | -0.12 | -0.27 | -0.33 | SEP4 | -0.04 | -0.03 | -0.06 | -0.06 |
| | (1.19) | (-0.73) | (-1.62) | (-1.94) | | (-0.06) | (-0.21) | (-0.37) | (-0.37) |
| SEP5 | 0.55 | -0.36 | -0.36 | -0.42 | SEP5 | -0.07 | -0.06 | -0.16 | -0.12 |
| | (0.79) | (-1.12) | (-1.49) | (-1.73) | | (-0.07) | (-0.17) | (-0.45) | (-0.39) |
| SEP5-1 | -1.15 | -1.11 | -1.45 | -1.74 | SEP5-1 | -0.46 | -0.46 | -0.52 | -0.51 |
| | (-2.24) | (-2.10) | (-2.65) | (-3.43) | | (-0.99) | (-1.00) | (-1.16) | (-1.14) |
| | (C.L): Kurtosis Exposure Portfolios | | | | | (C.H): Kurtosis Exposure Portfolios | | | |
| | Average Monthly Return | CAPM | Alpha Fama-French | Carhart | | Average Monthly Return | CAPM | Alpha Fama-French | Carhart |
| KEP1 | 0.90 | -0.02 | 0.06 | 0.04 | KEP1 | -0.27 | -0.27 | -0.34 | -0.31 |
| | (1.29) | (-0.06) | (0.24) | (0.16) | | (-0.31) | (-0.78) | (-1.01) | (-0.97) |
| KEP2 | 0.81 | 0.12 | 0.01 | -0.03 | KEP2 | 0.31 | 0.31 | 0.31 | 0.31 |
| | (1.76) | (0.64) | (0.05) | (-0.15) | | (0.49) | (2.51) | (2.60) | (2.52) |
| KEP3 | 0.69 | 0.03 | -0.07 | -0.11 | KEP3 | 0.24 | 0.25 | 0.26 | 0.25 |
| | (1.66) | (0.18) | (-0.62) | (-0.89) | | (0.39) | (2.52) | (2.70) | (2.70) |
| KEP4 | 0.81 | 0.08 | 0.03 | 0.07 | KEP4 | 0.15 | 0.15 | 0.14 | 0.14 |
| | (1.54) | (0.45) | (0.16) | (0.40) | | (0.22) | (1.04) | (0.96) | (0.96) |
| KEP5 | 1.42 | 0.48 | 0.75 | 0.89 | KEP5 | -0.00 | 0.00 | -0.09 | -0.06 |
| | (1.89) | (1.29) | (1.90) | (2.36) | | (-0.00) | (0.01) | (-0.29) | (-0.20) |
| KEP5-1 | 0.52 | 0.50 | 0.69 | 0.85 | KEP5-1 | 0.27 | 0.27 | 0.25 | 0.25 |
| | (1.05) | (1.00) | (1.30) | (1.62) | | (0.53) | (0.53) | (0.51) | (0.51) |

*Note:* In this table, we compare the average monthly returns and the alpha values of the volatility, skewness and kurtosis exposure portfolios over the low risk-aversion and the high risk-aversion periods.

observe an upward sloping pattern for the average monthly returns and the different alpha values of the five skewness exposure portfolios. However in panel (B.L), this is not the case, which is against the ICAPM intuition. Remarkably, the average monthly return and the different alpha values of SEP5-1 are statistically and economically significant, and the price of markets skewness risk is negative. In line with the results for market volatility, the observed patterns suggest that investors appear to be more risk-seeking in the low risk-aversion periods. Similarly according to the ICAPM, in panel (C.L), we would expect to see descending patterns in the average monthly returns and the different alpha values of the market kurtosis exposure portfolios. But in contrast, these patterns are ascending, which again, is in line with our risk-aversion-based explanation.

In summary, in up-markets (low risk-aversion periods), the observed cross-sectional patterns for market volatility, skewness and kurtosis risk suggest that investors are temporally more risk-seeking, and consequently we will observe anomalies in the market prices of the moments' risk.

In contrast to the low risk-aversion periods, in high risk-aversion periods VEP5-1 shows a negative average monthly return and statistically significant alpha values. In fact, the sharply declining patterns of the average monthly returns and the alpha values of the market volatility exposure portfolios in panel (A.H) show that in high risk-aversion periods, investors demand a premium for bearing the market volatility risk. Our result also corresponds to the arguments by Bakshi and Madan (2006) and Chabi-Yo (2012) that high risk-aversion implies a high volatility premium.

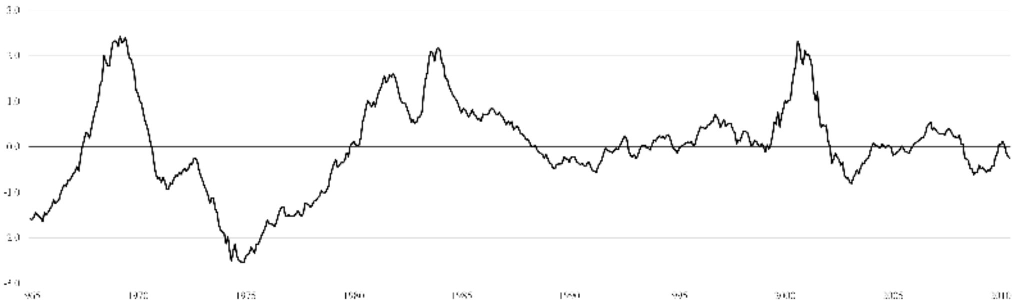
Moreover, in contrast to investors' risk-seeking behavior in the low risk-aversion periods, when they price the market skewness risk negatively and the market kurtosis risk positively, these moments are not significantly priced in the high risk-aversion periods. In particular, as shown in panel (B.H), in the high risk-aversion periods, the average monthly returns and the alpha values of the skewness exposure portfolios do not follow any particular pattern and SEP5-1 does not result in a significant monthly return or alpha. In addition, panel (C.H) shows that the positive average monthly return and the alpha values of KEP5-1 in the low risk-aversion periods are now contrasted with smaller values, suggesting that the price of market kurtosis risk in high risk-aversion periods is not against the ICAPM intuition.

## 2.4 Sentiment and Risk Premia

In a separate strand of the literature, authors proclaim that investors' sentiment is the reason of many phenomena or even anomalies in asset pricing. For example, Baker and Wurgler (2006) find that hard-to-arbitrage securities have higher expected returns once the sentiment is low. Yu and Yuan (2011) empirically show that in low sentiment periods, the risk-return relation becomes stronger. And Stambaugh, Yu and Yuan (2012) study the impact of sentiment on a broad set of anomalies, and find that in high sentiment periods, the trading strategies which are based on each of these anomalies are more profitable. To test the validity of this line of argumentation, in this section we test whether sentiment fluctuation can also explain the variation in the market moments' risk premia.

Previous literature shows that waves of investors' sentiment impact the number of IPOs and the average returns of the first day after IPOs (Ibbotson, Sindelar and Ritter (1994)), the share of equity issues in total equity and debt issues (Baker and Wurgler (2000)), the NYSE share turnover (Baker and Stein (2004)), and the dividend premium (Baker and Wurgler (2004*a*) and Baker and Wurgler (2004*b*)). Some of these proxies reflect the variation in investors' sentiment more rapidly than others. Hence to compute their common variations and formulate an investor sentiment index, Baker and Wurgler (2006) adjust these time series according to their lead-lag relationships, and determine their first principal component. We obtain the monthly time series of the investor sentiment index from 1967 to 2010, from the personal website of Jeffrey Wurgler. Figure (2.3) displays this index.

Figure 2.3: Investor Sentiment Index



*Note:* Baker and Wurgler (2006) measure the investor sentiment index as the first principal component of the close-end fund discount, the IPO volume, the average return of the first day after IPO, the share of equity issues in total equity and debt issues, the NYSE share turnover and the dividend premium time series. This figure plots this index from 1967 to 2010.

### 2.4.1 The Impact of Risk-Aversion on Investor Sentiment

Quantities such as the number of IPOs or the NYSE share turnover are likely to be high in periods of low risk-aversion, when risk premia are low. Therefore, an index measuring IPOs or equity issues is likely to pick up risk premia. We also expect to see that once investors become more risk-averse, sentiment declines and vice versa, because the sentiment index is composed of proxies, such as the number of IPOs and the NYSE share turnover, which are greatly influenced by the time variation in the risk-aversion.

To test this hypothesis, we first fit two independent AR (1) processes to the risk-aversion and the sentiment index time series. The residuals of the AR (1) processes in each period are the detrended changes in the relative risk-aversion and the sentiment index. Then we regress the values of the sentiment index innovations on the 1-month, 3-month, 6-month and 12-month lagged values of the relative risk-aversion time series, independently and jointly. The regression results are reported in table (2.6).

Table 2.6: The Impact of Risk-Aversion on the Investor Sentiment Index

| | | Sentiment Index Innovation | | | | |
|---|---|---|---|---|---|---|
| | | Reg (1) | Reg (2) | Reg (3) | Reg (4) | Reg (5) |
| Relative Risk-Aversion Innovation | 1-Month Lagged | 0.131 | | | | 0.164 |
| | | (0.86) | | | | (1.08) |
| | 3-Month Lagged | | -0.252 | | | -0.206 |
| | | | (-1.66) | | | (-1.36) |
| | 6-Month Lagged | | | -0.326 | | -0.297 |
| | | | | (-2.15) | | (-1.97) |
| | 12-Month Lagged | | | | -0.400 | -0.390 |
| | | | | | (-2.67) | (-2.59) |

*Note:* We regress the innovations in the investor sentiment index on the lagged values of the innovations in the relative risk-aversion time series.

The results in table (2.6) confirm our expectation. The rise of relative risk-aversion negatively affects investor sentiment. Nevertheless this influence is not immediate. As table (2.6) shows, innovations in the relative risk-aversion does not have any predictive power for the investor sentiment in the subsequent month. However the significant values of the coefficients in column (2) to (5) suggest that as time passes, the sentiment index starts to be negatively affected. This is an evidence that once an economic distress happens and the risk-aversion increases, gradually the financial activities, such as the number of IPOs and the NYSE share turnover, slow down. As a result the Baker and Wurgler sentiment index, which capture the common variations of such financial activity proxies, declines over the subsequent periods, around 3 to 12 months later. In the following section, we repeat our asset pricing analysis using sentiment to distinguish between market conditions.

### 2.4.2 The Impact of Sentiment on Market Moments' Risk Premia

In order to test the impact of variation in investor sentiment on the market moments risk premia, we compare the prices of the market volatility, skewness and kurtosis over the high and low sentiment periods. As showed in the previous section, high (low) sentiment periods are associated with low (high) risk-aversion periods, and as a result only during high sentiment periods, we would expect to see the anomalies in the market moments' risk premia. We refer to the months with the sentiment index value above its median as the high sentiment periods, and the months with the sentiment index value below the median as the low sentiment periods. Table (2.7) summarize our results for this analysis.

As expected, the results in table (2.7) are very similar to our finding in table (2.5). With the same line of reasoning as what we had for high risk-aversion periods, the volatility is priced in low sentiment periods, while this is not the case in high sentiment periods. The conclusions for the market skewness and the market kurtosis are also very similar, such that the anomalies in the market moments' risk premia only exist in high sentiment periods, and they disappear once the investor sentiment decline. This is also in line with Chung, Hung and Yeh (2012), who show that the higher investor sentiment in expansion periods cause stronger anomalies in the cross-section of stocks.

## 2.5 Robustness Tests

By splitting the sample between high and low risk-aversion periods or low and high sentiment periods, we ignored the continuous nature of these variables. To study the impact of monthly variations in the risk-aversion and sentiment index on the market moments' risk premia, for our whole data sample from January 1996 to June 2010, we regress the monthly time series of VEP5-1, SEP5-1 and KEP5-1 on the incremental lagged changes of the risk-aversion and sentiment time series, the contemporaneous market excess return, the Fama-French and the Carhart factors.

$$\begin{aligned} XEP_t^{5-1} = \alpha + \beta_{RRA}\Delta RRA_{t-1} + \beta_{Mrkt}(R_{M,t} - R_{F,t}) + \\ \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{MOM}MOM_t + \varepsilon_t. \end{aligned} \tag{2.12}$$

$$\begin{aligned} XEP_t^{5-1} = \alpha + \beta_{Sent}\Delta Sent_{t-1} + \beta_{Mrkt}(R_{M,t} - R_{F,t}) + \\ \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{MOM}MOM_t + \varepsilon_t. \end{aligned} \tag{2.13}$$

In these equations XEP5-1 represents VEP5-1, SEP5-1 or KEP5-1. Table (2.8) reports the results of regression equation (2.12) and (2.13).

For example, as shown in panel (A) of table (2.8), $\beta_{RRA}$ is significantly positive for SEP5-1. Therefore with an incremental increase in the relative risk-aversion, the return on SEP5-1 is expected to rise, and once the relative risk-aversion is sufficiently high,

Table 2.7: Exposure Portfolios over High Sentiment and Low Sentiment Periods

| | High Sentiment Periods | | | | | Low Sentiment Periods | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (A.L): Volatility Exposure Portfolios | | | | | (A.H): Volatility Exposure Portfolios | | | |
| | Average Monthly Return | CAPM | Alpha Fama-French | Carhart | | Average Monthly Return | CAPM | Alpha Fama-French | Carhart |
| VEP1 | -0.31 | -0.35 | -0.33 | 0.2 | VEP1 | 1.66 | 0.77 | 0.72 | 0.7 |
| | (-0.37) | (-0.87) | (-0.82) | (-0.53) | | (-2.03) | (-2.81) | (-2.65) | (-2.62) |
| VEP2 | 0.1 | 0.07 | 0.02 | 0.1 | VEP2 | 1.01 | 0.3 | 0.33 | 0.34 |
| | (-0.17) | (-0.35) | (-0.08) | (-0.54) | | (-1.66) | (-2.41) | (-2.66) | (-2.74) |
| VEP3 | 0.46 | 0.43 | 0.37 | 0.31 | VEP3 | 0.57 | -0.1 | -0.07 | -0.06 |
| | (-0.86) | (-3.09) | (-2.86) | (-2.36) | | (-0.98) | (-0.98) | (-0.62) | (-0.59) |
| VEP4 | 0.3 | 0.26 | 0.26 | 0.1 | VEP4 | 0.7 | -0.02 | -0.03 | -0.04 |
| | (-0.49) | (-1.3) | (-1.32) | (-0.46) | | (-1.08) | (-0.13) | (-0.27) | (-0.32) |
| VEP5 | -0.59 | -0.63 | -0.39 | -0.46 | VEP5 | 0.92 | 0.04 | -0.1 | -0.15 |
| | (-0.66) | (-1.49) | (-1.07) | (-1.20) | | (-1.06) | (-0.12) | (-0.34) | (-0.55) |
| VEP5-1 | -0.28 | -0.28 | -0.06 | -0.67 | VEP5-1 | -0.74 | -0.73 | -0.82 | -0.85 |
| | (-0.44) | (-0.44) | (-0.10) | (-1.04) | | (-1.71) | (-1.72) | (-1.94) | (-2.04) |
| | (B.L): Skewness Exposure Portfolios | | | | | (B.H): Skewness Exposure Portfolios | | | |
| | Average Monthly Return | CAPM | Alpha Fama-French | Carhart | | Average Monthly Return | CAPM | Alpha Fama-French | Carhart |
| SEP1 | 0.42 | 0.37 | 0.65 | 1.16 | SEP1 | 1.69 | 0.89 | 0.81 | 0.79 |
| | (-0.49) | (-0.89) | (-1.62) | (-2.98) | | (-2.2) | (-3.27) | (-3.05) | (-3.05) |
| SEP2 | 0.49 | 0.45 | 0.44 | 0.51 | SEP2 | 0.68 | -0.03 | 0 | 0 |
| | (-0.82) | (-2.63) | (-2.73) | (-2.95) | | (-1.1) | (-0.23) | (-0.01) | (-0.00) |
| SEP3 | 0.36 | 0.33 | 0.2 | 0.13 | SEP3 | 0.68 | 0 | 0.02 | 0.02 |
| | (-0.67) | (-2.31) | (-1.57) | (-0.93) | | (-1.15) | (0) | (-0.18) | (-0.2) |
| SEP4 | -0.12 | -0.15 | -0.23 | -0.34 | SEP4 | 0.67 | -0.07 | -0.07 | -0.07 |
| | (-0.19) | (-0.83) | (-1.25) | (-1.80) | | (-1.02) | (-0.47) | (-0.44) | (-0.46) |
| SEP5 | -0.86 | -0.91 | -0.78 | -0.77 | SEP5 | 1.36 | 0.43 | 0.35 | 0.32 |
| | (-1.03) | (-2.33) | (-2.28) | (-2.19) | | (-1.5) | (-1.3) | (-1.17) | (-1.08) |
| SEP5-1 | -1.28 | -1.28 | -1.43 | -1.93 | SEP5-1 | -0.33 | -0.46 | -0.46 | -0.48 |
| | (-2.13) | (-2.13) | (-2.45) | (-3.19) | | (-0.70) | (-0.99) | (-1.02) | (-1.07) |
| | (C.L): Kurtosis Exposure Portfolios | | | | | (C.H): Kurtosis Exposure Portfolios | | | |
| | Average Monthly Return | CAPM | Alpha Fama-French | Carhart | | Average Monthly Return | CAPM | Alpha Fama-French | Carhart |
| KEP1 | -0.52 | -0.57 | -0.44 | -0.37 | KEP1 | 1.17 | 0.33 | 0.25 | 0.22 |
| | (-0.63) | (-1.48) | (-1.30) | (-1.07) | | (-1.38) | (-1) | (-0.82) | (-0.75) |
| KEP2 | 0.08 | 0.05 | -0.01 | -0.11 | KEP2 | 1.04 | 0.35 | 0.36 | 0.36 |
| | (-0.14) | (-0.28) | (-0.04) | (-0.59) | | (-1.75) | (-2.75) | (-2.77) | (-2.8) |
| KEP3 | 0.41 | 0.38 | 0.32 | 0.21 | KEP3 | 0.53 | -0.15 | -0.11 | -0.1 |
| | (-0.75) | (-2.46) | (-2.24) | (-1.5) | | (-0.91) | (-1.49) | (-1.15) | (-1.08) |
| KEP4 | 0.2 | 0.17 | 0.12 | 0.19 | KEP4 | 0.76 | 0.01 | 0.02 | 0.02 |
| | (-0.33) | (-0.93) | (-0.67) | (-1.06) | | (-1.15) | (-0.04) | (-0.2) | (-0.16) |
| KEP5 | 0.29 | 0.24 | 0.43 | 0.81 | KEP5 | 1.14 | 0.24 | 0.15 | 0.11 |
| | (-0.33) | (-0.59) | (-1.09) | (-2.12) | | (-1.34) | (-0.87) | (-0.55) | (-0.43) |
| KEP5-1 | 0.81 | 0.81 | 0.86 | 1.18 | KEP5-1 | -0.02 | -0.09 | -0.11 | -0.11 |
| | (1.4) | (1.4) | (1.52) | (1.98) | | (-0.05) | (-0.20) | (-0.24) | (-0.26) |

*Note:* In this table, we compare the average monthly returns and the alpha values of the volatility, skewness and kurtosis exposure portfolios over the high sentiment and the low sentiment periods.

Table 2.8: The Impact of Incremental Changes in Relative Risk-Aversion and Sentiment

Panel (A): The Impact of Incremental Changes in the Relative Risk-Aversion

| Portfolio | $\alpha$ | $\beta_{RRA}$ | $\beta_{Mrkt}$ | $\beta_{SMB}$ | $\beta_{HML}$ | $\beta_{MOM}$ |
|---|---|---|---|---|---|---|
| VEP5-1 | -0.007 | -0.065 | 0.082 | 0.316 | 0.113 | 0.046 |
| | (-1.73) | (-0.369) | (0.744) | (1.505) | (0.616) | (0.364) |
| SEP5-1 | -0.010 | 0.239 | 0.101 | 0.155 | 0.241 | 0.081 |
| | (-2.8) | (2.125) | (1.841) | (2.039) | (1.82) | (0.781) |
| KEP5-1 | 0.005 | -0.154 | -0.075 | 0.107 | -0.056 | -0.150 |
| | (1.428) | (-1.109) | (-1.04) | (1.187) | (-0.404) | (-1.916) |

Panel (B): The Impact of Incremental Changes in the Sentiment Index

| Portfolio | $\alpha$ | $\beta_{Sent}$ | $\beta_{Mrkt}$ | $\beta_{SMB}$ | $\beta_{HML}$ | $\beta_{MOM}$ |
|---|---|---|---|---|---|---|
| VEP5-1 | -0.007 | 0.039 | 0.098 | 0.325 | 0.115 | 0.035 |
| | (-1.979) | (2.119) | (1.035) | (1.476) | (0.856) | (0.258) |
| SEP5-1 | -0.011 | -0.061 | 0.084 | 0.153 | 0.26 | 0.111 |
| | (-3.345) | (-2.617) | (1.42) | (2.359) | (1.891) | (0.948) |
| KEP5-1 | 0.005 | 0.052 | -0.076 | 0.094 | -0.093 | -0.18 |
| | (1.533) | (1.914) | (-0.848) | (1.233) | (-0.623) | (-2.275) |

*Note:* To be able to analyze the impact of the changes in the relative risk-aversion and the investor sentiment index, we regress the monthly time series of VEP5-1, SEP5-1 and KEP5-1 on the incremental changes in the relative risk-aversion time series and the sentiment index, the market excess return, the Fama-French and Carhart factors. We adjust the t-statistics using the Newey and West (1987) technique with 12 month lags.

the counterintuitive negative return that we observed for SEP5-1 tends towards positive (rational) values. The values of $\beta_{RRA}$ for VEP5-1 and KEP5-1 are not statistically significant, however, their negative signs show that by any increase in the relative risk-aversion, the monthly returns of VEP5-1 and KEP5-1 becomes more negative, meaning that with an increase in the relative risk-aversion, investors tend to price the market volatility and market kurtosis more rationally.

Since the sentiment index, moves in the opposite direction of the relative risk-aversion time series, the interpretation of $\beta_{Sent}$ is exactly the opposite of the interpretation of $\beta_{RRA}$. For example since the value $\beta_{Sent}$ for VEP5-1 is positive, an increase in the sentiment will push the return on VEP5-1 towards positive (less-rational) values. The results for market skewness risk suggest that the relationship of changes in sentiment and SEP5-1 is negative. In other words, once the sentiment increase the return on SEP5-1 tends towards negative (less-rational) values. In line with the results for market volatility risk, the relationship of changes in sentiment and KEP5-1 is positive, such that an increase in the investor sentiment increases the return on KEP5-1, and therefore push it towards positive (less-rational) values.

Furthermore, the alpha values reported in table (2.8) suggest that our previous results are robust. In line with intuition, the alpha values of VEP5-1 in panel (A) and (B) are significantly negative, suggesting a negative price of market volatility risk. Furthermore, the alpha values of SEP5-1 are also significantly negative, suggesting a negative price of market skewness risk, which we found to only be present, counter-intuitively, in up-markets, and disappear when the risk-aversion increase and the sentiment decline.

## 2.6 Concluding Remarks

Previous research suggests that the cross-section of stock returns has exposure to market risk captured by the higher moments. According to the ICAPM, the prices of the market volatility, skewness and kurtosis risks should be significantly negative, positive and negative, respectively. However, previous studies find the opposite signs for the market skewness and the market kurtosis risk premia. Using the higher risk-neutral moments implied by the S&P500 index option prices, we study these anomalies in the market moments' risk premia and find that these risk premia are time-varying and have significantly different patterns under different market conditions, proxied by investors' risk-aversion.

In particular, our results suggest that only in down-markets, when investors are more risk-averse, the market volatility risk is priced significantly negative, and this significance disappears in up-markets, when investors become more risk-seeking. Also we find that the price of the market skewness risk is significantly negative (against the ICAPM intuition), only when investors exhibit low risk-aversion. Our findings further suggest the price of market kurtosis risk is positive (against the ICAPM intuition), only in low risk-aversion periods. These counterintuitive prices for the market skewness and kurtosis disappear once the risk-aversion rises. Importantly, our findings confirm the previous results for volatility in the cross-section of stocks, but suggest that the previously counter-intuitive results for skewness are mainly caused by investors' more risk-seeking behavior in up-markets. These results highlight the importance of considering risk-aversion in studying market anomalies.

Furthermore, we investigate the relationship between investors' risk-aversion and sentiment, and find that our proxy of risk-aversion affects the investor sentiment index with 3 to 12 months lags. In other words, periods of low (high) sentiment are typically preceded by periods of increased (decreased) risk-aversion in the market. Therefore, our previous results on the market moments' risk premia can also be replicated by analyzing periods of high and low sentiment, separately.

## 2.7 Appendix A: Measuring the Risk-Neutral Moments

Based on the BKM, one can measure the volatility, the skewness and the kurtosis of S&P500 index return, using the prices of the European options written on this index with

$$Vol_t = \sqrt{exp(r\tau)V(t,\tau) - \mu(t,\tau)^2}, \tag{2.14}$$

$$Skew_t = \frac{exp(r\tau)W(t,\tau) - 3exp(r\tau)\mu(t,\tau)V(t,\tau) + 2\mu(t,\tau)^3}{Vol_t^3}, \tag{2.15}$$

$$Kurt_t = \frac{exp(r\tau)X(t,\tau) - 4exp(r\tau)\mu(t,\tau)W(t,\tau) + 6exp(r\tau)\mu(t,\tau)^2V(t,\tau) - 3\mu(t,\tau)^4}{Vol_t^4}, \tag{2.16}$$

where,

$$\mu(t,\tau) = exp(r\tau) - 1 - \frac{exp(r\tau)}{2}V(t,\tau) - \frac{exp(r\tau)}{6}W(t,\tau) - \frac{exp(r\tau)}{24}X(t,\tau), \tag{2.17}$$

$$V(t,\tau) = \int_{S_t}^{\infty} \frac{2\Big(1 - ln\Big(\frac{K}{S_t}\Big)\Big)}{K^2} C(t,\tau;K)dK + \int_0^{S_t} \frac{2\Big(1 + ln\Big(\frac{S_t}{K}\Big)\Big)}{K^2} P(t,\tau;K)dK, \tag{2.18}$$

$$W(t,\tau) = \int_{S_t}^{\infty} \frac{6ln\Big(\frac{K}{S_t}\Big) - 3\Big(ln\Big(\frac{K}{S_t}\Big)\Big)^2}{K^2} C(t,\tau;K)dK - \int_0^{S_t} \frac{6ln\Big(\frac{S_t}{K}\Big) + 3\Big(ln\Big(\frac{S_t}{K}\Big)\Big)^2}{K^2} P(t,\tau;K)dK, \tag{2.19}$$

and,

$$X(t,\tau) = \int_{S_t}^{\infty} \frac{12\Big(ln\Big(\frac{K}{S_t}\Big)\Big)^2 - 4\Big(ln\Big(\frac{K}{S_t}\Big)\Big)^3}{K^2} C(t,\tau;K)dK + \int_0^{S_t} \frac{12\Big(ln\Big(\frac{S_t}{K}\Big)\Big)^2 + 4\Big(ln\Big(\frac{S_t}{K}\Big)\Big)^3}{K^2} P(t,\tau;K)dK. \tag{2.20}$$

In these formulas, $\tau$ is the time-to-maturity of the options used for calculating the market moments, which can also be interpreted as the horizon, over which we compute the moments. Also, $r$ is the risk-free rate and $S_t$ is the price of the option underlying (here the S&P500 index value) at day $t$. $C(t,\tau;K)$ and $P(t,\tau;K)$ represent the prices of the European call and put options (written on the S&P500 index), with strike price $K$ and time-to-maturity of $\tau$.

Options with near maturity reflect investors' short-term expectations more clearly, therefore for each day we calculate the risk-neutral moments for the horizon of the next 30 days. We obtain the daily prices of the European options written on the S&P 500 index from the Ivy DB of OptionMetrics. Due to illiquidity and microstructural limitations, we eliminate the options with less than 6 days-to-maturity and cheaper than \$3/8.

Options with exactly 30 days-to-maturity are not traded in all days, therefore for these days we calculate the market moments for the two closest available maturities, smaller and bigger than 30 days, and then use linear interpolation to find estimations of the market moments for the horizon of the next 30 days.

In order to calculate the integrals in equation (2.18) to (2.20) accurately, we need to have a fine continuum of OTM options for every strike price. However options are not written on every strike price. Therefore following Chang, Christoffersen and Jacobs (2013), on each day we fit a natural cubic spline to the volatility smile of the OTM options with a specific time-to-maturity, so that we can find an estimation of the implied volatility and thereby option prices for every moneyness ratio ($\frac{K}{S_t}$), using the Black and Scholes (1973) formula. To do so we take the put options, whose moneyness ratios are less than 1.03 and the call options whose moneyness ratios are more than 0.97 as OTM options, and fit a cubic spline to them. For the moneyness values above the maximum available moneyness and below the minimum available moneyness, we assume the implied volatility is constant and equal to the implied volatility of the highest and the lowest available moneyness values, respectively. Using this spline, we can find an estimation of the implied volatility for every moneyness level between 0.01 and 2. We break this interval to 1000 equal slices and compute the integrals in equation (2.18) to (2.20). To make it more comparable to other studies, we report the annualized volatility as

$$Annualized \quad Vol_t = Vol_t\sqrt{\frac{365}{\tau}}. \tag{2.21}$$

# Chapter 3

# Does Oil and Gold Price Uncertainty Matter for the Stock Market?

## 3.1 Introduction

Uncertainty cuts investment, reduces the production of consumer durable goods (Bernanke (1983)) and creates temporary drops in employment and aggregate output (Bloom (2009)). Uncertainty originates from different sources. For example, it might arise from uncertainty about future stock returns, uncertainty about future price of energy or inflationary uncertainty. Moreover, different sectors of the economy have different levels of exposure to each source of uncertainty; while uncertainty about the future price of oil is a crucial factor for firms investing on shale oil extraction, it has a negligible impact on firms in the health care industry.

Throughout the literature there are different definitions and interpretations for economic uncertainty. Bansal and Yaron (2004) define economic uncertainty as time variation in the conditional volatility of consumption; economic uncertainty is high if investors are doubtful about the conditional volatility of consumption growth in upcoming periods. They show that investors' aversion to this unpredictability explains the large equity premium puzzle, the low risk free rate puzzle, the predictive power of price-dividend ratio for future returns and the persistency of market volatility.

Previous studies show that rising economic uncertainty also affects the stock market; Bansal, Khatchatrian and Yaron (2005) show that economic uncertainty predicts and is predicted by valuation ratios. Boguth and Kuehn (2013) find that sensitivity of firms' cash flow to economic uncertainty explains cross sectional variation in firms' expected returns. Bansal, Kiku, Shaliastovich and Yaron (2014) show that time varying economic uncertainty explains the joint dynamics of returns on equity and human capital. Anderson, Ghysels and Juergens (2009) and Bali and Zhou (2016) provide strong evidence for a positive relationship between price uncertainty and expected stock returns. Moreover, numerous studies show that the economic impact of uncertainty is not limited to the stock market, but it extends to other asset classes, such as bonds (see e.g. Connolly, Stivers and Sun (2005), Baele, Bekaert and Inghelbrecht (2010), Bhamra, Kuehn and Strebulaev (2010) Buraschi, Trojani and Vedolin (2013) and Bansal and Shaliastovich (2013)). The extensive amount of evidence regarding the impact of uncertainty on financial markets motivates the need for gaining deeper insight about different sources of uncertainty.

Since oil price uncertainty negatively affects macroeconomic variables such as investment, aggregate output and durables consumption (Elder and Serletis (2010)), we believe that it is also an important factor for stock valuations. Furthermore, investors use gold to hedge against inflation uncertainty and the uncertainty surrounding monetary policies of central banks. Due to the negative relation between gold price and stock markets (Chan, Treepongkaruna, Brooks and Gray (2011), Elder, Miao and Ramchander (2012), Baur and McDermott (2010) and Baur and Lucey (2010)), uncertainty about the future price of gold can potentially convey decisive information about the monetary situation of the market for stock valuations.

In the same spirit as Bansal and Yaron (2004), we define uncertainty in the stock, oil and gold markets as time variations in the conditional volatility of return on each of these assets.[1] Based on this interpretation, (e.g.) oil price is uncertain, if the conditional volatility of its return is extremely time varying; it is not clear that, in the near future, the oil market will be calm or volatile. This unpredictability increases the price of a hedge against time variation in oil volatility. Consequently, we can proxy the level of uncertainty in the oil market with the variance risk premium of this asset. Section 2 provides more details about our uncertainty proxy choice.

We estimate the economic uncertainty that originates from the stock, oil and gold markets with the variance risk premia of the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar, respectively. Subsequently, we investigate the distinctive impact of the uncertainty that originates from each of these asset classes on the time

[1] Indeed, this interpretation about uncertainty differs from other well-known definitions in the literature. For instance, Knight (1921) defines uncertainty as the inability to quantify the probability distribution of the outcomes. Ellsberg (1961) shows that risk and uncertainty are different and agents have distinctive aversions towards these two concepts. Also pioneered by Miller (1977), some authors define uncertainty as different-in-opinion and beliefs disagreement. The theoretical model of Buraschi, Trojani and Vedolin (2014) shows that beliefs disagreement creates variance risk premia, which is our proxy for uncertainty.

series and the cross section of stock prices. While recent studies investigate the effect of oil or gold price shocks on the equity market, we explore the impact of the uncertainty that originates from these two major alternative asset classes on stock prices.

We find that rising uncertainty in the stock, oil or gold markets is accompanied by falling stock prices; uncertainty makes firm valuations, investment decisions and cash flow forecasts non-transparent, and thereby, investors will buy the stocks, affected by uncertainty shocks, at a discount. Moreover, a comparison between the three sources of uncertainty shows that although the stock market uncertainty has the dominant effect, stocks are also negatively affected by oil and gold market uncertainty.

Having shown that stocks are exposed to these three alternative uncertainty factors, we further investigate whether these sources of uncertainty are priced risk factors in the cross section of stock expected returns. Rational investors require extra compensation for holding assets that are negatively affected by a *systematic* uncertainty shock. Our empirical results show that, in contrast to oil and gold price uncertainty which are diversifiable risk factors, the stock market uncertainty is a systematic factor that is priced across different industries; stocks that are negatively affected by stock market uncertainty shocks are compensated with significantly higher returns, compared to the ones with otherwise similar characteristics.

Previous studies show that an oil price shock affects the stock markets negatively (Jones and Kaul (1996), Driesprong, Jacobsen and Maat (2008) and Narayan and Sharma (2011)), however, oil price shock is not a priced risk factor and it does not affect the discount rate or the equity risk premium (Chen, Roll and Ross (1986), Jones and Kaul (1996) and Driesprong, Jacobsen and Maat (2008)). We empirically document the same results for oil price uncertainty and conclude that, although it is relevant for the overall economy, oil price uncertainty is not a systematically priced factor that affects the expected return of every stock. This finding is in line with the interpretation of Driesprong, Jacobsen and Maat (2008) that oil-price-based return predictability can not be explained by a time-varying risk premium.

Our further intra-industry investigation reveals interesting results for oil; while oil uncertainty is not a priced risk factor for all types of stocks and therefore it is diversifiable across industries, it is priced within oil-relevant industries. In each of these industries, stocks that are negatively affected by oil price uncertainty shocks are compensated with significantly higher returns. Therefore, oil price uncertainty is not a relevant risk factor for the equity premium in every industry, but only for stocks in oil-relevant industries. An economic interpretation of this result suggests industry segmentation of the market. In accordance with the interpretation of Pollet (2005) and Hong, Torous and Valkanov (2007), industry-specialized investors, who hold undiversified portfolios, cause oil uncertainty to be a priced factor within the oil-relevant industries, as they react to oil-relevant news more quickly and efficiently.

Lee and Ni (2002), Narayan and Sharma (2011) and Scholtens and Yurtsever (2012) find that the impact of oil return shocks on stock returns is not homogeneous, but it depends on the industry that stocks belong to. We unravel a similar finding for the price of oil uncertainty; while escalating uncertainty about the future price of oil prevents cash flow forecasts and stock valuations in oil-relevant industries, it is irrelevant, and thus not a distinctive pricing factor, for the rest of the market.

These findings imply that for pricing any stock, investors must consider its exposure to the stock market uncertainty factor, because this is a systematically priced factor that affects the risk premium and the expected return of every stock. The investors in oil-relevant industries, in addition, must consider oil price uncertainty risk because as a sector-specific factor, it affects the risk premium and the expected return of the stocks in those industries. The investors, who hold sufficiently diversified portfolios, can ignore gold price uncertainty, as this type of uncertainty is asset-specific and it has negligible impact on diversified portfolios.

## 3.2 Variance Risk Premium, Measure of Uncertainty

One major challenge is to obtain a robust measure of uncertainty that is comparable across different markets. Anderson, Ghysels and Juergens (2005) point out the limitations of relying on analysts' forecasts dispersion as a measure of uncertainty. They conclude that because of analysts' optimism (pessimism) on long-term (short-term) forecasts, agency issues and behavioral biases, analysts' beliefs disagreements cannot be a reliable proxy. In addition, they note that similar education, goals and interactions prevent analysts' forecasts dispersion from being a generic survey of disagreement in a heterogeneous market with different participants.

On the other hand, Bansal and Yaron (2004) define economic uncertainty as time variation in the conditional volatility of consumption growth (i.e. volatility-of-volatility), and show that this phenomenon can explain the large equity premium puzzle, the low risk free rate puzzle, the predictive power of price-dividend ratio for future returns and the persistency of market volatility. Bollerslev, Tauchen and Zhou (2009) show that the economic uncertainty, defined in this fashion, is tightly linked to the variance risk premium: "*any temporal variation in the endogenously generated variance risk premium ... is solely due to the volatility-of-volatility* [uncertainty]" (Bollerslev, Tauchen and Zhou (2009), page 4469).

Also, Drechsler and Yaron (2011) show that investors' aversion to uncertainty about shocks to influential state variables creates a variance risk premium. Drechsler (2013) find that time variations in uncertainty creates fluctuations in the variance risk premium, and these fluctuations can predict stock returns even at short horizons (also see Drechsler and Yaron (2011), Bollerslev, Tauchen and Zhou (2009) and Bollerslev, Marrone, Xu and Zhou (2014)).[2]

This interpretation about uncertainty is also linked to the other definitions and proxies of economic uncertainty. For example, Buraschi, Trojani and Vedolin (2014) show that investors' disagreements about the growth of future dividends create large variance risk premia for the market portfolio and for individual assets. Therefore, Bali and Zhou (2016) take the variance risk premium of the S&P 500 index as a market-wide measure of uncertainty, and show that it is highly correlated with many other uncertainty proxies, such as the conditional variance of the Chicago Fed National Activity Index (CFNAI) and the conditional variance of the growth rate of industrial production.

Following the previous literature, we proxy uncertainty with the variance risk premium.[3] The variance risk premium at time $t$ is equal to the difference between the expected variance, under the risk-neutral and the physical measures, i.e.

$$VRP_t^{\tau} = Var_t^Q(t, t+\tau) - Var_t^P(t, t+\tau). \tag{3.1}$$

Here $Var_t^Q(t, t+\tau)$ and $Var_t^P(t, t+\tau)$ are, respectively, the variance expectations under the risk-neutral and the physical measures. These variance expectations for the period of $[t, t+\tau]$ are measured with the information available at time $t$.

Under the theoretical framework of Bali and Zhou (2016), variance is time varying and investors dislike the volatile states of the economy. Under these assumptions the risk-neutral variance expectation exceeds the physical variance expectation, and thereby, the variance risk premium ($VRP_t^{\tau}$) is always positive. Moreover when investors' uncertainty goes up, both, the risk-neutral and the physical variance expectations increase, and the Bali and Zhou (2016) framework would suggest that the variance risk premium becomes even more positive. Admittedly, this is only true under the assumed conditions and cannot be generalized.[4] To put it differently, by buying a variance swap contract,

[2] The theoretical models, cited here, are all based on agents with Epstein and Zin (1989) recursive utility preferences. Since in these models the risk aversion is assumed to be constant, fluctuations in variance risk premium is only driven by time variations in uncertainty. However, if risk aversion was also variable then shocks to variance risk premium would be a function of the changes in both uncertainty and risk aversion. Even some authors, such as Bollerslev, Gibson and Zhou (2011) and Bekaert and Hoerova (2014), consider the variance risk premium as a proxy for the level of risk aversion.
In our study we investigate the impact of *daily changes* in variance risk premium on the stock market. Since investors' risk aversion (the curvature of agents' utility function), changes over long business cycles (see e.g. Brandt and Wang (2003)), we believe that changes in investors' risk aversion has negligible effect on the shocks in variance risk premium at daily frequency; day-to-day changes in variance risk premium is virtually only driven by the fluctuations in the level of uncertainty.

[3] In the previous version of this paper, available upon request, we proxy the uncertainty with volatility risk premium instead of the variance risk premium, and we obtain qualitatively similar results.

[4] We thank the referee for pointing this out. Variance is indeed time varying, but whether the marginal investors *always* dislike the volatile states of the economy or not remains as an empirical question.

investors can protect themselves against future variance shocks. Then the variance risk premium is equivalent to the expected payoff of a variance swap seller. When uncertainty escalates the variance swap seller, who provides an insurance against variance shocks, expects a higher payoff and therefore the variance risk premium becomes more positive.

### 3.2.1 Data

We obtain historical data of futures and option contracts traded on the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar from the Commodity Research Bureau (CRB) database. This database provides us with various information, such as closing price, transaction date and expiration date of futures contracts and the American put and call options, written on these futures contracts. Option contracts for oil and gold are only written on their futures contracts, rather than their spot prices. We take returns on futures as proxies for price changes in each of these three markets. We match each option with its corresponding futures contract on the same day and eliminate the ones, for which we cannot find the underlying futures contract in the database. Also to avoid illiquidity and micro-structural anomalies, following Chang, Christoffersen and Jacobs (2013), we omit all option contracts with less than 6 days to maturity and options that are cheaper than 3/8 dollars. Table 3.1 provides summary statistics on our data.

Prices of options with shorter time-to-maturity reflect investors' short-term expectations and uncertainty more evidently. Hence, we measure the variance risk premia for a reasonably small time horizon. As table 3.1 shows, the futures contracts on the S&P 500 index are written quarterly, which is less frequent compared to West Texas Intermediate crude oil and 100-oz gold bar futures. In order to have a unique horizon for our analysis, we take the shortest common time-to-maturity i.e. 90 days ($\tau = 1/4$ year) for the variance risk premia computations.

The number of observations in our database rises drastically over time, suggesting considerably higher transaction volumes in recent years. Due to the insufficiency of the data for measuring the oil variance risk premium with $\tau = 1/4$ in the earlier years, we conduct our analysis based on the last 18 years of the data, i.e. from January 1996 to December 2013.[5]

Consistent with Bali and Zhou (2016), our empirical results in figure 3.1 show that, in the beginning of 2009, the variance risk premium of the S&P500 index becomes extremely low or even negative. This event has coincided with the "resurrection" of the financial markets from the great recession of 2007-2008.

[5] To obtain the risk-neutral variance time series, one could alternatively use the volatility indexes, computed and released by the Chicago Board Options Exchange (CBOE). Although the time series of the S&P 500 volatility index (VIX) starts 1986 and it covers our entire study period, the time series of oil risk-neutral volatility (OVX) and gold risk-neutral volatility (GVZ) are short and non-applicable for this research. Since the correlation between our measure of risk-neutral volatility for the S&P 500 index and VXV is 0.96, we are confident that our methodology is accurate and robust.

Table 3.1: Data Summary Statistics

**Panel A: Futures Contracts**

| | S&P 500 Index | West Texas Intermediate Oil | 100-oz Gold Bar |
|---|---|---|---|
| Exchange | CME | NYMEX | COMEX |
| First Date | 21/04/1982 | 30/03/1983 | 31/12/1974 |
| Last Date | 31/12/2013 | 31/12/2013 | 31/12/2013 |
| Trading Months | March, June, September, December | Every Month | February, April, June, August, October, December |

**Panel B: Option Contracts**

| | | S&P 500 index | | Oil | | Gold | |
|---|---|---|---|---|---|---|---|
| First Date | | 28/01/1983 | | 30/09/1988 | | 01/09/1988 | |
| Last Date | | 31/12/2013 | | 31/12/2013 | | 31/12/2013 | |
| Number of Options | | 4,355,473 | | 6,505,303 | | 10,162,803 | |
| | Year | Calls | Puts | Calls | Puts | Calls | Puts |
| Number of Option Observations Matched with Their Underlying Futures | 1983 | 3,405 | 3,035 | 0 | 0 | 0 | 0 |
| | 1984 | 3,728 | 3,257 | 0 | 0 | 0 | 0 |
| | 1985 | 4,388 | 4,233 | 0 | 0 | 0 | 0 |
| | 1986 | 6,002 | 6,065 | 0 | 0 | 0 | 0 |
| | 1987 | 9,696 | 9,469 | 0 | 0 | 0 | 0 |
| | 1988 | 7,755 | 8,725 | 20 | 20 | 219 | 224 |
| | 1989 | 8,905 | 8,866 | 5,595 | 5,957 | 10,601 | 8,555 |
| | 1990 | 9,111 | 10,359 | 16,356 | 16,356 | 19,354 | 19,290 |
| | 1991 | 9,483 | 11,362 | 21,004 | 17,762 | 18,961 | 18,826 |
| | 1992 | 9,658 | 11,487 | 14,729 | 13,539 | 18,574 | 18,584 |
| | 1993 | 10,274 | 12,275 | 17,824 | 14,951 | 28,478 | 28,468 |
| | 1994 | 9,912 | 11,431 | 22,136 | 16,591 | 26,560 | 26,373 |
| | 1995 | 18,155 | 18,254 | 28,088 | 18,404 | 27,613 | 27,608 |
| | 1996 | 21,831 | 22,961 | 33,165 | 25,324 | 33,869 | 33,861 |
| | 1997 | 19,245 | 20,995 | 25,750 | 19,931 | 28,019 | 26,251 |
| | 1998 | 20,230 | 20,427 | 24,499 | 18,673 | 26,806 | 25,132 |
| | 1999 | 20,416 | 21,534 | 43,836 | 35,386 | 39,209 | 39,196 |
| | 2000 | 33,720 | 39,066 | 71,291 | 70,482 | 50,033 | 50,086 |
| | 2001 | 32,803 | 40,531 | 72,382 | 58,792 | 48,920 | 48,978 |
| | 2002 | 36,832 | 40,781 | 77,902 | 62,838 | 57,011 | 56,990 |
| | 2003 | 31,562 | 34,253 | 74,257 | 70,050 | 70,267 | 70,259 |
| | 2004 | 33,318 | 35,168 | 101,443 | 106,123 | 82,461 | 82,491 |
| | 2005 | 36,020 | 40,035 | 171,342 | 181,409 | 93,403 | 93,379 |
| | 2006 | 45,476 | 65,899 | 193,751 | 193,873 | 152,012 | 152,056 |
| | 2007 | 55,582 | 94,871 | 216,838 | 202,190 | 145,954 | 145,893 |
| | 2008 | 87,644 | 109,993 | 416,054 | 397,672 | 189,043 | 189,106 |
| | 2009 | 80,224 | 93,837 | 406,853 | 376,433 | 229,073 | 228,988 |
| | 2010 | 89,522 | 94,184 | 340,485 | 301,540 | 464,596 | 460,777 |
| | 2011 | 155,511 | 154,007 | 354,199 | 321,435 | 693,676 | 693,239 |
| | 2012 | 168,511 | 168,689 | 371,861 | 329,077 | 828,837 | 829,065 |
| | 2013 | 181,649 | 181,503 | 270,695 | 236,532 | 846,092 | 846,092 |
| | Total | 1,260,568 | 1,397,552 | 3,392,355 | 3,111,340 | 4,229,641 | 4,219,767 |
| OTM Option Observations Used for Calculating 90-Day Variance | | 229,431 | 180,546 | 208,467 | 105,685 | 285,715 | 135,278 |
| Average Observations per Day | | 55.19 | 43.43 | 50.15 | 25.42 | 68.73 | 32.54 |

*Note:* This table provides information about the futures contracts and the options, written on the future contracts of the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar. We obtain this data from the Commodity Research Bureau database.

### 3.2.2 Variance Risk Premium Estimation

In order to proxy the variance risk premium ($VRP_t^\tau$) from equation (3.1), we need reliable estimates of the variance expectation under the risk-neutral and the physical measures. In particular these estimates must be forward looking and conditionally measurable at time $t$.

We use the model-free methodology of Bakshi, Kapadia and Madan (2003) to calculate the variance expectation under the risk-neutral measure. This methodology extracts the risk-neutral variance of each day from the out-of-money [OTM] European options traded on that particular day. Hence, the computed variance is strictly conditional and forward looking. Since our option contacts are written on futures, rather than spot prices, we adjust the formulas of Bakshi, Kapadia and Madan (2003) to have,

$$\widehat{Var_t^Q}(t, t+\tau) = \frac{exp(r\tau)V(t, t+\tau) - \mu(t, t+\tau)^2}{\tau}, \tag{3.2}$$

where,

$$\mu(t, t+\tau) = -\frac{exp(r\tau)}{2}V(t, t+\tau) - \frac{exp(r\tau)}{6}W(t, t+\tau) - \frac{exp(r\tau)}{24}X(t, t+\tau), \tag{3.3}$$

$$V(t, t+\tau) = \int_{F_t^\tau}^{\infty} \frac{2\Big(1 - ln\Big(\frac{K}{F_t^\tau}\Big)\Big)}{K^2} C(t, \tau; K)dK + \int_0^{F_t^\tau} \frac{2\Big(1 + ln\Big(\frac{F_t^\tau}{K}\Big)\Big)}{K^2} P(t, \tau; K)dK, \tag{3.4}$$

$$W(t, t+\tau) = \int_{F_t^\tau}^{\infty} \frac{6ln\Big(\frac{K}{F_t^\tau}\Big) - 3\Big(ln\Big(\frac{K}{F_t^\tau}\Big)\Big)^2}{K^2} C(t, \tau; K)dK - \int_0^{F_t^\tau} \frac{6ln\Big(\frac{F_t^\tau}{K}\Big) + 3\Big(ln\Big(\frac{F_t^\tau}{K}\Big)\Big)^2}{K^2} P(t, \tau; K)dK, \tag{3.5}$$

and,

$$X(t, t+\tau) = \int_{F_t^\tau}^{\infty} \frac{12\Big(ln\Big(\frac{K}{F_t^\tau}\Big)\Big)^2 - 4\Big(ln\Big(\frac{K}{F_t^\tau}\Big)\Big)^3}{K^2} C(t, \tau; K)dK + \int_0^{F_t^\tau} \frac{12\Big(ln\Big(\frac{F_t^\tau}{K}\Big)\Big)^2 + 4\Big(ln\Big(\frac{F_t^\tau}{K}\Big)\Big)^3}{K^2} P(t, \tau; K)dK. \tag{3.6}$$

In equation (3.2) to (3.6), $r$ is the risk-free rate, $F_t^\tau$ shows the price of the underlying futures contract at day $t$, and $C(t, \tau; K)$ and $P(t, \tau; K)$ respectively represent the price of a European call option and a European put option at day $t$, with $\tau$ years to maturity and strike price of $K$. The appendix to the paper provides more details about our computations of the risk-neutral variance expectation.

In order to calculate the variance expectation under the physical measure, some authors rely on the assumption that the ex-post realized variance is an unbiased estimator of the ex-ante variance expectation. Hence, they proxy $Var_t^P(t, t+\tau)$ with the realized variance of returns between times $t$ and $t+\tau$.[6] However, in this case the variance expectation is not measurable with the available information at time $t$. Instead, we estimate the physical variance expectation as follows: First we calculate the realized volatility between time $t$ and $t+\tau$, as

$$v(t, t+\tau) = \sqrt{252 \times \sum_{s=t}^{t+365\times\tau} \frac{R_{s,\tau}^2}{N_t - 1}}. \tag{3.7}$$

Here, $N_t$ is the number of return observations between time $t$ and $t+\tau$ and $R_{s,\tau} = ln(F_s^\tau) - ln(F_{s-1}^\tau)$ is the logarithmic return of a futures contract with $\tau$ years to maturity on day $s \in [t, t+\tau]$.[7]

Then assuming that the physical volatility expectation follows an autoregressive process, we fit the following regression equation to the realized volatility time series over our entire sample.

$$v(t, t+\tau) = a + b \times v(t-\tau, t) + \varepsilon_t. \tag{3.8}$$

Finally, using the estimates of $a$ and $b$ in regression equation (3.8), we compute investors' physical variance expectation as the square of the projected volatility, i.e. $\widehat{Var_t^P}(t, t+\tau) = \big(a + b \times v(t-\tau, t)\big)^2$. Table 3.2 displays the estimated values of $a$ and $b$ for stock, oil and gold physical variances.[8]

[6]This is a common assumption used to compute the volatility risk premium (e.g. Buraschi, Trojani and Vedolin (2014)), and the variance risk premium (e.g. Carr and Wu (2009), Trolle and Schwartz (2010) and Prokopczuk and Wese Simen (2014)).

[7]Futures with exactly $\tau$ years to maturity are not traded on every day. To calculate futures returns with the constant maturity of $\tau$, on each day, we interpolate between the prices of two futures contracts with shorter and longer maturities than $\tau$.

[8]Strictly speaking, this method is not free of look-ahead bias, as $a$ and $b$ are estimated based on our entire sample. Here, we have assumed that investors are aware of the auto-regressive nature of the variance time series and the values of $a$ and $b$ are included in investors' information set from the beginning of our sample. In order to estimate the physical variance expectation precisely, a perfect alternative solution would be to use high-frequency data and the HAR methodology of Corsi (2009). Unfortunately, we could not obtain the high-frequency time series of return on oil and gold futures contracts.

Table 3.2: Autoregressive Parameters of Physical Variance Expectation

| Coefficients Estimates | Stock | Oil | Gold |
|---|---|---|---|
| $a$ | 0.080 | 0.108 | 0.064 |
| | (7.03)*** | (3.42)*** | (4.49)*** |
| $b$ | 0.558 | 0.615 | 0.591 |
| | (8.76)*** | (4.84)*** | (6.29)*** |
| R-Squared | 0.85 | 0.93 | 0.91 |

*Note:* We estimate the realized volatility $v(t, t+\tau)$ for any interval $[t, t+\tau]$, and regress it on its $\tau = 1/4$ year lagged values,

$$v(t, t+\tau) = a + b \times v(t-\tau, t) + \varepsilon_t.$$

Then we take the square of the projected volatility, i.e. $\widehat{Var_t^P}(t, t+\tau) = \big(a + b \times v(t-\tau, t)\big)^2$, as investors' physical variance expectation at time $t$. This table reports the estimated coefficients, and their corresponding t-statistics. The t-statistics, reported in the parenthesis, are adjusted with the Newey and West (1987) technique. *, **, and ***, respectively, denote significance at the 10%, 5% and 1% levels.

### 3.2.3 Descriptive Statistics

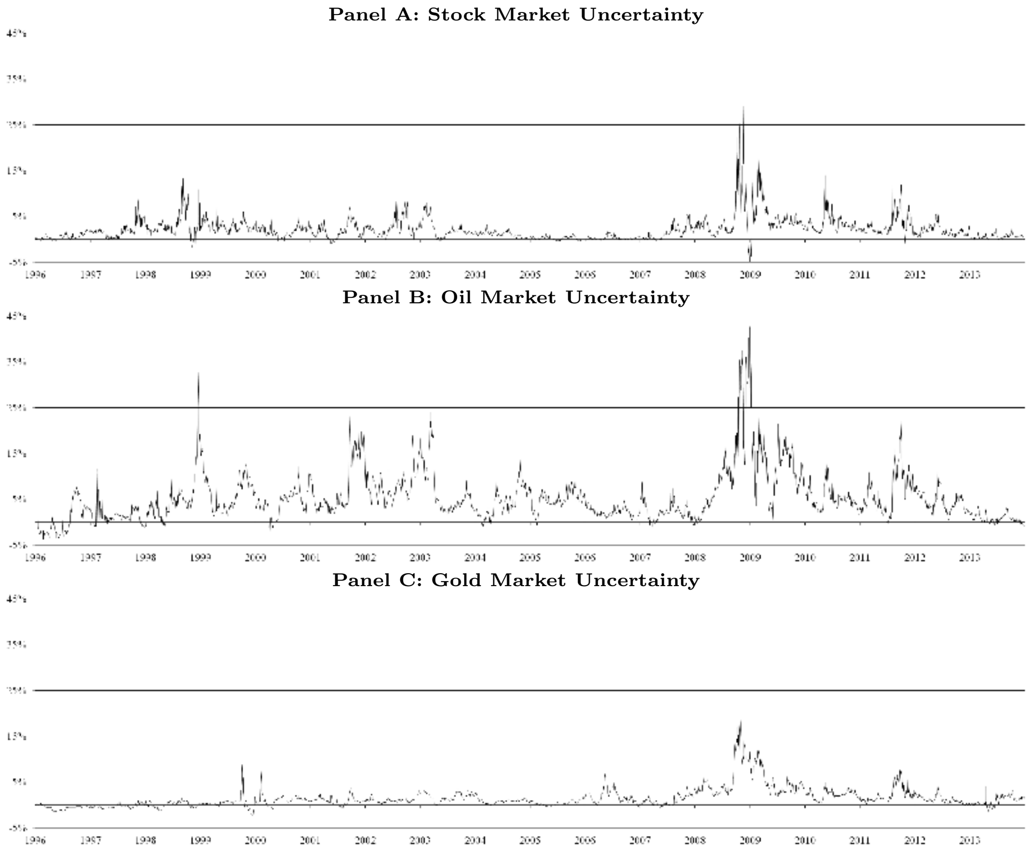
Panel A to C in figure 3.1 display our estimated variance risk premia time series for the stock, oil and gold markets from 1996 to 2013. These time series are mostly positive, indicating that on average, investors pay to hedge against the shocks in the variance of the S&P 500 index, oil and gold.

The remarkable common variation in these three time series reveals that some systematic patterns exist across the markets. For example with the plunge of the financial markets in September 2008, the three variance risk premia set their new highest records, indicating the huge level of uncertainty in all three market.

The three time series also exhibit some divergence movements. For example from 2004 to 2007, while the variance risk premium of the S&P 500 index was stable around zero, the variance risk premium of crude oil was relatively volatile. This suggests the existence of asset-specific components in uncertainty, which motivates our investigation of their distinctive impact on stock prices. An even more compelling case is the oil uncertainty escalation from September 2001 until June 2003, the period of tension in the Middle-East. During this period the price of a hedge against oil variance shocks averaged at 9.69 percent, and it reach a new peak of 24.84 percent. The oil market situation during this period is well summarized by the New York Times on June 25, 2002: *"Yet in such unpredictable times, with one conflict worsening in the Middle East and the rumor of another rising, the 10-member cartel's inaction amounts to a gamble that could send the price of oil rocketing in the coming months." (Banerjee (2002))*

Table 3.3 presents descriptive statistics on the variance risk premia time series, our proxy for the level of uncertainty. The average of the variance risk premia is significantly positive for all three markets, showing the substantial cost of hedging against variance

Figure 3.1: Variance Risk Premia Time Series, Our Proxy for Uncertainty




*Note:* We calculate the variance risk premium as the difference between the expected variance, under the risk-neutral and the physical measures

$$VRP_t^{\tau} = Var_t^Q(t, t+\tau) - Var_t^P(t, t+\tau).$$

We use the methodology of Bakshi, Kapadia and Madan (2003) and extract investors' risk-neutral variance expectation ($Var_t^Q(t, t+\tau)$) from the price of OTM options. Moreover, we estimate the realized volatility $v(t, t+\tau)$ for any interval $[t, t+\tau]$, and regress it on its $\tau = 1/4$ year lagged values $v(t, t+\tau) = a + b \times v(t - \tau, t) + \varepsilon_t$. Then we take the square of the projected volatility, i.e. $\widehat{Var_t^P}(t, t+\tau) = \left(a + b \times v(t-\tau, t)\right)^2$, as investors' physical variance expectation at time $t$. This figure displays the variance risk premia time series of the S&P 500 index, as well as, oil and gold.

Table 3.3: Descriptive Statistics on Variance Risk Premia, Our Proxy for Uncertainty

| | Variance Risk Premia | | |
|---|---|---|---|
| **Statistics** | **Stock Market** | **Oil Market** | **Gold Market** |
| Number of Observations | 4157 | 4157 | 4157 |
| Mean (%) | 2.13 | 5.27 | 1.47 |
| | (56.55)*** | (63.06)*** | (42.43)*** |
| Standard Deviation (%) | 2.43 | 5.39 | 2.24 |
| **Percentiles** | | | |
| 5th Percentile (%) | -0.07 | -0.38 | -0.61 |
| 25th Percentile (%) | 0.57 | 1.96 | 0.25 |
| Median (%) | 1.63 | 3.97 | 0.92 |
| 75th Percentile (%) | 2.89 | 7.02 | 2.07 |
| 95th Percentile (%) | 6.24 | 15.83 | 4.99 |
| **Correlations** | | | |
| Oil | 0.51 | | |
| Gold | 0.60 | 0.59 | |
| **Fitted ARMA(1,1) Parameters** | | | |
| Intercept | 0.0010 | 0.0010 | 0.0002 |
| | (2.93)*** | (3.06)*** | (3.16)*** |
| Autoregressive | 0.953 | 0.980 | 0.985 |
| | (50.97)*** | (134.26)*** | (134.01)*** |
| Moving-average | -0.168 | -0.087 | 0.045 |
| | (-2.70)*** | (-1.43) | (1.01) |

*Note:* We calculate the variance risk premium as the difference between the expected variance, under the risk-neutral and the physical measures

$$VRP_t^{\tau} = Var_t^{Q}(t, t+\tau) - Var_t^{P}(t, t+\tau).$$

We use the methodology of Bakshi, Kapadia and Madan (2003) and extract investors' risk-neutral variance expectation ($Var_t^{Q}(t, t+\tau)$) from the price of OTM options. Moreover, we estimate the realized volatility $v(t, t+\tau)$ for any interval $[t, t+\tau]$, and regress it on its $\tau = 1/4$ year lagged values $v(t, t+\tau) = a + b \times v(t-\tau, t) + \varepsilon_t$. Then we take the square of the projected volatility, i.e. $\widehat{Var_t^{P}}(t, t+\tau) = \big(a + b \times v(t-\tau, t)\big)^2$, as investors' physical variance expectation at time $t$. This table reports summary statistics on the variance risk premia time series of the S&P 500 index, as well as, oil and gold price. The t-statistics are computed based on heteroskedasticity-robust covariance matrix for the estimated parameters. The t-statistics are shown in parentheses. *, **, and ***, respectively, denote significance at the 10%, 5% and 1% levels.

shocks. In line with the results of Prokopczuk and Wese Simen (2014), gold has a relatively smaller variance risk premium, and consistent with Trolle and Schwartz (2010), the large oil variance risk premium is caused by the additional exposure of the oil price to political uncertainty.

We want to study the reaction of stock prices to a shock (innovation) in our alternative uncertainty measures. Thus, similar to Chang, Christoffersen and Jacobs (2013), we fit an $ARMA(1,1)$ process to each variance risk premium time series and take the residuals as the uncertainty shocks.[9] Table 3.4 reports summary statistics on the daily time series of uncertainty shocks, i.e. the ARMA residuals, as well as the market excess return ($R_{MRKT,t}$), the size ($R_{SMB,t}$) and the value ($R_{HML,t}$) factors of Fama and French (1993), and the momentum factor ($R_{MOM,t}$) of Carhart (1997).

The significantly positive correlations between the variance risk premia time series (in table 3.3) support our previous conjecture that there is a common systematic factor across all three markets' uncertainty. However, the correlations among the daily uncertainty shocks (in table 3.4) are rather low, suggesting the existence of market-specific components.

Remarkably, table 3.4 shows that the correlation between the stock market uncertainty shocks ($\Delta VRP_{S\&P,t}$) and the market excess returns ($R_{MRKT,t}$) is extremely negative (-0.65). This implies that usually an increase in stocks uncertainty is accompanied with falling stock prices. The correlations between the shocks in the other two sources of uncertainty (i.e. $\Delta VRP_{OIL,t}$ for oil and $\Delta VRP_{GOLD,t}$ for gold) and the market excess return ($R_{MRKT,t}$) are also negative, but with smaller magnitudes.

## 3.3 Empirical Analysis

We expect that different sources of uncertainty have distinctive effects on individual industries. In this section, we investigate the impact of the uncertainty shocks that originates from the stock, oil and gold markets on the time series and the cross section of the equity market. This is in contrast to Bollerslev, Tauchen and Zhou (2009), Drechsler and Yaron (2011), Drechsler (2013), Bali and Zhou (2016) who solely focus on stock market uncertainty.

### 3.3.1 Time Series Evidence

Narayan and Sharma (2011) and Elyasiani, Mansur and Odusami (2011) show that different industries have various level of exposure to oil price shocks or oil volatility shocks.

[9] As table 3.3 shows, the three autoregressive parameters are extremely close to one, and the moving-average parameters are much smaller. Thus fitting any $ARMA(p,q)$ process, with $p \geq 1$ and $q \geq 0$, does not change our results qualitatively.

Table 3.4: Descriptive Statistics on Uncertainty Shocks and Equity Risk Factors

| Statistics | $\Delta VRP_{S\&P,t}$ | $\Delta VRP_{OIL,t}$ | $\Delta VRP_{GOLD,t}$ | $R_{S\&P,t}$ | $R_{OIL,t}$ | $R_{GOLD,t}$ | $R_{MRKT,t}$ | $R_{SMB,t}$ | $R_{HML,t}$ | $R_{MOM,t}$ | $R_{F,t}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean (%) | 0.00 | 0.00 | 0.00 | 0.03 | 0.03 | 0.02 | 0.03 | 0.01 | 0.01 | 0.02 | 0.01 |
| Standard Deviation (%) | 0.88 | 1.21 | 0.38 | 1.33 | 1.96 | 1.10 | 1.27 | 0.61 | 0.64 | 0.98 | 0.01 |
| **Percentiles** | | | | | | | | | | | |
| 5th Percentile (%) | -0.82 | -1.16 | -0.40 | -2.03 | -3.13 | -1.77 | -1.94 | -0.95 | -0.95 | -1.41 | 0.00 |
| 25th Percentile (%) | -0.23 | -0.37 | -0.10 | -0.56 | -1.05 | -0.51 | -0.54 | -0.34 | -0.28 | -0.37 | 0.00 |
| Median (%) | -0.07 | -0.07 | -0.02 | 0.07 | 0.11 | 0.01 | 0.07 | 0.03 | 0.01 | 0.06 | 0.01 |
| 75th Percentile (%) | 0.16 | 0.28 | 0.07 | 0.67 | 1.14 | 0.60 | 0.64 | 0.36 | 0.29 | 0.45 | 0.02 |
| 95th Percentile (%) | 1.04 | 1.41 | 0.45 | 1.93 | 3.03 | 1.72 | 1.84 | 0.94 | 0.97 | 1.37 | 0.02 |
| **Correlations** | | | | | | | | | | | |
| $\Delta VRP_{S\&P,t}$ | | 0.21 | 0.17 | -0.65 | -0.21 | -0.01 | -0.64 | -0.01 | -0.09 | 0.25 | -0.02 |
| $\Delta VRP_{OIL,t}$ | | | 0.18 | -0.21 | -0.28 | -0.04 | -0.17 | 0.01 | -0.05 | 0.09 | -0.02 |
| $\Delta VRP_{GOLD,t}$ | | | | -0.10 | 0.00 | 0.13 | -0.08 | 0.01 | -0.06 | 0.02 | -0.02 |
| $R_{S\&P,t}$ | | | | | 0.20 | -0.01 | 0.94 | -0.06 | -0.11 | -0.25 | 0.00 |
| $R_{OIL,t}$ | | | | | | 0.23 | 0.20 | 0.04 | 0.10 | -0.07 | -0.01 |
| $R_{GOLD,t}$ | | | | | | | 0.00 | 0.04 | 0.02 | 0.06 | -0.02 |
| $R_{MRKT,t}$ | | | | | | | | 0.03 | -0.14 | -0.26 | -0.01 |
| $R_{SMB,t}$ | | | | | | | | | -0.12 | 0.07 | -0.02 |
| $R_{HML,t}$ | | | | | | | | | | -0.26 | 0.01 |
| $R_{MOM,t}$ | | | | | | | | | | | 0.03 |

*Note:* We take the residuals of three $ARMA(1,1)$ processes, fitted to the variance risk premia time series, as uncertainty shocks. This table reports summary statistics on the daily time series of uncertainty shocks, i.e. the ARMA residuals, as well as the market excess return ($R_{MRKT,t}$), the size ($R_{SMB,t}$) and the value ($R_{HML,t}$) factors of Fama and French (1993), and the momentum factor ($R_{MOM,t}$) of Carhart (1997).

Considering this heterogeneity of industries, we perform the following time series regressions for equally weighted portfolios of each industries. We construct industry portfolios based on stocks' Standard Industry Classification (SIC) code, obtained from the US Department of Labor. We include all the ordinary shares traded on NYSE, AMEX and NASDAQ from the CRSP database, and our sample spans from January 1996 to December 2013.

**Model 1:**

$$R_{I,t} = \alpha_I + \beta_I^{MRKT} R_{MRKT,t} + \beta_I^{SMB} R_{SMB,t} + \beta_I^{HML} R_{HML,t} + \beta_I^{MOM} R_{MOM,t} + \delta_I^{S\&P} \Delta VRP_{S\&P,t} + \gamma_I^{S\&P} R_{S\&P,t} + \varepsilon_{I,t}. \quad (3.9)$$

$$R_{I,t} = \alpha_I + \beta_I^{MRKT} R_{MRKT,t} + \beta_I^{SMB} R_{SMB,t} + \beta_I^{HML} R_{HML,t} + \beta_I^{MOM} R_{MOM,t} + \delta_I^{OIL} \Delta VRP_{OIL,t} + \gamma_I^{OIL} R_{OIL,t} + \varepsilon_{I,t}. \quad (3.10)$$

$$R_{I,t} = \alpha_I + \beta_I^{MRKT} R_{MRKT,t} + \beta_I^{SMB} R_{SMB,t} + \beta_I^{HML} R_{HML,t} + \beta_I^{MOM} R_{MOM,t} + \delta_I^{GOLD} \Delta VRP_{GOLD,t} + \gamma_I^{GOLD} R_{GOLD,t} + \varepsilon_{I,t}. \quad (3.11)$$

**Model 2:**

$$R_{I,t} = \alpha_I + \beta_I^{MRKT} R_{MRKT,t} + \beta_I^{SMB} R_{SMB,t} + \beta_I^{HML} R_{HML,t} + \beta_I^{MOM} R_{MOM,t} + \delta_I^{S\&P} \Delta VRP_{S\&P,t} + \delta_I^{OIL} \Delta VRP_{OIL,t} + \delta_I^{GOLD} \Delta VRP_{GOLD,t} + \gamma_I^{S\&P} R_{S\&P,t} + \gamma_I^{OIL} R_{OIL,t} + \gamma_I^{GOLD} R_{GOLD,t} + \varepsilon_{I,t}. \quad (3.12)$$

In equations (3.9) to (3.12) $R_{I,t}$ is the excess return of industry $I$ on day $t$. Moreover, $\Delta VRP_{S\&P,t}$, $\Delta VRP_{OIL,t}$ and $\Delta VRP_{GOLD,t}$ are the daily uncertainty shocks of the stock, oil and gold markets, and $R_{S\&P,t}$, $R_{OIL,t}$ and $R_{GOLD,t}$ represent the daily return on futures contracts, written on the S&P 500 index, crude oil and gold bar.[10] To account for heteroscedasticity, we run these regressions with the feasible generalized least square estimation technique. For this purpose, we estimate the asymptotic covariance matrices with the heteroscedasticity-consistent estimator of White (1980). Since the positive values of $\Delta VRP_{S\&P,t}$, $\Delta VRP_{OIL,t}$ and $\Delta VRP_{GOLD,t}$ are associated with rising uncertainty, negative estimates of $\delta_I^{S\&P}$, $\delta_I^{OIL}$ or $\delta_I^{GOLD}$ mean that industries lose value

[10]Since the correlation coefficient between $R_{MRKT,t}$ and $R_{S\&P,t}$ is 0.94 (see table 3.4), to avoid multi-co-linearity, we rerun regressions (3.9) and (3.12), after dropping $R_{S\&P,t}$ from the regressors. The results (not reported, but available from the authors) are numerically similar and qualitatively the same, and therefore our conclusions remain unchanged.

when the uncertainty escalates.

Table 3.5: Contemporaneous Effect of Uncertainty Shocks on Individual Industries

| Industry | Number of Stocks | Panel A: Model 1 | | | Panel B: Model 2 | | |
|---|---|---|---|---|---|---|---|
| | | $\delta_I^{S\&P}$ | $\delta_I^{OIL}$ | $\delta_I^{GOLD}$ | $\delta_I^{S\&P}$ | $\delta_I^{OIL}$ | $\delta_I^{GOLD}$ |
| Agriculture, Forestry and Fishing | 57 | -0.119 | -0.004 | 0.002 | -0.113 | 0.002 | 0.036 |
| | | (-3.57)*** | (-0.27) | (0.04) | (-3.29)*** | (0.16) | (0.62) |
| Mining | 634 | -0.292 | -0.053 | -0.103 | -0.225 | -0.043 | -0.010 |
| | | (-5.72)*** | (-2.86)*** | (-1.07) | (-5.67)*** | (-2.67)*** | (-0.14) |
| Construction | 742 | -0.102 | -0.030 | -0.052 | -0.094 | -0.024 | -0.014 |
| | | (-6.54)*** | (-3.28)*** | (-1.78)* | (-6.41)*** | (-2.80)*** | (-0.53) |
| Manufacturing | 4939 | -0.099 | -0.030 | -0.118 | -0.084 | -0.021 | -0.086 |
| | | (-6.90)*** | (-3.52)*** | (-3.73)*** | (-6.44)*** | (-2.77)*** | (-2.97)*** |
| Transportation, Communications, Electric, Gas and Sanitary Service | 1191 | -0.100 | -0.023 | -0.063 | -0.093 | -0.016 | -0.030 |
| | | (-5.84)*** | (-2.80)*** | (-2.23)** | (-5.47)*** | (-1.96)** | (-1.14) |
| Wholesale Trade | 190 | -0.095 | -0.031 | -0.106 | -0.076 | -0.023 | -0.076 |
| | | (-3.87)*** | (-2.29)** | (-2.28)** | (-3.30)*** | (-1.76)* | (-1.70)* |
| Retail Trade | 912 | -0.040 | -0.016 | 0.008 | -0.045 | -0.013 | 0.028 |
| | | (-2.11)** | (-1.76)* | (0.26) | (-2.41)** | (-1.37) | (0.89) |
| Finance, Insurance and Real Estate | 2820 | -0.043 | -0.017 | -0.043 | -0.041 | -0.013 | -0.026 |
| | | (-3.71)*** | (-3.24)*** | (-2.46)** | (-3.52)*** | (-2.52)** | (-1.43) |
| Services | 3223 | -0.089 | -0.029 | -0.120 | -0.076 | -0.021 | -0.092 |
| | | (-5.97)*** | (-3.67)*** | (-3.99)*** | (-5.49)*** | (-2.94)*** | (-3.23)*** |
| Public Administration | 22 | -0.160 | -0.023 | -0.070 | -0.142 | -0.018 | -0.031 |
| | | (-2.28)** | (-0.72) | (-0.61) | (-2.01)** | (-0.56) | (-0.26) |

*Note:* With all the ordinary shares traded in NYSE, AMEX and NASDAQ from the CRSP database, we construct equally weighted portfolios of each industry over our entire sample from 1996 to 2013. Then we regress the industry return time series on the uncertainty shocks of the stocks, oil and gold markets. (See regression equations (3.9) to (3.12).) This table reports the sensitivity (regression coefficient) of each industry to each type of uncertainty shocks. *, **, and ***, respectively, denote significance at the 10%, 5% and 1% levels.

The first column in table 3.5 shows the number of stocks in each industry from the CRSP database. Also, panel A and B in this table report the estimated values of $\delta_I^{S\&P}$, $\delta_I^{OIL}$ and $\delta_I^{GOLD}$ and their corresponding t-statistics for model 1 (i.e. regression equations (3.9) to (3.11)) and model 2 (i.e. regression equation (3.12)). According to the first column of panel A, the estimated values of $\delta_I^{S\&P}$ in regression equations (3.9) are significantly negative, across all industries. In other words, industries are all substantially negatively affected by rising uncertainty in the stock market. The second and the third column in panel A show the estimated values of $\delta_I^{OIL}$ and $\delta_I^{GOLD}$ in regression equation (3.10) and (3.11), respectively. Obviously, with a few exceptions, industries have negative sensitivities to the oil and gold market uncertainty, as well. However, the strength of these sensitives are not as high as industries sensitivity to the stock market uncertainty.

Moreover, industries show different levels of exposure to each source of uncertainty. For example, while the “Agriculture, Forestry and Fishing” industry or the “Public Administration” industry show insignificant exposure to the oil uncertainty shocks, oil-relevant industries such as the “Mining” and the “Construction” are significantly vulnerable to this risk factor. The disproportion in industry sensitivity to the uncertainty shocks is our motivation for preforming an intra-industry investigation in section 4.

By comparing the results of Model 1 and Model 2, we observe that even after controlling for the effect of stock uncertainty shocks ($\Delta VRP_{S\&P}$), some industries still show significantly negative exposure to the oil and gold market uncertainty shocks. In addition to Jones and Kaul (1996), Driesprong, Jacobsen and Maat (2008) and Narayan and Sharma (2011) who document a negative relationship between the oil price and the stock market, we find that the uncertainty in the oil market also negatively affects stock prices.

Finally, the results of panel B for Model 2 show that stock market uncertainty has the dominant effect in every industry. Industries remain sensitive to stock market uncertainty, even after controlling for the uncertainty that originates from the oil and gold market or the typical equity risk factors, such as the size, the value or the momentum factors. This finding suggests that stock market uncertainty is related to the overall economic outlook.

### 3.3.2 Cross-Sectional Evidence

In the previous section, we showed that industries are exposed to the uncertainty that originates from the stock, oil and gold markets. The question that now rises is whether stock holders are compensated for their exposure to these factors. Do these sources of uncertainty explain the cross section of expected stock returns? An increase in *systematic* uncertainty represents an unfavorable outlook for uncertainty-averse agents. Consequently, a premium is expected for assets that correlate with the systematic uncertainty factor.

Imagine that an increase in a systematic risk factor $\mathcal{M}_t$ has a negative effect on the investment opportunity set and on investors' consumption $\mathcal{C}_t$. Then based on the intertemporal capital asset pricing model [ICAPM] of Merton (1973), risk averse investors hedge against $\mathcal{M}_t$ by buying an asset that is positively correlated with it. In a day that $\mathcal{M}_t$ spikes up, this asset tends to have a positive return and thus it smoothens investors' consumption. This hedging demand for buying assets with positive exposure to (covariance with) $\mathcal{M}_t$ increases the price of these assets and reduces their expected returns. Consequently, $\mathcal{M}_t$ will be priced negatively in the cross section of assets. With the same line of reasoning, we believe that the systematic uncertainty must be negatively priced, such that assets with higher covariance with it are compensated with lower expected returns.

#### Fama-Macbeth Analysis

We perform a Fama and MacBeth (1973) analysis to see whether stocks that are negatively affected by the different sources of uncertainty shocks are compensated with higher returns. We run this test on the cross section of monthly returns for all ordinary shares traded on NYSE, AMEX and NASDAQ, from January 1996 to December 2013.

For this purpose, we regress the daily returns of each stock in each calendar year, on a combination of $R_{MRKT,t}$, $\Delta VRP_{S\&P,t}$, $\Delta VRP_{OIL,t}$ and $\Delta VRP_{GOLD,t}$ to find stocks' market beta or their exposure to the uncertainty shocks. Consistent with Ang, Chen and Xing (2006) and Cremers, Halling and Weinbaum (2015), the reason for using a 1-year non-overlapping rolling window of data in these regressions is to capture the time variations of stocks' exposure to each of these risk factors. To be included in our sample, a stock must have 245 daily observations per year. Furthermore, we set the size of a stock in month $T$ equal to the logarithm (with the base of 10) of its market capitalization at the end of June in the previous year, and compute its book-to-market ratio with its shares book-value at the end of the previous fiscal year divided by the market price of each share at the same time. For constructing their size and value factors in each year, Fama and French (1993) also take the corresponding values from the preceding year. We obtain shares book-value from the Compustat database. Also consistent with Jegadeesh and Titman (1993), we set the momentum of a stock in month $T$ equal to its cumulative return from month $T-12$ to month $T-2$. Finally, we calculate a stock's illiquidity in month $T$ with the logarithm (with the base of 10) of its Amihud (2002) ratio over this month, i.e.

$$ILLIQ_{i,T} = \log_{10}\Big(\frac{1}{N}\sum_{t\in T}\frac{|R_{i,t}|}{Volume_{i,t}}\Big), \tag{3.13}$$

where, $Volume_{i,t}$ is the trading volume of share $i$ at day $t$, in dollar terms. Table 3.6 reports the estimated risk premium for each of the aforementioned risk factors. The risk premia are in percentage and the t-statistics are adjusted for potential auto-correlation in the time series, with the Newey and West (1987) technique.

The results in table 3.6 show that in almost every configuration the size factor is significantly negative, suggesting lower returns on larger firms. Moreover consistent with Jegadeesh and Titman (1993), the momentum factor is always significantly positive. As we can see in model (2) and (5) of this table, the risk of uncertainty in the stock market is significantly negatively priced. This is consistent with our theoretical conjecture that stocks with more positive exposure to stock market uncertainty shocks have lower returns, because these stocks provide a hedge when stock market uncertainty spikes up. Model (3) shows that oil uncertainty is not a distinguished priced risk factor for the entire cross section of the stock market. In model (4), the gold uncertainty premium turns out to be significantly positive. However model (5) shows that the gold uncertainty premium is not robust to the inclusion of the stock market uncertainty risk. Therefore, the Fama and French (1993) analysis in this section shows that the stock market uncertainty risk is a systematic risk factor that is priced over the entire cross section of stock returns, while the oil and gold uncertainty factors are not.

Although the sign and the economic significance of the other risk premia in this

Table 3.6: Monthly Risk Premia Computation with Fama-Macbeth Analysis

| Model | Intercept | Market | Stock Uncertainty | Oil Uncertainty | Gold Uncertainty | Size | Value | Momentum | Liquidity |
|---|---|---|---|---|---|---|---|---|---|
| (1) | 2.313 | 0.655 | | | | -0.049 | 0.021 | 0.084 | 0.129 |
| | (1.64) | (1.39) | | | | (-1.64) | (0.60) | (1.77)* | (0.83) |
| (2) | 2.305 | 0.654 | -0.364 | | | -0.051 | 0.020 | 0.085 | 0.126 |
| | (1.65)* | (1.44) | (-1.81)* | | | (-1.67)* | (0.57) | (1.83)* | (0.82) |
| (3) | 2.340 | 0.609 | | 0.322 | | -0.048 | 0.019 | 0.086 | 0.127 |
| | (1.67)* | (1.30) | | (1.23) | | (-1.60) | (0.55) | (1.81)* | (0.82) |
| (4) | 2.392 | 0.610 | | | 0.194 | -0.051 | 0.023 | 0.083 | 0.131 |
| | (1.72)* | (1.26) | | | (1.94)* | (-1.73)* | (0.67) | (1.76)* | (0.84) |
| (5) | 2.175 | 0.605 | -0.353 | 0.200 | 0.052 | -0.052 | 0.022 | 0.091 | 0.105 |
| | (1.60) | (1.35) | (-1.87)* | (0.78) | (0.56) | (-1.74)* | (0.65) | (1.94)* | (0.70) |

*Note:* We perform the two-step Fama and MacBeth (1973) analysis on the monthly returns of each stock traded on NYSE, AMEX and NASDAQ, from January 1996 to December 2013. Stocks' market beta or stocks' exposure to the uncertainty shocks are computed from a regression of daily returns on each of these factors, over every calendar year. For the cross sectional regression, we set the size of a stock in month $T$ equal to the logarithm of its market capitalization at the end of June in the previous year, and compute its book-to-market ratio as its shares book-value at the end of the previous fiscal year divided by the market price of each share at the same time. In our analysis, the momentum of a stock in month $T$ is equal to its cumulative return from month $T-12$ to month $T-2$. Finally, we calculate a stock's illiquidity in month $T$ with the logarithm of its Amihud (2002) ratio in this month. This table reports the monthly premia for each risk factor (in percentages), and the corresponding t-statistics, adjusted with the Newey and West (1987) technique. *, **, and ***, respectively, denote significance at the 10%, 5% and 1% levels.

table are consistent with previous studies, our estimates for them are not statistically significant. For example across different models in table 3.6, the market premium is estimated around 0.60 percent per month, which translates into about 7.2 percent market return per year. The statistical insignificance of our result for the other risk factors can be due to our relatively short sample size of 18 years. Unfortunately due to data unavailability (price of futures and option contracts on oil and gold), we could not set the beginning of our sample in an earlier year, than 1996. Still, in our relatively short sample the stock market uncertainty is a significantly priced risk factor.

Despite its competency in measuring risk premia, the Fama and MacBeth (1973) analysis does result in an actually tradable strategy. In the next section, we measure the risk premia by constructing tradable portfolios.

### Tradable Strategy

To see whether stocks with various exposures to uncertainty shocks have different expected returns, we adopt the out-of-sample methodology of Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013). Accordingly we construct portfolios with different levels of exposure to the uncertainty shocks, and compare their performance over the subsequent periods. We measure the relative exposure of a stock to the shocks in the stock, oil and gold market uncertainty with the parameter estimates $\delta_i^{S\&P}$, $\delta_i^{OIL}$ and $\delta_i^{GOLD}$, obtained from regression equations (3.14) to (3.16).

$$R_{i,t} = \alpha_i + \beta_i R_{MRKT,t} + \delta_i^{S\&P} \Delta VRP_{S\&P,t} + \varepsilon_{i,t}. \tag{3.14}$$

$$R_{i,t} = \alpha_i + \beta_i R_{MRKT,t} + \delta_i^{OIL} \Delta VRP_{OIL,t} + \varepsilon_{i,t}. \tag{3.15}$$

$$R_{i,t} = \alpha_i + \beta_i R_{MRKT,t} + \delta_i^{GOLD} \Delta VRP_{GOLD,t} + \varepsilon_{i,t}. \tag{3.16}$$

For each stock in each month, we estimate $\delta_i^{S\&P}$, $\delta_i^{OIL}$ and $\delta_i^{GOLD}$ using a 1-month non-overlapping rolling window on the daily time series of stock returns. Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) also use 1-month rolling windows, as it creates a good balance between the precision and the conditionality of the estimated factor loadings. Following Ang, Hodrick, Xing and Zhang (2006), Chang, Christoffersen and Jacobs (2013) and Bali and Zhou (2016), to reduce the noise, we do not control for the other typical equity risk factors, such as the size, the value and the momentum factors in these regressions. However, we do control for the effect of these factors, later, when we compare the performance of the constructed exposure portfolios.

For each month, we sort stocks based on their loadings on the stock market uncertainty shocks (i.e. $\delta_i^{S\&P}$ from regression equation (3.14)), and construct five value-weighted exposure portfolios. The first exposure portfolio (P1) contains one fifth of stocks with the smallest loadings, and the fifth exposure portfolio (P5) holds one fifth of stocks with the largest loadings. We record the returns of these portfolios over the subsequent month. By rolling the window one month ahead and repeating the same procedure, we will have five portfolio time series with different levels of exposure to the stock market uncertainty shocks ($\Delta VRP_{S\&P,t}$). We repeat the same algorithm, independently, for oil and gold markets uncertainty, so we construct five portfolios with different levels of exposure to the oil uncertainty shocks ($\Delta VRP_{OIL,t}$) and five portfolios with different levels of exposure to the gold uncertainty shocks ($\Delta VRP_{GOLD,t}$).

In order to obtain sufficient cross-sectional dispersion, we include all the ordinary shares traded on NYSE, AMEX and NASDAQ from the CRSP database, and our sample spans from January 1996 to December 2013. Stocks with missing observations in a particular month are excluded from our sample in that month. Table 3.7 reports the performance of the exposure portfolios in terms of the average monthly return and different alpha values. In this table, P5-P1 is a self-financing long-short portfolio that invests in P5 and short-sells P1.

In table 3.7, Panel A shows the performance of the five portfolios that are sorted based on their exposure to the stock market uncertainty, and Panel B and C are dedicated to the exposure portfolios of the oil and gold markets uncertainty. As we move from P1 to P5 in panel A, by construction portfolios' exposure to the stock market uncertainty (average $\delta_i^{S\&P}$) rise, and at the same time, we observe a decreasing pattern in the average monthly return of the exposure portfolios; stocks with more positive exposure to the stock market uncertainty are compensated with lower returns. Investors prefer the stocks in the last quintile portfolio (P5) and expect lower returns for holding them, as these stocks tend to have positive returns on the days that stock market uncertainty spikes up. The P5-P1 portfolio yields -0.51 percent on a monthly basis, which translates into an economically significant value of -6.12 percent per year. The excess return of P1 over P5 remains statistically significant even after we control for the size and the value factors of Fama and French (1993), the momentum factor of Carhart (1997) and the liquidity factor of Pástor and Stambaugh (2003). Therefore, the stock market uncertainty is a systematic market-wide priced risk factor.

The clear pattern that we observe in panel A contrasts with the results for the oil and gold market uncertainty. The performance measures of exposure portfolios in Panel B and C do not display a robustly decreasing pattern from P1 to P5. In other words, there is no significant relationship between stocks' exposure to oil or gold price uncertainty and their expected returns. In both panels, the P5-P1 portfolios do not yield a significant return or alpha, implying that the uncertainty in the oil or gold market is not a market-wide priced risk factors.

Thus the results in table 3.6 and 3.7 provide strong evidence that shocks in variance

Table 3.7: Expected Return of Uncertainty Exposure Portfolios

**Panel A: Price of Stock Uncertainty**

| Exposure Portfolios | Ave. $\delta_i^{S\&P}$ | Market Cap. (%) | BM Ratio | Ave. Return (%) | CAPM Alpha (%) | FF Alpha (%) | FF + Mom. Alpha (%) | FF + Mom. + Liq. Alpha (%) |
|---|---|---|---|---|---|---|---|---|
| P1 | -4.15 | 11.5% | 0.45 | 0.82 | 0.11 | 0.12 | 0.24 | 0.23 |
| | | | | (2.17)** | (0.46) | (0.51) | (1.08) | (1.00) |
| P2 | -1.40 | 25.2% | 0.40 | 0.61 | 0.03 | 0.02 | 0.04 | 0.02 |
| | | | | (1.77)* | (0.44) | (0.28) | (0.47) | (0.24) |
| P3 | 0.01 | 26.9% | 0.40 | 0.50 | -0.01 | -0.04 | -0.08 | -0.07 |
| | | | | (1.55) | (-0.10) | (-0.67) | (-1.39) | (-1.29) |
| P4 | 1.39 | 24.5% | 0.40 | 0.60 | 0.02 | 0.00 | -0.01 | -0.04 |
| | | | | (1.58) | (0.29) | (0.05) | (-0.20) | (-0.58) |
| P5 | 4.21 | 11.9% | 0.43 | 0.31 | -0.41 | -0.43 | -0.37 | -0.36 |
| | | | | (0.65) | (-3.27)*** | (-3.38)*** | (-2.73)*** | (-2.64)*** |
| P5-P1 | 8.36 | | | -0.51 | -0.52 | -0.54 | -0.61 | -0.60 |
| | (22.29)*** | | | (-2.09)** | (-2.07)** | (-1.86)* | (-2.00)** | (-1.86)* |

**Panel B: Price of Oil Uncertainty**

| Exposure Portfolios | Ave. $\delta_i^{OIL}$ | Market Cap. (%) | BM Ratio | Ave. Return (%) | CAPM Alpha (%) | FF Alpha (%) | FF + Mom. Alpha (%) | FF + Mom. + Liq. Alpha (%) |
|---|---|---|---|---|---|---|---|---|
| P1 | -1.48 | 11.8% | 0.44 | 0.70 | -0.01 | -0.01 | 0.08 | 0.00 |
| | | | | (1.61) | (-0.07) | (-0.08) | (0.50) | (0.03) |
| P2 | -0.50 | 25.0% | 0.41 | 0.60 | 0.04 | 0.02 | 0.03 | -0.01 |
| | | | | (1.69)* | (0.45) | (0.21) | (0.23) | (-0.08) |
| P3 | 0.01 | 26.9% | 0.39 | 0.65 | 0.15 | 0.13 | 0.11 | 0.11 |
| | | | | (2.29)** | (1.58) | (1.49) | (1.26) | (1.37) |
| P4 | 0.53 | 24.5% | 0.40 | 0.59 | 0.02 | 0.01 | 0.01 | 0.01 |
| | | | | (1.58) | (0.49) | (0.25) | (0.17) | (0.13) |
| P5 | 1.55 | 11.7% | 0.44 | 0.47 | -0.30 | -0.31 | -0.27 | -0.24 |
| | | | | (0.95) | (-1.58) | (-1.49) | (-1.27) | (-1.16) |
| P5-P1 | 3.02 | | | -0.23 | -0.28 | -0.30 | -0.35 | -0.24 |
| | (25.34)*** | | | (-0.76) | (-0.96) | (-0.84) | (-1.08) | (-0.81) |

**Panel C: Price of Gold Uncertainty**

| Exposure Portfolios | Ave. $\delta_i^{GOLD}$ | Market Cap. (%) | BM Ratio | Ave. Return (%) | CAPM Alpha (%) | FF Alpha (%) | FF + Mom. Alpha (%) | FF + Mom. + Liq. Alpha (%) |
|---|---|---|---|---|---|---|---|---|
| P1 | -6.24 | 11.9% | 0.44 | 0.28 | -0.49 | -0.49 | -0.33 | -0.35 |
| | | | | (0.53) | (-1.97)** | (-2.08)** | (-1.80)* | (-2.09)** |
| P2 | -2.06 | 25.3% | 0.41 | 0.54 | -0.04 | -0.04 | 0.00 | 0.01 |
| | | | | (1.43) | (-0.38) | (-0.31) | (0.01) | (0.06) |
| P3 | 0.03 | 26.6% | 0.40 | 0.57 | 0.08 | 0.06 | 0.03 | 0.05 |
| | | | | (1.77)* | (2.04)** | (1.25) | (0.43) | (0.85) |
| P4 | 2.17 | 24.8% | 0.40 | 0.80 | 0.25 | 0.22 | 0.20 | 0.17 |
| | | | | (2.23)** | (1.71)* | (1.71)* | (1.64) | (1.46) |
| P5 | 6.60 | 11.4% | 0.43 | 0.62 | -0.09 | -0.12 | -0.11 | -0.18 |
| | | | | (1.79)* | (-0.54) | (-0.96) | (-0.92) | (-1.80)* |
| P5-P1 | 12.84 | | | 0.34 | 0.40 | 0.37 | 0.22 | 0.17 |
| | (14.72)*** | | | (1.02) | (1.25) | (1.25) | (0.92) | (0.76) |

*Note:* At the end of each month, we sort the stocks three times based on their exposure to the uncertainty shocks (obtained from regression equations (3.14) to (3.16)), and each time form five value-weighted portfolios. We refer to these portfolios as exposure portfolios, and record the return of these portfolios in the subsequent month. By repeating the same algorithm over the entire sample, from January 1996 to December 2013, we achieve fifteen portfolio return time series. We report the average exposure to uncertainty shocks, the percentage of the total market capitalization, the average book-to-market ratio, the average monthly expected returns and the different alpha values for each of these exposure portfolios. The t-statistics, shown in parentheses, are adjusted with the Newey and West (1987) technique that controls for auto-correlation in the time series. *, **, and ***, respectively, denote significance at the 10%, 5% and 1% levels.

risk premium or uncertainty of the stock market is a priced risk factor and it explains the cross section of expected stock returns. This finding is consistent with theory and economic intuition; a stock that yields a negative return, when systematic uncertainty escalates, is not a good hedge for uncertainty-averse investors. Therefore based on the intertemporal CAPM of Merton (1973), this stock must be compensated with a higher expected return. On the other hands, although various industries covary negatively with oil and gold price uncertainty shocks, these linkages across markets do not exist at the expected return level, because oil and gold price uncertainty are not systematic factors. These results confirm the findings of Bali and Zhou (2016) that the S&P 500 index uncertainty is a market-wide priced risk factor, and in addition, show that the nature of uncertainty matters.[11] Oil and gold uncertainty factors are asset-specific, idiosyncratic and diversifiable. Stock market uncertainty, however, represents a systematic risk factor that affects the whole economy, and is relevant for the entire cross section of expected stock returns.

## 3.4 Market Segmentation and Industry Effect

Another important question to ask is whether oil and gold uncertainty are sector-specific priced risk factors. The time series regressions of section 3.1 showed that oil and gold uncertainty is more relevant for certain industries. Because of this heterogeneity across different industries, in this section, we investigate the existence of significantly negative uncertainty risk premia within each industry. The "Public Administration" industry is excluded as it has less than 50 stocks, and therefore, its cross-sectional dispersion cannot provide a meaningful and interpretable result.

Just like in section 3.2.2, we compute stocks' loadings on the uncertainty measures using regression equations (3.14) to (3.16) with a 1-month non-overlapping rolling window. However since there are fewer stocks in each industry, we split the cross section of industries into three value-weighted exposure portfolios, named P1, P2 and P3, respectively. We record the returns of these portfolios over the subsequent month. Table 3.8 reports the performance measures of the long-short portfolio P3-P1 that invests in the portfolio with the highest exposure to uncertainty shocks (P3), and short-sells the portfolio with the lowest exposure (P1).

[11] Our methodology diverges from Bali and Zhou (2016) in several ways. First to find the uncertainty premia in stocks' cross section, we use the whole CRSP universe, rather than portfolios of stocks, sorted on size and book-to-market ratio. Second to obtain the conditional exposures and to form the portfolios, we rely on past realized correlations, while Bali and Zhou (2016) adopt a seemingly unrelated regression method together with a dynamic conditional covariance estimation. Thirdly, unlike them who use monthly observations, we run all our analysis with daily time series. Finally, we use 3-month option-implied information instead of the 1-month VIX index. Despite the differences in our approach, we obtain similar results.

Table 3.8: Uncertainty Risk Premia within Different Industries

| Industry | Performance Measure | Panel (A): Price of Stock Uncertainty | | Panel (B): Price of Oil Uncertainty | | Panel (C): Price of Gold Uncertainty | |
|---|---|---|---|---|---|---|---|
| Agriculture, Forestry and Fishing | Ave. Return | -1.85 | (-3.06)*** | -0.28 | (-0.24) | -0.20 | (-0.29) |
| | FF Alpha | -1.85 | (-2.93)*** | -0.29 | (-0.26) | -0.04 | (-0.06) |
| | FF + Mom. Alpha | -1.85 | (-3.26)*** | -0.44 | (-0.34) | -0.27 | (-0.41) |
| | FF + Mom. + Liq. Alpha | -1.77 | (-3.09)*** | -0.32 | (-0.25) | -0.31 | (-0.45) |
| Mining | Ave. Return | -0.06 | (-0.30) | -0.70 | (-2.53)** | -0.20 | (-0.40) |
| | FF Alpha | -0.09 | (-0.40) | -0.71 | (-2.67)*** | -0.15 | (-0.29) |
| | FF + Mom. Alpha | -0.07 | (-0.30) | -0.65 | (-2.53)** | -0.33 | (-0.64) |
| | FF + Mom. + Liq. Alpha | -0.08 | (-0.34) | -0.60 | (-2.32)** | -0.32 | (-0.56) |
| Construction | Ave. Return | -0.30 | (-1.50) | -0.78 | (-2.05)** | 0.02 | (0.08) |
| | FF Alpha | -0.26 | (-1.27) | -0.75 | (-2.03)** | 0.11 | (0.38) |
| | FF + Mom. Alpha | -0.27 | (-1.25) | -0.77 | (-2.00)** | 0.02 | (0.08) |
| | FF + Mom. + Liq. Alpha | -0.30 | (-1.27) | -0.70 | (-1.76)* | -0.03 | (-0.10) |
| Manufacturing | Ave. Return | -0.19 | (-0.81) | 0.16 | (0.58) | 0.40 | (1.14) |
| | FF Alpha | -0.18 | (-0.78) | 0.16 | (0.62) | 0.45 | (1.30) |
| | FF + Mom. Alpha | -0.27 | (-0.96) | 0.12 | (0.48) | 0.20 | (0.80) |
| | FF + Mom. + Liq. Alpha | -0.32 | (-1.01) | 0.18 | (0.79) | 0.14 | (0.56) |
| Transportation, Communications, Electric, Gas and Sanitary Service | Ave. Return | -0.29 | (-1.48) | -0.41 | (-1.89)* | -0.03 | (-0.10) |
| | FF Alpha | -0.26 | (-1.32) | -0.44 | (-1.92)* | 0.04 | (0.13) |
| | FF + Mom. Alpha | -0.44 | (-2.15)** | -0.40 | (-1.75)* | -0.10 | (-0.41) |
| | FF + Mom. + Liq. Alpha | -0.41 | (-1.94)* | -0.37 | (-1.52) | -0.13 | (-0.52) |
| Wholesale Trade | Ave. Return | -0.85 | (-2.31)** | -0.44 | (-0.86) | -1.17 | (-1.50) |
| | FF Alpha | -0.94 | (-2.39)** | -0.53 | (-0.98) | -1.22 | (-1.54) |
| | FF + Mom. Alpha | -1.04 | (-2.05)** | -0.48 | (-0.89) | -1.11 | (-1.55) |
| | FF + Mom. + Liq. Alpha | -0.98 | (-1.86)* | -0.48 | (-0.82) | -1.11 | (-1.48) |
| Retail Trade | Ave. Return | -0.12 | (-0.53) | 0.43 | (1.29) | 0.27 | (1.34) |
| | FF Alpha | -0.13 | (-0.57) | 0.51 | (1.53) | 0.22 | (0.99) |
| | FF + Mom. Alpha | -0.09 | (-0.39) | 0.50 | (1.37) | 0.26 | (1.11) |
| | FF + Mom. + Liq. Alpha | -0.14 | (-0.60) | 0.67 | (2.10)** | 0.31 | (1.18) |
| Finance, Insurance and Real Estate | Ave. Return | -0.21 | (-1.92)* | -0.48 | (-2.26)** | 0.35 | (2.15)** |
| | FF Alpha | -0.21 | (-1.67)* | -0.55 | (-2.80)*** | 0.42 | (2.79)*** |
| | FF + Mom. Alpha | -0.22 | (-1.81)* | -0.60 | (-2.54)** | 0.30 | (2.31)** |
| | FF + Mom. + Liq. Alpha | -0.20 | (-1.57) | -0.54 | (-2.58)*** | 0.34 | (2.86)*** |
| Services | Ave. Return | -0.10 | (-0.31) | -0.02 | (-0.08) | 0.47 | (0.97) |
| | FF Alpha | -0.08 | (-0.27) | -0.01 | (-0.07) | 0.49 | (1.00) |
| | FF + Mom. Alpha | -0.15 | (-0.44) | -0.03 | (-0.11) | 0.42 | (0.90) |
| | FF + Mom. + Liq. Alpha | -0.18 | (-0.50) | 0.01 | (0.03) | 0.37 | (0.83) |

*Note:* Using the same methodology as we used for table 3.7, we split the cross section of each industry into three different exposure portfolios. Then we report the average monthly expected return and various alpha values of the high minus low exposure portfolios. The t-statistics, shown in parentheses, are adjusted with the Newey and West (1987) technique that controls for auto-correlation in the time series. *, **, and ***, respectively, denote significance at the 10%, 5% and 1% levels.

This more granular analysis shows that in every industry the exposure to the stock market uncertainty is compensated with a negative return. Moreover, although the results in section 3.2 showed that oil price uncertainty is not a priced risk factor in the entire cross section of stocks' expected returns, table 3.8 reveals that in four industries, oil uncertainty risk has a significantly negative price. In comparison with oil price uncertainty, gold price uncertainty is never priced negatively in any industry.

The four industries where oil uncertainty is priced are "Mining", "Construction", "Transportation, Communications, Electric, Gas and Sanitary Service", and "Finance, Insurance and Real Estate". For the first three sectors oil price is a key input for the core of the economic activity and for the latter oil has become an importance investment vehicle. This relevance was also highlighted by the time series regressions that showed these industries are significantly exposed to oil uncertainty shocks. Therefore, oil uncertainty is priced within oil dependent industries.

There are two explanations, why the premium for oil uncertainty is only identifiable in certain industries. The first explanation is related to econometric factors. In a cross-sectional test, in order to be able to detect a significant risk premium a sufficient dispersion among different observations, in our case exposure to uncertainty, is necessary. If all assets are virtually equally exposed to a risk factor, this factor can be priced but not be statistically identifiable.[12] This interpretation implies that in non-oil-relevant industries even if there is an oil-specific uncertainty premium, stocks are so homogeneously exposed to it that it is hard to detect such a premium.

This line of reasoning also explains the absence of a gold price uncertainty premium. Although certain sectors are relatively more exposed to gold price uncertainty, the gold uncertainty premium is not significantly negative in any industry. Stocks are exposed to gold uncertainty because it captures some variations in the macro-economic environment. However apart from the firms involved in the actual trading of gold, firms' exposure to gold price uncertainty is negligible.

The second and more economic reason relates to the segmentation of markets. Hong, Torous and Valkanov (2007) and Hong and Stein (2007) argue that a considerable portion of investors are industry specialized, who pay no attention or are unable to interpret the information from the markets that they do not specialize in. These investors only slowly become aware of events in related industries. Cohen and Frazzini (2008) show that due to investors' inattention, news is reflected with different speed and accuracy in different industries. Cavaglia, Brightman and Aked (2000) find that over years, while markets have become more integrated and the importance of country factors has declined, the

[12] For instance as Borgers, Derwall, Koedijk and Ter Horst (2015) show, the sin stock premium can only be detected for sin stock funds and not in case of standard mutual funds. Because the latter funds are homogeneous with respect to their "sin exposure". Also Ben-Rephael, Kadan and Wohl (2015) cannot identify the liquidity premium among large stocks, which are all fairly liquid.

benefits of industry diversification has increased.

Similarly, investors specialized and concentrated in an oil-relevant industry are more aware of the impact of oil on their investment. These investors cannot diversify oil uncertainty in their portfolio, and therefore, it directly affects their utility. This is also in line with Driesprong, Jacobsen and Maat (2008) and Narayan and Sharma (2011), who find that oil price information is incorporated faster in stock prices of oil-relevant industries. Also, Pollet (2005) shows that the impact of oil price predictability is mis-evaluated or incorporated slowly for non-oil-relevant industries. Hence, the impact of oil price uncertainty is only evaluated properly for oil-relevant industries but not in the expected return of the stocks in other industries.

As we saw in table 3.3, the average variance risk premium of oil is significantly positive which implies that oil-option traders, who seek protection against oil price uncertainty, pay a premium to hedge against this risk. However according to table 3.6 and 3.7, oil price uncertainty is not important for every investor and its premium is not reflected in the return of all stocks. Indeed based on the results in table 3.8, oil price uncertainty is only priced for the stocks in oil-relevant industries.

## 3.5 Concluding Remarks

Escalating uncertainty is generally accompanied with declining stock prices, because, when uncertainty escalates stock valuation and investment decision making become more difficult. Uncertainty-averse investors require a premium for investing in the stocks that are exposed to the *systematic* uncertainty factor. We identify stock market uncertainty, as a systematic factor that is priced in the entire cross section of stock expected returns, and therefore, it is an important factor for investment in any stock.

Oil price uncertainty, however, is a sector-specific factor which can be diversified across industries. The oil uncertainty risk is not diversifiable within oil-relevant industries. Industry-specialized investors who hold portfolios of oil-relevant stocks must consider their exposure to the oil price uncertainty shocks. Finally, gold price uncertainty is an asset-specific factor that is neither priced across nor within any particular industry.

## 3.6 Appendix A: Risk-neutral Variance Estimation

Theoretically, the BKM methodology is only applicable to European options. However Bakshi, Kapadia and Madan (2003) argue that, due to the ignorable early-exercise premium of OTM options, using American options does not change the results notably. Still to be on the safe side, we convert all the American options in our database to their European counterparts. To do so, following Trolle and Schwartz (2009), we adjust the prices by deducting the early-exercise premia, measured with the Barone-Adesi and Whaley (1987) procedure.

To implement the BKM methodology, for each day we need a fine continuum of OTM European options with different strike prices. We consider the put options whose underlying price is more than 97 percent of their strike price, and the call options whose underlying price is less than 103 percent of their strike price, as OTM options. Also because of illiquidity concerns, we eliminate put options with moneyness ($\frac{F_t^\tau}{K}$) values more than 1.5 and call options with moneyness ($\frac{F_t^\tau}{K}$) values less than 0.5. The last two rows in table 3.1 show the number of OTM option contracts that we used for calculating the 90-day risk-neutral variance expectation.

On each day, only a few OTM call and put options are traded. Hence to be able to compute the integrals of equations (3.4) to (3.6) more accurately, we fit a natural cubic spline to the Black-Scholes implied volatility of the available options. Therefore we can compute implied volatilities and options prices, for every moneyness value ($\frac{F_t^\tau}{K}$) from 0.01 to 3.00. Prices of OTM options with moneyness values outside these boundaries are negligible. In line with Chang, Christoffersen and Jacobs (2013), if a moneyness value exceeds the domain of the cubic spline, we set its implied volatility equal to the implied volatility of the closest point on the spline. The prices of the OTM options with moneyness values beyond [0.01, 3.00] are negligible.

Option contracts with exactly 90 days to maturity are not traded on every day. Therefore to calculate each day's risk-neutral variance with a constant horizon of 90 days, we calculate the risk-neutral variances of the two closest maturities shorter and longer than 90 days, and then interpolate between these two variance values.

# Chapter 4

# Why is the VIX index related to the liquidity premium?

## 4.1 Introduction

Think of an investor, who is desperate to sell asset $\mathcal{A}$. If the market is imperfectly-liquid, in order to attract a buyer, this "liquidity demander" must offer a price well below the fundamental value of $\mathcal{A}$. The more illiquid the market is, the cheaper he must sell. On the other hand the "liquidity supplier", who buys $\mathcal{A}$ at a discount, can wait until a new buyer shows up in the market. Then the liquidity supplier can sell $\mathcal{A}$ at its fundamental value and thus profit from the price reversion. The same story also applies when a liquidity demander wants to buy immediately; in this case he must propose a price well above the fundamental value of $\mathcal{A}$, so that he can convince someone to sell. The more illiquid the market is, the more he must compromise on the price and thereby the magnitude of price reversal over the subsequent periods becomes larger. The extent of the deviation of the transaction price from the fundamental value and the subsequent short-term price reversal is equivalent to the liquidity supplier's compensation for liquidity provision, and it can be considered as the liquidity premium in the time series of asset prices.

In an empirical study, Nagel (2012) finds that the VIX index positively correlates with the magnitude of short-term reversal in stock prices; when the VIX is high, liquidity demanders must pay a higher premium and compromise more on the price so they can trade. However, he explains that this "*does not necessarily imply that the VIX index itself is the state variable driving expected returns from liquidity provision. More likely, the VIX proxies for the underlying state variables that drive the willingness of market makers to provide liquidity and the public's demand for liquidity*". For example when the VIX is high, financial constraints are tighter and thus the market makers, who face excessive borrowing costs, charge a higher premium for liquidity provision. This higher price of liquidity, in turn, increases the magnitude of the short-term price reversal effect.

In this paper, we provide further explanations for the positive relationship between the VIX index and liquidity providers' compensation. For this purpose, we extend the theoretical framework of Vayanos and Wang (2012) to a setup with multiple risky assets and show that even in a perfect market with no financial constraints, higher investors' risk aversion, asset variances and asset correlations lead to a larger expected return and Sharpe ratio for liquidity providers. We argue since the VIX index encapsulates investors' risk aversion, stocks' average variance and stocks' average correlation (see e.g. Bollerslev, Gibson and Zhou (2011) and Bekaert and Hoerova (2014)), it is trivial that an increase in the VIX, caused by an increase in any of these factors, is accompanied by a higher expected return and Sharpe ratio for providers of liquidity in the stock market. The theory also explains the early empirical findings of LeBaron (1992) and Sentana and Wadhwani (1992), who find that higher volatility is accompanied by more negative autocorrelation in return time series.

In our model, we consider an investment universe consisting of one riskless bond and $N$ risky assets, that can be traded at three different time points ($t = 0, 1, 2$). The risky assets pay no dividend at time 0 and 1, and only yield some random liquidation payoffs at time 2. There are two types of investors: "liquidity demanders" who initiate a trade, and "liquidity suppliers" who accommodate this need for liquidity. Investors are assumed to be equally risk averse. Initially (at $t = 0$), they are indistinguishable and all hold the market portfolio, besides the riskless bond. However after a while (at $t = 1$), due to risk management considerations (see e.g. Adrian and Shin (2010)) or a change of perception about future payoffs, the liquidity demanders infer that they are more- or less-than-optimal exposed to the risk of certain assets. As a result, they desire to revert back to optimality by re-balancing their portfolio. Following Grossman and Miller (1988), Vayanos (1999), Vayanos (2001), Gromb and Vayanos (2002) and Vayanos and Wang (2012), our economic model creates this selling or buying motive by providing an extra risky endowment to the liquidity demanders. Before receiving the endowment, this party has been holding an optimal portfolio. Therefore, in the absence of any news on asset fundamentals, this extra endowment departs their portfolio from optimality and creates a buying or a selling demand.

On the other hand, the liquidity suppliers' portfolios are already optimal, because they do not receive any endowment. Therefore, they do not have any incentive to engage in any trade with the liquidity demanders, unless they would receive some price discounts. As a result, the trading prices of the assets at time 1 deviate from their fundamental (risk-adjusted) values. However since the future payoffs of assets are unaffected, later at the liquidation time (at $t = 2$), the asset prices revert back to their fundamental values. This phenomenon, in which the price of an asset diverts from its fundamental value and shortly after reverts back to it, is called the short-term price reversal and it yields a positive return for the liquidity suppliers. This deviation from the fundamental value is the price compromise, made by the liquidity demanders, so that they can trade immediately at time 1, rather than bearing the risk of excessive exposure to certain assets until time 2. This is the cost to convince liquidity suppliers to accept inventory imbalance. Our economic model shows that the intensity of the price reversal effect is an increasing function of investors' risk-aversion, asset variances and asset correlations.

When liquidity demanders are extremely risk-averse, even a small departure from optimality has a substantially negative impact on their expected utility. Therefore, they feel an extreme urgency to trade and they compromise more on asset prices. Similarly when liquidity suppliers are extremely risk-averse, in order to engage in any trade, they require a larger price discount. As a result, a higher level of investors' risk aversion gives rise to larger short-term price reversals and more expensive liquidity in the time series of asset prices. Hameed, Kang and Viswanathan (2010) (for stock market) and Bao, Pan and Wang (2011) (for bond market) show that after long market declines, the intensity of short-term price reversal is stronger. Our theoretical model suggests that this is probably the case, because at these times investors are more risk averse and thus they charge a higher premium for providing liquidity.

At an *individual-asset* level, we find that the impact of liquidity shocks in creating short-term price reversal is stronger when the asset is more volatile. Because at this time, the future payoff is more uncertain and thus a liquidity demander, whose portfolio has departed from optimality, feels a stronger urgency to trade. Moreover when the asset variance is high, due to more uncertainty about the future payoff, liquidity suppliers charge a larger premium to accept the new inventory and thus the subsequent short-term price reversal effect becomes stronger. This is also the case in the cross section of asset returns; at any point in time, there is a higher liquidity premium for more volatile assets. In an economic model with funding constraints, Brunnermeier and Pedersen (2009) show that market makers charge a higher liquidity premium on more volatile assets, as they require more collateral. Our theoretical model shows that even in the absence of financial constraints, as long as market makers are risk-averse, they charge a larger liquidity premium on more volatile assets. This could also be inferred from the single-asset models of Grossman and Miller (1988) and Vayanos and Wang (2012).

At an *inter-asset* level, we show that the correlation among two assets is the channel, through which an asset-specific liquidity shock flows from one asset to the other. When two assets are highly correlated, an asset-specific liquidity shock to one of them creates a trade demand in the other asset as well. Because the departure from optimality, created by a liquidity shock to an asset, can also be resolved by trading any other asset that is highly correlated with it. Liquidity shocks spread across correlated assets. Since higher correlations escalate the risk of spillover of liquidity shocks across assets, it increases liquidity suppliers' expected return and Sharpe ratio. Consistent with this finding, Andrade, Chang and Seasholes (2008) also show when market makers face inventory imbalance, asset correlations play a key role in price reversals. However these authors do not investigate the impact of time variation in asset correlations on the intensity of price reversals. Moreover nowadays, the act of liquidity provision is performed by many other market participants, such as high-frequency traders, day traders, hedge-funds, dealers and trading desks, (e.g. Kaniel, Saar and Titman (2007), Jylhä, Rinne and Suominen (2014) and Barrot, Kaniel and Sraer (2016)) and in different market conditions, investors might act as liquidity demander or supplier, interchangeably (Mitchell, Pedersen and Pulvino (2007)). Therefore, market makers' inventory imbalance cannot be a comprehensive proxy for liquidity pressure on the whole market. Instead, we proxy the liquidity pressure on the market with stocks' lagged returns.

We investigate the validity of these theoretical findings by constructing a portfolio that proxies for liquidity suppliers' return. This portfolio, which speculates on short-term reversals in stock prices, is re-allocated every day by buying the stocks that had a bad performance and short-selling the stocks that had a good performance, over the last trading day. Our sample includes all ordinary shares, traded at NYSE, AMEX and NASDAQ, and it spans for 20 years, from 1996 to 2015. Consistent with our theoretical conjecture, we find that the return and the Sharpe ratio of our reversal strategy portfolio is substantially positively related to proxies of investors' risk aversion, stocks' average variance and stocks' average correlation. One standard deviation increase in each of these factors raises liquidity providers' expected daily return (annualized Sharpe ratio) by 0.16%, 0.36% and 0.39% (0.84, 1.20 and 2.02), respectively. Besides a decimalization dummy variable, these factors can explain a significant amount of variation (R-squared = 27%) in the return time series of our reversal strategy portfolio.[1]

Nagel (2012) introduces funding and credit constraints as potential drivers of the positive relationship between the VIX and the intensity of the short-term price reversal effect. However our robustness tests show that alternative financial and credit constraint proxies, namely the 1-month LIBOR and the Ted-Spread, cannot undermine the importance of investors' risk aversion, stocks' average variance and stocks' average correlation in explaining the intensity of the short-term price reversal effect. The improvement in explanatory power, due to the inclusion of 1-month LIBOR and the Ted-Spread in the

[1] This explanatory power is huge. Over the same time periods and with the same data frequency (daily), the Fama-French model that is designed to explain stock returns can only capture 26%, 25% and 31% of the variations in the returns time series of Coca Cola, Apple Inc. and Wal-mart, respectively.

regressions, is negligible. Hence, the power of our three factors in explaining the intensity of the short-term price reversal effect is beyond the tightness of the funding and credit constraints, proposed by Nagel (2012).

This research is also related to several other studies. The economic model of this paper resembles the theoretical frameworks of Grossman and Miller (1988), Vayanos (1999), Vayanos (2001), Gromb and Vayanos (2002), Huang and Wang (2009), Huang and Wang (2010), and especially Vayanos and Wang (2012). However in contrast to these single-asset models, our setup includes multiple risky assets and therefore it enables us to investigate the relationship between asset correlations and liquidity premium.[2]

Chung and Chuwonganant (2014) show that the VIX index exerts systematic co-movement in liquidity measures of individual stocks. They conjecture that at least a part of the link between the VIX and liquidity might be related to the fact that liquidity providers are sensitive to market volatility and uncertainty, encapsulated in the VIX. They leave the rationality or irrationality of liquidity providers' sensitivity to the VIX index for further research. Our theoretical model, explicitly, describes the rationality behind the sensitivity of liquidity providers to the VIX index; the VIX is an important factor for liquidity providers because it captures investors' risk aversion, asset variances and asset correlations. Similar to So and Wang (2014) who find that rising uncertainty increases market makers' required return, we identify investors' risk aversion, asset variances and asset correlations as three factors that raise market makers' expected return, and more importantly, their Sharpe ratio.

Our theoretical model can also explain the empirical findings of Pástor and Stambaugh (2003), Watanabe and Watanabe (2007) and Korajczyk and Sadka (2008); stocks that are negatively affected by systematic liquidity risk must be compensated with a higher expected return. Consistent with Chordia, Sarkar and Subrahmanyam (2005), the model shows that when volatility goes up liquidity evaporates. In line with the empirical findings of Acharya, Schaefer and Zhang (2015), our model predicts that after a liquidity shock asset covariances increase. We provide another reason why investors dislike high values of the VIX (Ang, Hodrick, Xing and Zhang (2006)), asset variances (Chen and Petkova (2012)) and asset correlations (Driessen, Maenhout and Vilkov (2009) and Krishnan, Petkova and Ritchken (2009)); at these economic states liquidity becomes expensive.

[2]Kodres and Pritsker (2002) also develop a multi-asset model, however unlike us, they study financial contagion through cross-market re-balancing across different countries.

## 4.2 Theoretical Framework

A large trade has a significant price impact. Whether the price reverts or not depends on information (a)symmetry between the trade parties. Previous studies show that a trade with information asymmetry coincides with a permanent price adjustment. For example, the huge buying pressure of an insider trader, who anticipates higher future payoffs, might move the price up. This price increase will not revert, but instead with the gradual release of the good news about the future payoffs, the price continues to rise. On the other hand, a price change in a non-informed trade shortly reverts. For instance, the rush of uninformed investors for selling a particular asset might create a negative jump in the price, because the market capacity for absorbing this liquidity demand is limited. However as long as the future payoffs are unaffected, the price will subsequently revert back.[3] Since price reversal happens for non-informed trades, in this paper, we develop a perfect (frictionless) economy without information asymmetry between the trade parties. Furthermore, following Grossman and Miller (1988), we abstract from bid and ask quotes and develop our model based on the actual transaction prices.

### 4.2.1 Model

The economy contains one riskless bond and $N$ risky assets, traded at three time points ($t = 0, 1, 2$). The risky assets pay no dividend at time 0 and 1, and only yield some random liquidation payoffs at time 2. Investors trade at time 0 and 1, but they liquidate their portfolio and consume all their wealth at time 2. There is no consumption at time 0 and 1. Moreover, all investors have identical exponential utility functions

$$U(C_2) = -exp(-\alpha C_2), \tag{4.1}$$

where $\alpha$ and $C_2$ are, respectively, the coefficient of absolute risk aversion and the final consumption level. For the sake of tractability, we assume the coefficient of absolute risk aversion is the same for all investors and constant over time. Investors trade in a Walrasian auction and they are competitive, such that they take asset prices as given.

There are $B$ units of the riskless bond in the market. The risk-free rate is zero and the riskless bond is in perfect elastic supply, meaning that the quantities in which the investors buy or sell the riskless bond do not influence its price. This is equivalent to assuming that there is no funding constraint in the market. Moreover, the exogenous liquidation payoffs of the risky assets at the final moment ($t = 2$) are jointly normally

[3] Among many see Kyle (1985), Glosten and Milgrom (1985), Admati (1991), Campbell, Grossman and Wang (1993), Llorente, Michaely, Saar and Wang (2002), Avramov, Chordia and Goyal (2006), Da, Liu and Schaumburg (2013) and Cheng, Hameed, Subrahmanyam and Titman (2017).

distributed

$$P_2 \sim N(\bar{P}, \Sigma). \tag{4.2}$$

Here, $P_2$ is the $N \times 1$ vector of the risky assets' liquidation payoffs at $t = 2$, and $\Sigma = [\sigma_{ij}]$ is the corresponding $N \times N$ covariance matrix. To rule out information asymmetry, we assume that the liquidation payoffs distribution (equation (4.2)) is public information.

At $t = 0$, investors are identical and indistinguishable from each other. They have the same initial wealth, risk aversion coefficients and utility functions. Therefore at time 0, all investors hold the market portfolio besides the riskless bond, i.e.

$$\theta_0 = \theta, \tag{4.3}$$

where $\theta_0$ is the $N \times 1$ vector of the investors' portfolio at time 0, and $\theta$ is the $N \times 1$ vector of the market portfolio.

At $t = 1$, a liquidity shock happens, which segregates the investors in two different groups: A fraction $0 < f < 1$ becomes "liquidity demanders" and receives some risky endowment of $zM'(P_2 - \bar{P})$. The other $1 - f$, who does not get anything, acts as "liquidity suppliers". Here $z$, referred to as the "liquidity shock", is a normally distributed random variable ($z \sim N(0, \sigma_z^2)$) that is independent of $P_2$, and its value is realized at $t = 1$. Moreover, $M = [m_1, m_2, ..., m_N]'$ is the $N \times 1$ deterministic vector of asset loadings on the liquidity shock. With this endowment design, we can model both asset-specific and systematic liquidity shocks.

This endowment resembles the payoff of $zM'$ futures contracts written on individual risky assets (i.e. $zM'(P_2 - P_1)$) plus $zM'(P_1 - \bar{P})$ in cash. In the case of an asset-specific liquidity shock to asset $i$, where all elements of $M$ are zero except the $i^{th}$ element that is equal to 1 ($m_i = 1$ & $\forall j \neq i,\ m_j = 0$), the endowment looks like the payoff of $z$ futures contracts written on asset $i$ plus some cash. Similarly, a systematic liquidity shock (endowment) resembles the payoff of a portfolio of futures contracts, written on different risky assets. The weight of each futures contracts in this portfolio depends on the loading of its underlying asset on the common systematic liquidity risk.[4]

A few points are crucial here. First, at $t = 0$, investors are identical and indistinguishable such that anyone can potentially be a liquidity demander at $t = 1$. Second, the endowment is a private signal, only observable by the liquidity demanders. This endowment is the only source of heterogeneity among the investors. Third, at $t = 1$ the liquidity shock ($z$) is known but the liquidation payoffs ($P_2$) are unknown. This makes the endowment ($zM'(P_2 - \bar{P})$) a normally-distributed random cash flow, with a zero

[4]The endowment, itself, is not a portfolio of futures contracts, as a futures contract need a counter-position. However, the payoff of this endowment is similar to the payoff of a portfolio of futures contracts.

expected value. The realization of this endowment will be observed at $t = 2$. Fourth, this risky endowment is correlated with the assets' liquidation payoffs ($P_2$), and thereby, it will depart the liquidity demanders' current portfolio from optimality. Because these investors, who are already holding the market portfolio from $t = 0$, in addition at $t = 1$ receive some risky endowment that is correlated with their portfolio. Hence, the liquidity demanders' desire to share this risk and revert back to optimality by trading with the others, i.e. the liquidity suppliers.[5]

For example, consider an asset-specific liquidity shock ($z_i \sim N(0, \sigma^2_{z_i})$) to asset $i$. Furthermore, imagine that the realization of $z$ at $t = 1$ is positive. This endowment, which pays off in cash at $t = 2$, is perfectly correlated with the liquidation payoff of asset $i$ that already exists in liquidity demanders' portfolio. If at $t = 1$ liquidity demanders do nothing, their portfolio will be more-than-optimal exposed to the risk of asset $i$. Hence, receiving this endowment at $t = 1$ persuades them to re-balance their portfolio by selling a part of their holdings on asset $i$ or any other asset that is very similar to (correlated with) it.[6]

It worth mentioning that the exponential utility function, with constant absolute risk aversion, eliminates the wealth effect that is portfolio re-allocation due to a wealth shock. Therefore, when the liquidity demanders receive an endowment, they do not re-allocate their portfolio because they are richer, but because their portfolio has departed from optimality and they feel the need to share this risk.

### 4.2.2 Model Implications

Investors' preferences endogenously imply the asset prices at time 0 and 1. In order to quantify the extent of the deviation of the transaction prices from their fundamental values and the subsequent price reversals, we must first find the asset prices at these two time points. The implications of the outlined model are presented in the following four propositions. Appendix A provides the proofs of the propositions.

**Proposition 1 - Equilibrium prices at time 1:** At time $t = 1$, after realizing the liquidity shock ($z$), investors trade. The $N \times 1$ vector of the equilibrium asset prices at

[5] The endowment design of our model is borrowed from Grossman and Miller (1988), Gromb and Vayanos (2002), Huang and Wang (2009), Huang and Wang (2010), and especially Vayanos and Wang (2012). As an intuition for the endowment, consider two investment banks, labeled as $\mathcal{X}$ and $\mathcal{Y}$. These banks are the only investors in the US market. Bank $\mathcal{X}$ in addition invests in Europe. On a day that bank $\mathcal{X}$ gets the news of its exposure to a risky payoff in Europe, if the payoff is correlated to its US business activities, its portfolio will deviate from optimality. This makes bank $\mathcal{X}$ a liquidity demander and bank $\mathcal{Y}$ a liquidity supplier. In this example, the endowment comes from abroad. In this paper, we do not model for the business activities of bank $\mathcal{X}$ in Europe, but we just assume that due to its overseas activities it receives a risky endowment. Also see Vayanos (1999) for an example on inter-dealer market.

[6] Similarly if the realization of $z$ at $t = 1$ is negative, the endowment persuades the liquidity demanders' to buy more shares of asset $i$ or any other asset that is correlated with it.

this time is

$$P_1 = \bar{P} - \alpha \Sigma \theta - \alpha f z \Sigma M. \tag{4.4}$$

Here, $\bar{P}$ is the vector of expected payoffs (see equation (4.2)) and $\alpha\Sigma\theta$ is the vector of the market risk premia on the risky assets. At time 1, when the value of $z$ is realized, the only remaining source of risk is the market risk. Therefore, $\bar{P} - \alpha\Sigma\theta$ gives the vector of the asset fundamental values, that is expected payoff of the assets discounted for all the remaining risk factors. Moreover, in equation (4.4), $\alpha f z \Sigma M$ is the vector of the price adjustments due to the realized liquidity shock ($z$). Obviously, the occurrence of a liquidity shock at time 1 ($z \neq 0$) departs the asset prices from their fundamental values.[7,8]

**Corollary 1.1 - Asset-specific liquidity shock:** An asset-specific liquidity shock ($z_i \sim N(0, \sigma^2_{z_i}), m_i = 1$ & $\forall j \neq i,\ m_j = 0$) to asset $i$ diverts the price of this asset from its fundamental value

$$P_{1i} = \bar{P}_i - \alpha \sum_{k=1}^{N} \theta_k \sigma_{ki} - \alpha f z_i \sigma_{ii}. \tag{4.5}$$

Here, $P_{1i}$ represents the price of asset $i$ at $t = 1$, and $\bar{P}_i$ is its expected liquidation payoff. Thus $\bar{P}_i - \alpha \sum_{k=1}^{N} \theta_k \sigma_{ki}$ is the fundamental value of asset $i$ in a market with no liquidity shock, and $\alpha f z_i \sigma_{ii}$ is the price pressure on this asset due to the asset-specific liquidity shock $z_i$.

Obviously, an identical asset-specific liquidity shock ($z_i$) exerts a larger deviation ($\alpha f z_i \sigma_{ii}$) from the fundamental value for more volatile assets. Because, ceteris paribus, holding more-than-optimal of a volatile asset is much more unfavourable to the liquidity demanders, and thus, when an asset-specific liquidity shock hits a volatile asset they have a stronger urgency to sell. At the same time, due to the higher uncertainty about the future payoffs, the liquidity suppliers require a larger price discount to provide liquidity.

This asset-specific liquidity shock to asset $i$, also, diverts the price of any correlated asset $j$ from its fundamental value

$$P_{1j} = \bar{P}_j - \alpha \sum_{k=1}^{N} \theta_k \sigma_{kj} - \alpha f z_i \sigma_{ij}. \tag{4.6}$$

[7] The existence of liquidity risk ($z \sim N(0, \sigma^2_z)$) creates excess covariance in asset returns

$$Covar_0(P_2 - P_1) = \Sigma + \alpha^2 f^2 \sigma^2_z \Sigma M M' \Sigma'$$

Here, $\Sigma$ is the covariance matrix of asset fundamental values, and $\alpha^2 f^2 \sigma^2_z \Sigma M M' \Sigma'$ is the excess covariance, caused by the liquidity risk. This is in line with the empirical finding of Acharya, Schaefer and Zhang (2015) that liquidity risk creates excess correlation in asset prices.

[8] Equation (4.4) accommodates two sources for commonality in liquidity, highlighted by Chordia, Roll and Subrahmanyam (2000), Huberman and Halka (2001), Chordia, Roll and Subrahmanyam (2001) and Hasbrouck and Seppi (2001); assets' loadings ($M$) on a common systematic liquidity shock ($z$) or spillover of asset-specific liquidity shocks among correlated assets.

Here, $\bar{P_j} - \alpha \sum_{k=1}^{N} \theta_k \sigma_{kj}$ is the fundamental value of asset $j$ in a market with no liquidity shock, and $\alpha f z_i \sigma_{ij}$ is the price pressure on this asset due to an asset-specific liquidity shock to asset $i$. Liquidity shocks spread across correlated assets, because the departure from optimality, created by the liquidity shock to a specific asset, can also be resolved by trading any highly correlated asset.

Clearly, while asset variances influence the extent of deviation from the fundamental values (equation (4.5)), the correlation between two assets is the channel through which a liquidity shock flows from one asset to the other one (equation (4.6)). An asset-specific liquidity shock to asset $i$ spills over to any other asset correlated with it. Because when (e.g.) $z_i$ is positive, liquidity demanders feel that they have excessive exposure to the risk of asset $i$. Hence at time 1, they decide to re-optimize their portfolio by selling a portion of their holdings on asset $i$ or any asset which is highly correlated with (similar to) it. However since liquidity suppliers' portfolio is already optimal, they do not have any incentive to buy, unless the prices move in their favor; the liquidity suppliers provide liquidity by charging a price discount $\alpha f z_i \sigma_{ij}$ on any asset $j$.

**Proposition 2 - Liquidity suppliers' expected return:** At $t = 1$, the asset prices ($P_1$) depart from their fundamental values by $\alpha f z \Sigma M$. Consequently, it encourages the liquidity suppliers to trade and provide liquidity. Later, at the liquidation moment ($t = 2$), the prices revert back to their fundamental value ($P_2$). One can show that the expected return of the liquidity suppliers, due this price reversal effect, is

$$E_0[R] = \alpha f^2 \sigma_z^2 \; M' \Sigma M. \tag{4.7}$$

From equation (4.7), it is clear that liquidity providers' expected return is positive and its magnitude increases with the investors' risk aversion ($\alpha$), the proportion of investors affected by the liquidity shock ($f$), the intensity of the liquidity shock ($\sigma_z^2$), as well as, asset variances and asset correlations ($\Sigma$). Since the VIX index is an increasing function of investors' risk aversion, stocks' variances and stocks' pairwise correlations, we conclude that the VIX must positively correlate with the liquidity suppliers' expected return.

Hameed, Kang and Viswanathan (2010) (for stock market) and Bao, Pan and Wang (2011) (for bond market) show that after long market declines, the intensity of short-term price reversal is stronger. Our theoretical model suggests that this is probably the case, because at these times investors are more risk averse and thus they charge a higher premium for providing liquidity.

**Corollary 2.1 - Asset-specific liquidity shock:** The liquidity suppliers' expected return, due to an asset-specific liquidity shock ($z_i \sim N(0, \sigma_{z_i}^2), m_i = 1 \;\&\; \forall j \neq i,\; m_j = 0$) to asset $i$, is

$$E_0[R_i] = \alpha f^2 \sigma_{z_i}^2 \sigma_{ii}. \tag{4.8}$$

According to equation (4.8), the liquidity suppliers' expected return grows with the variance of asset $i$ ($\sigma_{ii}$) and the intensity of the liquidity risk ($\sigma^2_{z_i}$). Because, investors expect a higher return to provide liquidity on a volatile asset or an asset with large exposure to asset-specific liquidity risk.

**Proposition 3 - Liquidity suppliers' Sharpe ratio:** The expected Sharpe ratio of the liquidity suppliers is equal to

$$E_0[SR] = \alpha f \sigma_z \sqrt{\frac{2}{\pi} M' \Sigma M}, \tag{4.9}$$

where $\pi \approx 3.14$. Clearly, the expected Sharpe ratio of the liquidity suppliers increases with the investors' risk aversion ($\alpha$), the proportion of investors affected by the liquidity shock ($f$), the intensity of the liquidity shock ($\sigma^2_z$), as well as, asset variances and asset correlations ($\Sigma$). Since the VIX index is an increasing function of investors' risk aversion, stocks' variances and stocks' pairwise correlations, we conclude that larger values of the VIX must coincide with higher Sharpe ratios for the liquidity suppliers.

**Proposition 4 - Equilibrium prices at time 0:** The $N \times 1$ vector of the equilibrium asset prices at time 0, before observing a liquidity shock, is

$$P_0 = \bar{P} - \alpha \Sigma \theta - \frac{\kappa f}{1 - f + \kappa f} \left( \frac{\alpha \Delta_1}{\Delta_0} \right) \Sigma M, \tag{4.10}$$

where

$$\Delta_0 = 1 + \alpha^2 \sigma^2_z (f^2 - 2f) M' \Sigma M, \quad \Delta_1 = \alpha^2 \sigma^2_z \theta' \Sigma M,$$

and

$$\kappa = \sqrt{\frac{1 + \alpha^2 f^2 \sigma^2_z M' \Sigma M}{1 + \alpha^2 (f^2 - 2f) \sigma^2_z M' \Sigma M}} exp\left( \frac{\alpha^2 \Delta_1 \theta' \Sigma M}{2 \Delta_0} \right).$$

In equation (4.10), $\bar{P} - \alpha \Sigma \theta$ refers to the $N \times 1$ vector of asset prices discounted for the market risk, and $\frac{\kappa f}{1 - f + \kappa f} \left( \frac{\alpha \Delta_1}{\Delta_0} \right) \Sigma M$ is the $N \times 1$ vector of the cross sectional liquidity risk premia on individual risky assets. According to this equation, the size of the liquidity premium in assets' cross section depends on investors' risk aversion ($\alpha$), assets' loading on the common liquidity shock ($M$), the intensity of the liquidity shock ($\sigma^2_z$), as well as, asset variances and asset correlations ($\Sigma$). This confirms the empirical findings of Pástor and Stambaugh (2003) and Korajczyk and Sadka (2008) that firstly, an asset with a higher sensitivity to the systematic liquidity risk (i.e. an asset with a large element in $M$) is compensated with a larger expected return, and secondly, the cross sectional liquidity premium increases with asset volatilities (also see Watanabe and Watanabe (2007)).

In this paper, in order to keep the mathematical derivations tractable, investors' risk aversion ($\alpha$) and asset covariances ($\Sigma$) are assumed to be constant over the three time points of the model. Since the model horizon is short and we study the short-term price reversal effect that materialize in a few hours or days, this is not a strong assumption. However, the well-known fact that the VIX index is an increasing function of investors' risk aversion, stocks' average variance and stocks' average correlation only holds if these factors can vary over time. Moreover, in our empirical analysis, we are interested to see the impact of long-term time variation in these factors on liquidity providers' return and Sharpe ratio. To find the connection, it is useful to think about the repetition of the model horizon, successively, over time. While investors' risk aversion ($\alpha$) and asset covariances ($\Sigma$) are constant over the three periods in each individual iteration, they are free to change across different iterations.

## 4.3 Empirical Analysis

The theory predicts that higher investors' risk aversion, asset variances or asset correlations lead to a larger expected return (see equation (4.7)) and Sharpe ratio (see equation (4.9)) for liquidity providers. In this section, we test the validity of this theoretical finding using a portfolio that speculates on stocks short-term price reversals and proxies of investors' risk aversion, stocks' average variance and stocks' average correlation.

**Price Reversal Strategy Portfolio:** In order to construct a portfolio that exploits the short-term reversals in stock prices, we obtain the daily return time series of all ordinary shares traded at the NYSE, AMEX and NASDAQ from the CRSP database. These time series span for 20 years, from 1996 to 2015. Stocks with a zero volume of trade on a day are excluded from the sample in that particular day. Following Lehman (1990), we set the weight of stock $i$ on day $t$ as

$$w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}. \tag{4.11}$$

Here, $R_{i,t-1}$ and $R_{m,t-1}$ respectively correspond to the returns of stock $i$ and the equally-weighted market portfolio, on day $t-1$.[9] On each day, this portfolio speculates on price reversion by buying (selling) the stocks that have underperformed (outperformed) the equally-weighted market index over the last trading day. On each day, the size of

[9] Here, we have implicitly assumed that the time required for price reversal is one day. However, Hansch, Naik and Viswanathan (1998) show that especially for illiquid stocks, price reversion might take more than one day. Also, Hendershott and Menkveld (2014) find that the half-life of short-term price reversal ranges from 0.54 to 2.11 days for different market capitalization quintiles. In order to capture delayed price reversals, in appendix C.1, we also create a reversal strategy portfolio, in which the weight of each stock on any day $t$ depends on its five days lagged returns. Of course, by only using daily return time series, we are unable to capture return of intra-day liquidity providers, such as high-frequency traders.

the long and the short positions of this reversal strategy is 1 dollar. Since this reversal strategy portfolio always has both long and short positions, it has less exposure to factors other than the short-term price reversal, such as the market, size, value and momentum risk.

Liquidity providers expect returns to compensate them for adverse selection (trading with a counter-party with insider information) or absorbing inventory imbalance (deviating from optimality). Nagel (2012) shows that the reversal strategy of equation (4.11) efficiently captures the compensation for the second factor, while it has minimal exposure to the adverse selection risk.[10]

The weighting strategy of equation (4.11), by construction, tends to buy (sell) low-beta (high-beta) stocks after a day that the market return is positive. To ensure that the return on this portfolio is not driven by market fluctuations, following Nagel (2012), we orthogonalize it with respect to the market using regression equation (4.12).

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 \Big( R_{m,t} \times sign(R_{m,t-1}) \Big) + Res_t. \tag{4.12}$$

Here, $R_t = \sum_{i=1}^{N} w_{i,t} R_{i,t}$ is the return of the reversal strategy portfolio constructed with equation (4.11), and $sign(R_{m,t-1})$ denotes the sign of the market return on the previous trading day. In the next section, we perform our regression analyses based on the intercept plus the residuals of regression equation (4.12), i.e. $\beta_0 + Res_t$. The three-month moving-average return of this portfolio is plotted in figure (4.2) in appendix D.

For constructing the reversal strategy portfolio, in equation (4.11), we use the actual daily closing prices and close-to-close returns. Roll (1984) argues that price bounce between bid and ask quotes creates negative auto-correlation in return time series and thus profitable reversal strategies. Since liquidity suppliers do not initiate a trade but instead accommodates it, they usually sell at their own ask and buy at their own bid. Therefore, bid-ask bounce also captures a part of liquidity suppliers' return, and to fully capture their compensation, we must use transaction prices.[11]

Bid and ask quotes exist for variety of reasons, such as liquidity providers' aversion to absorb extra risky inventory while trading, or their aversion to the adverse selection risk. The argument of Roll (1984) might lead to the skepticism that our reversal strategy simply captures bid-ask bounce, caused by the adverse selection risk, rather than liquidity providers' compensation for other factors. The theoretical model of Glosten and Milgrom

[10] To check the robustness of our results, in appendix C.2, we construct alternative reversal strategy portfolios that are proposed by Lo and MacKinlay (1988) and Nagel (2012).

[11] Although bid-ask bounce creates negative auto-correlation in return time series, previous empirical studies (e.g. Bao, Pan and Wang (2011) on the US bond market) show that the size of price reversal is beyond what can be explained by bid-ask bounce.

(1985), however, shows that the bid-ask spread due to the adverse selection risk does not generate any auto-correlation in the return time series while other factors do; in the presence of adverse selection but absence of other factors, the transaction price still follows a martingale. Hence, our reversal strategy portfolio in equation (4.11) does not capture the adverse selection risk premium. Yet to be on the safe side, in appendix E, we test the robustness of our results once we construct our reversal strategy using mid-quote closing prices, i.e. the average of the best closing-bid and the best closing-ask on each day.

**VIX Index:** The VIX, which is the option-implied volatility of the S&P 500 index, represents investors' expectations about the volatility of the market over the next 30 days. The VIX index is computed under the risk-neutral measure, and therefore, it increases with investors' risk aversion and/or their expectation about the volatility of the S&P 500 index. (See e.g. Bakshi, Kapadia and Madan (2003), Bollerslev, Gibson and Zhou (2011) and Bekaert and Hoerova (2014).) Furthermore, the latter is an increasing function of the expected variance of the individual S&P 500 stocks and their expected pairwise correlations. Therefore, the VIX can be considered as an index that encapsulates investors' risk aversion, and their expectations about the average variance and the average correlation of stocks. We obtain the daily time series of the VIX index from the website of the Chicago Board of Options Exchange (CBOE). Panel A in figure (4.1) displays this time series.

**Investors' Risk Aversion:** Computing the level of investors' risk aversion is always an empirical challenge, and yet finding the time-variations in investors' risk aversion is a more difficult task. The classical asset pricing models fail to find a reasonable value for investors' risk aversion; an issue that creates the "equity premium puzzle" (Mehra and Prescott (1985)). There have been numerous efforts to explain or diminish the large estimations for investors' risk aversion, such as Campbell and Cochrane (1999), Bansal and Yaron (2004), Savov (2011), and recently Kroencke (2016). In contrast to the other three models, Campbell and Cochrane (1999) develop a habit-formation model, in which the level of risk aversion is time varying. In this framework, investors always consume more than their slowly-moving habit level. When consumption declines towards the habit level (i.e. when consumption grows less that the habit), investors' risk aversion rises. In the same spirit, we proxy the level of risk aversion at the end of quarter $T$ with the difference between the expected and the realized consumption growth,

$$RA_T = E_{T-1}\big[g_{c,T}\big] - g_{c,T}. \tag{4.13}$$

Here, $g_{c,T}$ stands for the consumption growth in quarter $T$, which will be observed at the end of this quarter, and $E_{T-1}\big[g_{c,T}\big]$ shows the expectation that investors had about $g_{c,T}$ at the end of the previous quarter. According to equation (4.13), if the actual consumption growth is less (more) than what investors had expected, then our proxy for the level of risk aversion ($RA_T$) will be positive (negative). The higher values of $RA_T$, which corresponds to more unsatisfied consumption growth expectations, represent more risk aversion. Of course, a negative estimation for $RA_T$ does not necessarily mean that investors' are risk-seeking, but it is associated with a low level of risk aversion.

We obtain the time series of seasonality-adjusted real personal consumption per capita of US consumers from the database of the Federal Reserve Bank of Saint Louis. This time series has a quarterly frequency and it spans from January 1947 to December 2015. In equation (4.13), we set $E_{T-1}\big[g_{c,T}\big]$ equal to the average of quarterly consumption growth in the past three years.[12] Our empirical analysis is not sensitive to the length of this window.

$$E_{T-1}\big[g_{c,T}\big] = \frac{1}{12}\sum_{t=T-12}^{T-1} g_{c,t}. \tag{4.14}$$

Since the time series of consumption growth has a quarterly frequency, the value of $RA_T$ is only observable at the end of quarter $T$. In order to obtain the value of $RA_t$ for any day $t$ in quarter $T$, we linearly interpolate between $RA_{T-1}$ and $RA_T$.[13] Panel B in figure (4.1) plots our proxy for investors' risk aversion.

**Stocks' Average Covariance:** In contrast to the VIX index that also increases with investors' risk aversion, the realized volatility of the S&P500 index is only a function of stock variances and correlations. We obtain the intradaily return time series of the S&P500 index from Tick Data and estimate the daily time series of realized variance of the S&P 500 index with the cumulative squared intradaily returns (5-minute) of each day (see e.g. Andersen and Bollerslev (1998)). We then set the realized volatility of each day equal to the square-root of the realized variance on that day. To make it annualized and therefore comparable with the VIX, we multiply the realized volatility of each day by $\sqrt{252}$. Panel C in figure (4.1) displays this time series.

**Stocks' Average Variance and Correlation:** We break-down the stocks' average covariance into its two components; stocks' average variance and stocks' average correlation. For this purpose, we use the methodology of Carr and Wu (2009) to extract the

[12] Alternatively, one could fit (e.g.) an ARMA(1,1) process to the consumption growth time series and take the fitted values as investors' expectations about consumption growth. This does not change our empirical conclusion qualitatively, but since it exposes us to the look-ahead bias we prefer to estimate $E_{T-1}\big[g_{c,T}\big]$ using equation (4.14).

[13] In line with the habit formation model of Campbell and Cochrane (1999), some authors such as Brandt and Wang (2003) and Bams, Honarvar and Lehnert (2015) assume that risk aversion follows an auto-regressive process and calibrate it to certain portfolios using the GMM technique. Our experience (in Bams, Honarvar and Lehnert (2015)) shows that the resulting risk aversion process is very sensitive to the choice of utility function and sample portfolios. In contrast, the methodology that we use in equation (4.13) is robust and follows the habit formation model of Campbell and Cochrane (1999); unfulfilled consumption growth expectations increase investors' risk aversion.

daily variance of individual stocks in the S&P 100 ($\sigma_{i,t}^2$ where $i \in$ S&P100 index) from option prices. Then we take their cross sectional average on each day as a proxy for the average variance of stocks in that particular day,

$$\overline{\sigma_t^2} = \sum_{i \in S\&P100} w_{i,t}\ \sigma_{i,t}^2. \tag{4.15}$$

One can expand the variance of the S&P 100 index as

$$\sigma_{S\&P100,t}^2 = \sum_{i \in S\&P100} w_{i,t}^2\ \sigma_{i,t}^2 + \sum_{i\&j \in S\&P100} \sum_{i \neq j} w_{i,t}\ w_{j,t}\ \sigma_{i,t}\ \sigma_{j,t}\ \rho_{ij,t}. \tag{4.16}$$

Thus, assuming that all pairwise correlations are equal ($\forall\ i\&j,\ \rho_{ij,t} = \overline{\rho_t}$), we compute the average correlation of stocks on each day as

$$\overline{\rho_t} = \frac{\sigma_{S\&P100,t}^2 - \sum_{i \in S\&P100} w_{i,t}^2\ \sigma_{i,t}^2}{\sum_{i\&j \in S\&P100} \sum_{i \neq j} w_{i,t}\ w_{j,t}\ \sigma_{i,t}\ \sigma_{j,t}}. \tag{4.17}$$

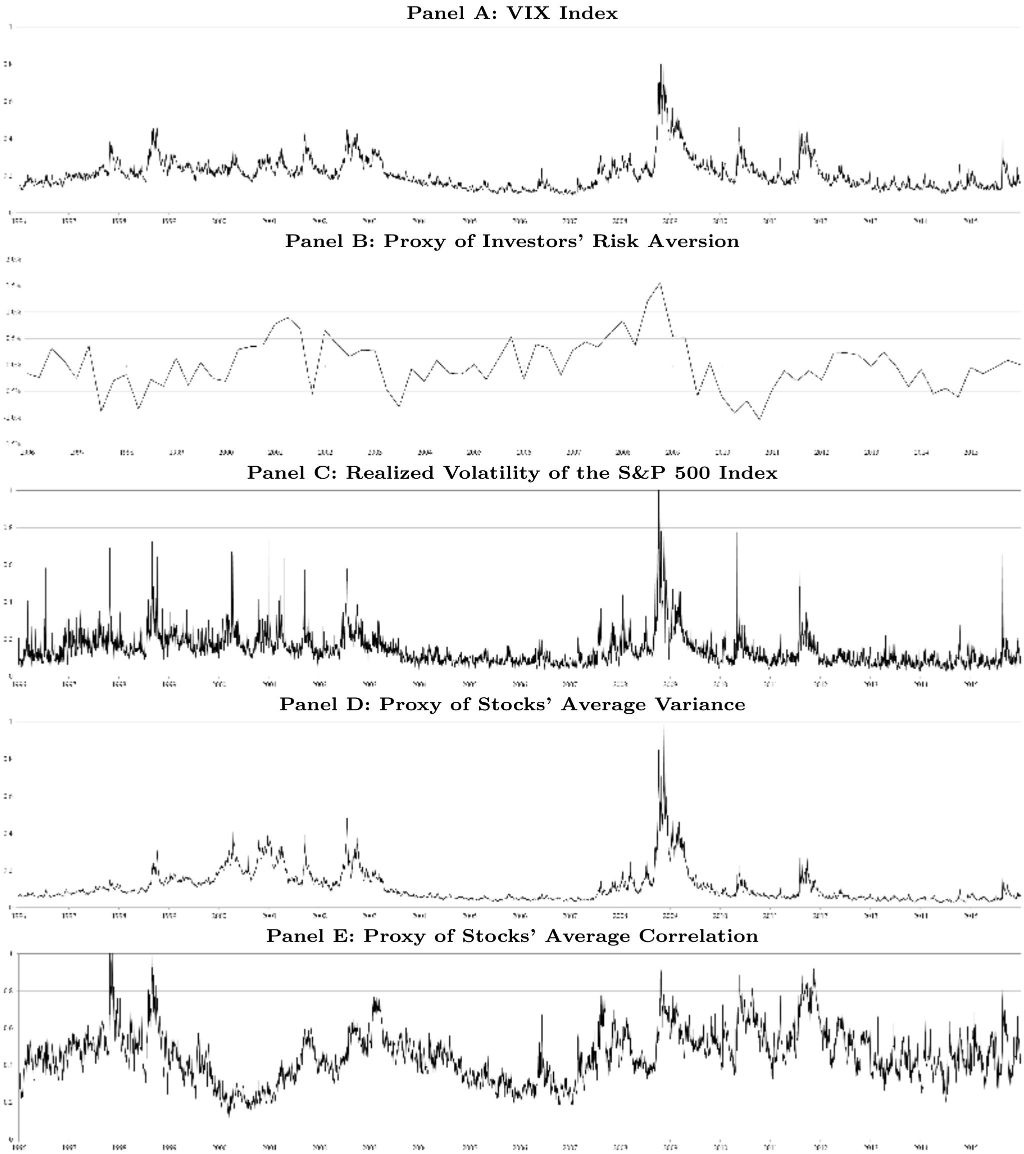
Since for computing the option-implied variance of each stock ($\sigma_{i,t}^2$), we only need the option prices on that particular day, our estimations for stocks' average variance and stocks' average correlations, in equation (4.15) and (4.17), are strictly conditional and forward-looking. We obtain the daily price of the options, traded on the S&P100 index and its constituent stocks, from the OptionMetrics database. Consistent with the VIX index, the horizon for which we calculate stocks' variance expectations is 30 days. Appendix B provides the details of our implementation. Our proxies for stocks' average variance and stocks' average correlation are plotted, respectively, in panel D and E of figure (4.1).

Using option-implied information, besides the big advantages of being strictly conditional and forward-looking, has one drawback; the resulting average variance and average correlation time series are estimated under the risk-neutral measure. In order to compute the corresponding time series, alternatively, we could use a rolling-window of past daily returns. Then to improve the accuracy of the estimations, one must increase the length of the window, which at the same time scarifies the conditionality. Due to the unconditionality and backward-looking nature of historical estimation techniques, we prefer to use option-implied information.

### 4.3.1 Summary Statistics

Panel A in table (4.1) provides summary statistics on the market, the reversal strategy portfolio, and two proxies for the tightness of financial and credit constraints. These proxies, which we obtain from the FactSet database, are the 1-month USD LIBOR and

Figure 4.1: Time Series



the Ted-Spread. The LIBOR is the interest rates that financial institutions charge for unsecured loans; a higher LIBOR means a higher cost of borrowing. Also, the Ted-Spread is the difference between the LIBOR and the T-bill yield of a particular maturity, generally three month. Since the US government debts are considered as risk-free assets, the Ted-Spread is a yardstick for the tightness of credit in the market.[14]

The frequency of all time series in table (4.1) is daily and they span from January 1996 to December 2015. In contrast to the market portfolio, a reversal strategy portfolio requires daily re-allocation and therefore it incurs sizable transaction costs. According to column (9), our short-term reversal strategy portfolio on average yields to 1.27% return per day, before deducting the transaction costs. Consequently, the annualized Sharpe ratio of this portfolio (11.76) is considerably higher than the same ratio for the market portfolio (0.39).[15] Column (10) reports the corresponding summary statistics for the reversal strategy portfolio, after it has been orthogonalized to market fluctuations using equation (4.12). As we can see, the effect of the orthogonalization on the distribution of the portfolio return is negligible.

In our setup, a liquidity shock creates a selling or a buying demand. While the first one requires an extra long position by the liquidity providers, in the latter case they must sell. Here, we split the reversal strategy portfolio of equation (4.11) into its two components:

- Price reversals driven by publics' selling demands that require long positions by the liquidity providers ($w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$ when $R_{m,t-1} > R_{i,t-1}$). On each day, this position provides liquidity by buying 1 dollar of stocks that underperformed the market portfolio over the last trading day.

- Price reversals driven by publics' buying demands that require short positions by the liquidity providers ($w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$ when $R_{m,t-1} < R_{i,t-1}$). On each day, this position provides liquidity by selling 1 dollar of stocks that outperformed the market portfolio over the last trading day.

The combination of these two portfolios gives the reversal strategy of equation (4.11). Summary statistics on these long and short positions are provided in column (11) and (12) of table (4.1). As we can see, from the total of 1.27% average daily return on the reversal strategy portfolio, 0.87% (more than two-third) comes from the long position and 0.40% originates from the short position.

Panel B in table (4.1) displays the corresponding correlation matrix. As one would expect, the VIX index is positively correlated with the proxy of investors' risk aversion,

[14] See (e.g.) Cornett, McNutt, Strahan and Tehranian (2011) and Nyborg and Östberg (2014).

[15] In fact, Avramov, Chordia and Goyal (2006) find that after considering transaction costs, a reversal strategy is not so strikingly profitable and it does not violate the market efficiency hypothesis.

the realized volatility of the S&P 500 index, the stocks' average variance and the stocks' average correlation. Remarkably, this table shows that the correlation coefficient between the average variance and the average correlation of the S&P 100 stocks is as small as 0.16. Moreover, the long and the short positions of the reversal strategy portfolio have the considerable negative correlation of -0.50.

### 4.3.2 Regression Analysis

**Return**

To empirically test whether liquidity providers' return grows with investors' risk aversion and stocks' covariances, we regress the daily return of our reversal strategy portfolio (after it is orthogonalized to the market using equation (4.12)) on the VIX, the risk aversion proxy, the realized volatility of the S&P500 index, the average variance and the average correlation of the S&P 100 stocks. We also include a dummy variable that is equal to one before the stock price decimalization (April 9th 2001) and zero after that.[16] The results, reported in table (4.2), confirm our theoretical conjecture.

The estimated coefficients for the decimalization dummy are significantly positive across all the regressions in table (4.2). This means that before the price decimalization the return on liquidity provision was higher and the short-term reversal strategy was more profitable. Consistent with Bessembinder (2003), this indicates an improvement in market liquidity after the decimalization. Also Lo and MacKinlay (1988) theoretically show that if stocks react to economic news with different speeds, then a short-term reversal strategy yields to a higher return. Therefore, one reason for the higher profitability of the reversal strategy portfolio, before the decimalization, might be the existence of more market inefficiency during that time.

Moreover consistent with Nagel (2012), our regression in column (1) shows that an increase in the VIX index leads to a higher return on our short-term price reversal strategy and a higher return for liquidity providers.[17] The VIX index can increase as a function of investors' risk aversion or stocks' covariances. Thus we decompose this index into a risk aversion component and an average covariance component (i.e. the realized volatility of the S&P 500 index). Consistent with our theoretical prediction, the results in column (2) reveal that both components, investors' risk aversion and stocks' covariances, contribute

[16] Note that April 9th 2001 was a deadline imposed by the SEC. However, many exchanges (including NYSE) converted to decimals already by January 29th 2001.

[17] Our theoretical model shows that there is no lead-lag effect in the relationship between the intensity of the short-term reversal and the VIX index; these times series correlate contemporaneously. In contrast to our argumentation and to test the predictability of the return on the short-term price reversal strategy, Nagel (2012) regresses this time series on the 5-days lagged value of the VIX index. The VIX index is extremely autocorrelated ($Corr(VIX_t, VIX_{t-5}) = 0.94$). Therefore, regressing the return of the reversal strategy on 5-days lagged value of the VIX still gives significant results, as Nagel (2012) finds. For further explanations see Lanne (2002).

Table 4.1: Time Series

| | VIX Index (1) | Risk Aversion Proxy (2) | S&P500 Realized Volatility (3) | S&P100 Average Variance (4) | S&P100 Average Correlation (5) | Market Portfolio (6) | 1M-LIBOR (7) | Ted-Spread (8) | Return (9) | Ortho. Return (10) | Long Position Return (11) | Short Position Return (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Summary Statistics** | | | | | | | | | | | | |
| 5th Percentile | 11.83% | -0.72% | 5.61% | 0.0384 | 0.2351 | -1.92% | 0.58% | 0.16% | -0.78% | -0.71% | -1.62% | -1.89% |
| 25th Percentile | 15.12% | -0.26% | 8.40% | 0.0525 | 0.3596 | -0.52% | 1.02% | 0.22% | 0.26% | 0.26% | 0.00% | -0.49% |
| Median | 19.47% | -0.06% | 12.39% | 0.0781 | 0.4432 | 0.07% | 2.61% | 0.36% | 0.97% | 0.97% | 0.80% | 0.33% |
| 75th Percentile | 24.39% | 0.27% | 17.53% | 0.1391 | 0.5357 | 0.62% | 5.36% | 0.61% | 2.14% | 2.10% | 1.67% | 1.25% |
| 95th Percentile | 36.21% | 0.79% | 29.66% | 0.2915 | 0.6985 | 1.78% | 6.40% | 1.23% | 4.08% | 4.03% | 3.36% | 2.95% |
| Average | 20.98% | 0.00% | 14.37% | 0.1099 | 0.4516 | 0.03% | 3.17% | 0.49% | 1.27% | 1.26% | 0.87% | 0.40% |
| St. Dev. | 8.32% | 0.44% | 8.96% | 0.0884 | 0.1381 | 1.23% | 2.18% | 0.42% | 1.71% | 1.68% | 1.71% | 1.69% |
| Skewness | 2.00 | 0.52 | 2.88 | 2.65 | 0.44 | -0.11 | 0.25 | 3.32 | 1.05 | 0.97 | 0.98 | 0.01 |
| Kurtosis | 9.92 | 3.74 | 18.79 | 14.21 | 3.29 | 10.04 | 1.47 | 21.17 | 17.25 | 17.53 | 11.57 | 20.10 |
| Market Beta | | | | | | 1.00 | | | 0.15 | 0.00 | 1.01 | -0.86 |
| Ann. Sharpe Ratio | | | | | | 0.39 | | | 11.76 | 11.95 | 8.12 | 3.77 |
| **Panel B: Correlation Matrix** | | | | | | | | | | | | |
| (1) | 1.00 | | | | | | | | | | | |
| (2) | 0.22 | 1.00 | | | | | | | | | | |
| (3) | 0.81 | 0.25 | 1.00 | | | | | | | | | |
| (4) | 0.87 | 0.43 | 0.79 | 1.00 | | | | | | | | |
| (5) | 0.59 | -0.23 | 0.35 | 0.16 | 1.00 | | | | | | | |
| (6) | -0.13 | -0.05 | -0.13 | -0.10 | -0.12 | 1.00 | | | | | | |
| (7) | 0.02 | 0.26 | 0.23 | 0.21 | -0.36 | -0.01 | 1.00 | | | | | |
| (8) | 0.52 | 0.47 | 0.53 | 0.56 | 0.11 | -0.03 | 0.43 | 1.00 | | | | |
| (9) | 0.32 | 0.08 | 0.35 | 0.32 | 0.12 | 0.11 | 0.31 | 0.23 | 1.00 | | | |
| (10) | 0.33 | 0.08 | 0.37 | 0.33 | 0.14 | -0.00 | 0.32 | 0.23 | 0.98 | 1.00 | | |
| (11) | 0.11 | 0.01 | 0.10 | 0.15 | -0.04 | 0.73 | 0.19 | 0.13 | 0.51 | 0.42 | 1.00 | |
| (12) | 0.21 | 0.07 | 0.25 | 0.18 | 0.17 | -0.63 | 0.12 | 0.10 | 0.50 | 0.56 | -0.50 | 1.00 |

*Note:* We proxy risk aversion with the difference between the expected and the realized consumption growth. We proxy the daily time series of realized volatility of the S&P 500 index with the cumulative squared intradaily returns on each day, and scale it by $\sqrt{252}$ to make it annualized. We extract the daily time series of stocks' average variance and stocks' average correlation from options data. In our reversal strategy, the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock $i$ on day $t$. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The annualized Sharpe ratio is calculated as the ratio of the average daily return to the daily standard deviation, multiplied by $\sqrt{252}$. The frequency of all time series is daily and they span from January 1996 to December 2015.

Table 4.2: Regression Analysis of Liquidity Providers' Return

| | (1) | (2) | (3) | (4) | (5) | (6) | (6.Long) | (6.Short) |
|---|---|---|---|---|---|---|---|---|
| Intercept | -0.0034 | 0.0021 | -0.0058 | -0.0054 | 0.0033 | -0.0084 | -0.0013 | -0.0071 |
| | (-4.75) | (3.94) | (-5.87) | (-6.01) | (4.18) | (-6.35) | (-1.43) | (-6.51) |
| Decimalization Dummy | 0.0149 | 0.0135 | 0.0160 | 0.0130 | 0.0153 | 0.0145 | 0.0098 | 0.0047 |
| | (18.14) | (15.45) | (20.31) | (13.60) | (13.24) | (12.61) | (13.08) | (4.90) |
| VIX Index | 0.0575 | | | 0.0669 | | | | |
| | (14.89) | | | (14.65) | | | | |
| Risk Aversion | | 0.1417 | 0.2863 | | 0.2754 | 0.3616 | 0.1072 | 0.2516 |
| | | (2.21) | (3.89) | | (3.05) | (3.91) | (1.72) | (3.34) |
| S&P500 Realized Volatility | | 0.0484 | | | 0.0511 | | | |
| | | (11.48) | | | (9.81) | | | |
| S&P 100 Average Variance | | | 0.0337 | | | 0.0412 | 0.0302 | 0.0112 |
| | | | (6.51) | | | (7.54) | (6.44) | (2.35) |
| S&P 100 Average Correlation | | | 0.0233 | | | 0.0280 | 0.0094 | 0.0185 |
| | | | (9.07) | | | (9.89) | (5.07) | (8.87) |
| 1M-LIBOR | | | | 0.0669 | -0.0359 | 0.0727 | 0.0126 | 0.0595 |
| | | | | (3.78) | (-1.86) | (3.41) | (0.91) | (3.40) |
| Ted-Spread | | | | -0.3321 | -0.1965 | -0.4634 | -0.1777 | -0.2802 |
| | | | | (-2.70) | (-1.77) | (-3.46) | (-2.24) | (-2.74) |
| R-Squared | 0.26 | 0.25 | 0.27 | 0.27 | 0.25 | 0.28 | 0.23 | 0.07 |

*Note:* Column (1) to (6) reports the estimated coefficients when we regress the return of our reversal strategy portfolio on investors' risk aversion, proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock $i$ on day $t$. The return of this portfolio is then orthogonalized with respect to the market fluctuations. For the regressions in column (6.Long) and (6.Short), we decompose the return of our reversal strategy into a long position ($w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$ when $R_{m,t-1} > R_{i,t-1}$) and a short position ($w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$ when $R_{m,t-1} < R_{i,t-1}$). The time series frequency is daily and they range from January 1996 to December 2015. The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

to stronger short-term price reversals and a higher liquidity premium. Furthermore in regression (3), we find that both components of the stocks' average covariance, i.e. stocks' average variance and stocks' average correlation, lead to a higher return for liquidity providers.

Nagel (2012) introduces funding and credit constraints (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) and Acharya, Schaefer and Zhang (2015)), captured by the VIX index, as potential drivers of the positive relationship between the VIX and liquidity providers' return. He argues that when the VIX is high, market makers are probably facing tighter financial constraints and thereby they charge a higher premium for liquidity provision. In order to test this conjecture, we investigate whether other proxies of financial and credit constraints can be better explanatory variables than investors' risk aversion and asset covariances in explaining the short-term price reversal effect. For this purpose, we repeat the previous regressions after adding the 1-month LIBOR and the Ted-Spread to the independent variables. The results, shown in column (4) to (6), reveal that neither of these proxies can undermine the substantial relationship that exist between investors' risk aversion and stocks' average covariance, and the intensity of the short-term price reversal effect.

A positive regression coefficient for the 1-month LIBOR or the Ted-Spread means that higher borrowing costs or tighter credit constraints contribute to a stronger short-term price reversal effect. Remarkably, for the regressions in column (4) to (6), the estimated coefficients of the 1-month LIBOR are not always significantly positive and the sign of the estimated coefficients for the Ted-Spread are mostly significantly negative. At the same time, comparing column (1) to (3) with column (4) to (6) shows that the size and the statistical significance of the estimated coefficients for proxies of investors' risk aversion and stocks' average covariance are unaffected, after we control of financial and credit constraints. This finding suggests that financial constraints can not play the role of risk aversion and asset covariances in explaining the liquidity premium in the time series of stock returns.

Based on column (4), one standard deviation increase in the VIX index (0.0832) is associated with $(0.0669 \times 0.0832 =)$ 0.56% higher return, per day. Also based on column (6) one standard deviation increase in our proxies of investors' risk aversion (0.0044), stocks' average variance (0.0884) and stocks' average correlation (0.1381) correspond to $(0.3616 \times 0.0044 =)$ 0.16%, $(0.0412 \times 0.0884 =)$ 0.36% and $(0.0280 \times 0.1381 =)$ 0.39% higher return in this strategy. Comparing these values with the average daily return of the reversal strategy, i.e. 1.27% per day (see table (4.1)), highlights the impact of investors' risk aversion, asset variances and asset correlations on the price of liquidity. This is because when asset variances are higher, liquidity shocks create more urgency to trade. Moreover, rising asset correlations increases the risk of spillover of liquidity shocks among assets. In these cases or when investors are more risk-averse, they require a higher compensation to provide liquidity, and thus, the short-term price reversal effect intensifies.

Furthermore, our results in column (6.Long) and (6.Short) of table (4.2) show that investors' risk aversion, stocks' average variance and stocks' average correlation have significant explanatory powers for the variations in both long and short positions of the reversal strategy. Remember from table (4.1) that liquidity providers' expected return from buying stocks when the public sells (the return on the long position of the reversal strategy) is on average 0.87% per day. Column (6.Long) shows that when investors' risk aversion, stocks' average variance or stocks' average correlation increase by one standard deviation, the expected return of liquidity providers for buying while the public sells raises by respectively $(0.1072 \times 0.0044 =)$ 0.05%, $(0.0302 \times 0.0884 =)$ 0.27% and $(0.0094 \times 0.1381 =)$ 0.13%. Similarly table (4.1) shows that liquidity providers' expected return from selling stocks when the public has urgency to buy (the return on the short position of the reversal strategy) is on average 0.40% per day. From the results in column (6.Short) of table (4.2) we can see that when investors' risk aversion, stocks' average variance or stocks' average correlation increase by one standard deviation, the expected return of liquidity providers for selling while the public buys raises by $(0.2516 \times 0.0044 =)$ 0.11%, $(0.0112 \times 0.0884 =)$ 0.10% and $(0.0185 \times 0.1381 =)$ 0.26%.

Although the long and the short positions of the reversal strategy portfolio have the considerable negative correlation of -0.50 (see table (4.1)), column (6.Long) and (6.Short) of table (4.2) show that they both have large positive loadings on the proxies of investors' risk aversion and stocks' average covariances.

### Sharpe Ratio

Proposition (3) predicts that the expected Sharpe ratio of the return on liquidity provision is also an increasing function of investors' risk aversion, asset variances and asset correlations. In this section, we compute the daily time series of conditional Sharpe ratio for our short-term reversal strategy portfolio and test the empirical validity of this theoretical finding. For this purpose first we find the conditional volatility of daily returns, by fitting a GARCH(1,1) model to the return time series of the reversal strategy portfolio. Then we set the Sharpe ratio of each day equal to the ratio of return to volatility in that particular day. In order to annualize this ratio, we multiply it by $\sqrt{252}$. Table (4.3) reports the results for the regression of conditional Sharpe ratio time series on our proxies of investors' risk aversion and stocks' average covariances.

According to the regressions in table (4.3), before the decimalization, the Sharpe ratio of liquidity providers was significantly higher. Moreover, as we can see in this

Table 4.3: Regression Analysis of Liquidity Providers' Sharpe Ratio

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | 3.58 | 5.46 | 1.89 | 1.77 | 5.10 | -0.78 |
| | (6.38) | (13.31) | (2.46) | (2.32) | (8.19) | (-0.72) |
| Decimalization Dummy | 4.45 | 3.88 | 5.22 | 2.37 | 3.13 | 3.02 |
| | (10.76) | (8.72) | (12.48) | (3.56) | (3.94) | (3.77) |
| VIX Index | 21.63 | | | 27.26 | | |
| | (9.02) | | | (9.35) | | |
| Risk Aversion | | 90.68 | 204.88 | | 100.60 | 190.87 |
| | | (1.88) | (3.54) | | (1.72) | (2.96) |
| S&P500 Realized Volatility | | 19.59 | | | 22.52 | |
| | | (7.69) | | | (7.31) | |
| S&P 100 Average Variance | | | 8.92 | | | 13.55 |
| | | | (3.13) | | | (4.48) |
| S&P 100 Average Correlation | | | 11.18 | | | 14.65 |
| | | | (6.69) | | | (7.85) |
| 1M-LIBOR | | | | 64.92 | 25.85 | 75.36 |
| | | | | (3.85) | (1.47) | (3.84) |
| Ted-Spread | | | | -181.26 | -140.44 | -249.81 |
| | | | | (-2.52) | (-2.10) | (-3.30) |
| R-Squared | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.06 |

*Note:* We regress the daily conditional Sharpe Ratio of our reversal strategy portfolio on investors' risk aversion, proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = \dfrac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock $i$ on day $t$. The return of this portfolio is then orthogonalized with respect to the market fluctuations. We set the Sharpe ratio of each day equal to the ratio of return to volatility in that particular day. The time series frequency is daily and they range from January 1996 to December 2015. The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

table, this Sharpe ratio is an increasing function of the VIX, investors' risk aversion and stocks' average covariance, and in particular, stocks' average variance and stocks' average correlation.

Based on column (4), one standard deviation increase in the VIX index (0.0832) is associated with ($27.26 \times 0.0832 =$) 2.27 units higher annualized Sharpe ratio. Also based on column (6) one standard deviation increase in investors' risk aversion (0.0044), stocks' average variance (0.0884) and stocks' average correlation (0.1381) correspond to ($190.87 \times 0.0044 =$) 0.84, ($13.55 \times 0.0884 =$) 1.20 and ($14.65 \times 0.1381 =$) 2.02 units higher annualized Sharpe ratio on the short-term reversal strategy portfolio. Compared to the Sharpe ratio of the market portfolio over our 20-year sample (i.e. 0.39), these estimates are also economically significant.

According to column (4) to (6) in table (4.3) when the cost of borrowing, proxied with the 1M-LIBOR, rises the Sharpe ratio of the reversal strategy increases. However surprisingly, as the estimated coefficients for the Ted-spread are negative across all regressions, it seems that this Sharpe ratio declines with the tightness of credit in the market. Comparing the regression results in column (1) to (3) with the results in column (4) to (6) shows that financial constraint proxies cannot undermine the importance of investors' risk aversion, stocks' average variance and stocks' average correlation in explaining the variations in the liquidity providers' Sharpe ratio.[18]

### 4.3.3 Cross Sectional Evidence

Corollary (2.1) suggests that an asset with a large variance ($\sigma_{ii}$) or a large exposure to asset-specific liquidity shocks ($\sigma_{z_i}$) experiences stronger short-term price reversals, as it has a higher price of liquidity. In this section, we perform an out-of-sample test to investigate the validity of this theoretical finding in the cross section of stock returns. Thus for each year, we double-sort the cross section of stocks and group them in 3-by-3 categories of variance and exposure to asset-specific liquidity risk. Then we implement the reversal strategy of equation (4.11) for the stocks of each categories, using their daily returns in the subsequent year.

We calculate the variance of individual stocks, in each year, with the sample variance of its daily returns in that particular year. For a stock, exposure to asset-specific liquidity shocks creates abnormally-large trading volumes on some days. We take the residuals of regression equation (4.18) as the abnormal trading volume of stock $i$ on day $t$

$$Vol_{i,t} = \beta_{0,i} + \beta_{1,i} \; MrktVol_t + AbnormVol_{i,t}. \tag{4.18}$$

[18] In contrast to table (4.2), table (4.3) does not break-down the regression results between the long and the short positions of the reversal strategy portfolio. Because computing the marginal contribution of these positions to the overall Sharpe ratio is not as straightforward.

Here, $Vol_{i,t}$ and $MrktVol_t$, respectively, represent the trading volumes of stock $i$ and the whole market on day $t$, in dollar terms (i.e. the number of traded shares, times the closing price). We compute the sample skewness of $AbnormVol_{i,t}$ to measure the exposure of stock $i$ to asset-specific liquidity shocks in each year. A large positive skewness for $AbnormVol_{i,t}$ indicates the presence of large sudden trading shocks for stock $i$.

For every year, we double-sort the stocks universe, independently, based on their variance and exposure to asset-specific liquidity risk in 3-by-3 categories. We perform the short-term reversal strategy of equation (4.11) for the stocks in each category, using their daily returns in the subsequent year. By repeating this algorithm for all stocks in the CRSP database from January 1996 to December 2015, we obtain the return time series of nine reversal strategy portfolios with different levels of exposure to variance and asset-specific liquidity risk. We orthogonalized these return time series to the market fluctuations, using regression equation (4.12).

Table (4.4) provides summary statistics on these reversal strategy portfolios and reports the estimated coefficients for regressing the corresponding return time series on our proxies for investors' risk aversion, stocks' average variance and stocks' average correlation.

According to panel A in table (4.4), the reversal strategy implemented for the stock categories with higher variance or higher exposure to asset-specific liquidity risk yields better average daily returns. In other words, stocks with higher variance or higher exposure to asset-specific liquidity shocks experience stronger price reversals, as liquidity providers expect a larger compensation to provide liquidity on them.

Moreover, the regression results in panel B show positive coefficients for investors' risk aversion, stocks' average variance and stocks' average correlation. This means that when investors are more risk-averse, or stocks are more volatile or stocks are more correlated, the price of liquidity in the time series of stocks is higher.

## 4.4 Concluding Remarks

Compensation for liquidity provision depends on short-term price reversal. Existing studies find that the intensity of short-term price reversal in stock prices is highly correlated with the VIX index; when the VIX goes up, the intensity of short-term price reversal is larger and liquidity becomes more expensive.

In this paper, we develop a 3-period economic model and explain why this is the case. In this model, there are two types of investors. Initially, investors are identical and all hold the market portfolio beside the riskless bond. However after a while, a proportion of investors receive a risky endowment. Receiving the endowment persuades

Table 4.4: Liquidity Premium in the Cross Section of Stocks

| Asset-specific Liquidity | Lowest | | | Middle | | | Highest | | |
|---|---|---|---|---|---|---|---|---|---|
| Variance | Lowest | Middle | Highest | Lowest | Middle | Highest | Lowest | Middle | Highest |
| **Panel A: Summary Statistics** | | | | | | | | | |
| 5th Percentile | -1.08% | -1.54% | -3.11% | -0.87% | -1.15% | -2.05% | -0.94% | -1.02% | -2.01% |
| 25th Percentile | -0.23% | -0.32% | -0.27% | -0.10% | -0.08% | 0.26% | -0.09% | 0.00% | 0.51% |
| Median | 0.15% | 0.30% | 1.17% | 0.29% | 0.55% | 1.69% | 0.35% | 0.67% | 1.97% |
| 75th Percentile | 0.56% | 1.01% | 3.27% | 0.73% | 1.33% | 3.95% | 0.83% | 1.51% | 4.25% |
| 95th Percentile | 1.51% | 2.70% | 7.53% | 1.70% | 3.05% | 7.82% | 2.04% | 3.23% | 8.88% |
| Average | 0.17% | 0.40% | 1.60% | 0.35% | 0.71% | 2.21% | 0.42% | 0.83% | 2.54% |
| St. Dev. | 0.80% | 1.31% | 3.22% | 0.83% | 1.34% | 3.12% | 0.95% | 1.32% | 3.37% |
| Ann. Sharpe Ratio | 3.45 | 4.80 | 7.91 | 6.62 | 8.35 | 11.23 | 6.99 | 9.92 | 12.00 |
| **Panel B: Regression Analysis** | | | | | | | | | |
| Intercept | 0.0001 | 0.0001 | -0.0098 | -0.0004 | -0.0001 | -0.0089 | 0.0001 | -0.0014 | -0.0091 |
| | (0.22) | (0.16) | (-5.61) | (-0.82) | (-0.11) | (-4.99) | (0.16) | (-1.85) | (-4.34) |
| Decimalization Dummy | 0.0013 | 0.0049 | 0.0331 | 0.0018 | 0.0073 | 0.0271 | 0.0015 | 0.0080 | 0.0277 |
| | (4.10) | (8.87) | (23.36) | (5.68) | (13.22) | (19.36) | (4.05) | (14.47) | (16.12) |
| Risk Aversion | 0.0304 | 0.1085 | 0.1860 | 0.1197 | 0.0129 | 0.3631 | 0.0739 | 0.2022 | 0.5382 |
| | (0.87) | (1.96) | (1.40) | (3.50) | (0.22) | (2.65) | (1.62) | (3.55) | (3.27) |
| Average Variance | 0.0047 | 0.0144 | 0.0102 | 0.0140 | 0.0303 | 0.0593 | 0.0209 | 0.0352 | 0.0705 |
| | (1.78) | (3.24) | (1.08) | (5.39) | (6.59) | (6.20) | (6.96) | (9.14) | (6.71) |
| Average Correlation | 0.0017 | 0.0021 | 0.0353 | 0.0041 | 0.0042 | 0.0383 | 0.0032 | 0.0082 | 0.0430 |
| | (1.70) | (1.21) | (8.21) | (4.05) | (2.35) | (8.24) | (2.82) | (4.54) | (8.03) |
| R-Squared | 0.01 | 0.05 | 0.21 | 0.05 | 0.12 | 0.22 | 0.06 | 0.17 | 0.22 |

*Note:* This table reports the summary statistics and the regression results of the reversal strategy portfolios, constructed for 3-by-3 categories of stocks. In each year stocks are categorized into terciles, based on their variance and their exposure to asset-specific liquidity shocks. From the intersection of these terciles, we get nine stock categories. Using the return of these stock categories over the subsequent year, we construct reversal strategy portfolios such that the weight of stock $i$ on day $t$ is $w_{i,t} = \dfrac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. By rolling the window one year ahead and repeating the same procedure, we obtain the time series of nine reversal strategy portfolios. The return of these portfolios are then orthogonalized with respect to the market fluctuations. The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

these investors to trade with the others and makes them *liquidity demanders*. However the other investors, who do not receive any endowment, are essentially reluctant to trade. These investors would only trade and act as *liquidity suppliers*, if they receive sufficient price discount. The magnitude of this discount is equivalent to the price that liquidity demanders pay so that they can convince the liquidity suppliers to trade immediately and provide liquidity.

When the liquidity demanders are more risk averse, even a small departure from optimality has a large impact on their utility. Consequently, when they are extremely risk averse, they accept to pay a higher liquidity premium so that they can convince the liquidity suppliers to trade with them. Also when the liquidity suppliers are more risk averse, they expect larger discounts so that they bear the risk of inventory imbalance, due to the trade with the liquidity demanders. Moreover when assets are extremely volatile, due to the higher uncertainty about the future payoffs, identical liquidity shocks create a stronger trade motivation in the liquidity demanders and urge them to pay a higher liquidity premium for trading immediately. Finally when asset correlations are high, liquidity shocks spread across assets more efficiently, and thereby, the liquidity suppliers demand a larger premium for their service. The VIX index encapsulates investors' risk aversion, stocks' average variance and stocks' average correlation. Thus an increase in the VIX, caused by an increase in any of these factors, is accompanied by a higher expected return and Sharpe ratio for the liquidity suppliers.

To empirically test these theoretical findings, we construct a portfolio that proxies for liquidity suppliers' return. This trading strategy on average yields to 1.27% return per day (before deducting the transaction costs). When investors' risk aversion, stocks' average variance and stocks' average correlation increase by one standard deviation, the average daily return on this portfolio increases by 0.16%, 0.36% and 0.39%, respectively. Also while the unconditional annualized Sharpe ratio of this portfolio is 11.76, one standard deviation increase in each of these factors lead to 0.84, 1.20 and 2.02 units higher Sharpe ratio for liquidity suppliers.

## 4.5 Appendix A: Proofs

The proofs, provided in this section, are inspired by Vayanos and Wang (2012).

**Proposition 1:** Liquidity demanders maximize their expected utility of the liquidation time, by choosing the optimal value of $\theta_1^d$ at time 1. The liquidity demanders' wealth at $t = 2$ is constituted of their wealth from time 1 ($W_1$), their capital gain from investing on the risky assets ($\theta_1^{d\prime}(P_2 - P_1)$), and the endowment that they receive ($zM'(P_2 - \bar{P})$. Thus

$$W_2{}^d = W_1 + \theta_1^{d\prime}(P_2 - P_1) + zM'(P_2 - \bar{P}). \tag{4.19}$$

From equation (4.1) and (4.19), the liquidity demanders' expected utility at time 1 is

$$U_1^d = -E_1\Big[exp\Big(-\alpha W_1 - \alpha\theta_1^{d\prime}(P_2 - P_1) - \alpha zM'(P_2 - \bar{P})\Big)\Big]. \tag{4.20}$$

At time 1, the size of the liquidity shock ($z$) is known, and the asset liquidation payoffs ($P_2$) are the only random variables in equation (4.20). Thus equation (4.2) and (4.20) yields

$$U_1^d = -exp\Big(-\alpha W_1 + \alpha\theta_1^{d\prime}(P_1 - \bar{P}) + \frac{\alpha^2}{2}(\theta_1^d + zM)'\Sigma(\theta_1^d + zM)\Big). \tag{4.21}$$

To maximize the expected utility in terms of the risky assets weights ($\theta_1^d$), we must set the corresponding derivative to zero, i.e.

$$\frac{\partial U_1^d}{\partial \theta_1^d} = \big(\alpha P_1 - \alpha\bar{P} + \alpha^2\Sigma(\theta_1^d + zM)\big) \times U_1^d = 0. \tag{4.22}$$

Equation (4.22) gives the liquidity demanders' optimal holding at time 1 as

$$\theta_1^d = \frac{1}{\alpha}\Sigma^{-1}(\bar{P} - P_1) - zM. \tag{4.23}$$

The liquidity suppliers do not observe any liquidity shock. Thus by setting $z = 0$ in equation (4.21), we have the liquidity suppliers' expected utility at time 1 as

$$U_1^s = -exp\Big(-\alpha W_1 + \alpha\theta_1^{s\prime}(P_1 - \bar{P}) + \frac{\alpha^2}{2}\theta_1^{s\prime}\Sigma\theta_1^s\Big). \tag{4.24}$$

By setting the derivative of equation (4.24) to zero, one can show that the liquidity suppliers' optimal holding at time 1 is

$$\theta_1^s = \frac{1}{\alpha}\Sigma^{-1}(\bar{P} - P_1). \tag{4.25}$$

According to equation (4.23) and (4.25), the asset prices ($P_1$), the riskiness of the liquidation payoffs ($\Sigma$) and the investors' risk aversion ($\alpha$) negatively affect the amount of the risky assets that both types of investor would hold at $t = 1$.

At time 1, a random population $f$ of the investors (liquidity demanders) hold $\theta_1^d$ and the rest (liquidity suppliers) hold $\theta_1^s$. The aggregate holdings must be equal to the market portfolio ($\theta$).

$$f\theta_1^d + (1 - f)\theta_1^s = \theta. \tag{4.26}$$

The unique vector ($P_1$) that satisfies equation (4.26) contains the equilibrium asset prices. By replacing the values of $\theta_1^d$ and $\theta_1^s$ from equation (4.23) and (4.25) into equation (4.26), we get the equilibrium asset prices at time 1 as

$$P_1 = \bar{P} - \alpha\Sigma(\theta + fzM). \tag{4.27}$$

**Proposition 2:** From equation (4.25) and (4.27), we have

$$\theta_1^s = \theta + fzM. \tag{4.28}$$

This means that liquidity suppliers, who held the market portfolio ($\theta$) at $t = 0$, after the liquidity shock at $t = 1$ buy $fzM$ extra amount of the risky assets. One can rewrite equation (4.27) as

$$P_2 - P_1 = P_2 - \bar{P} + \alpha\Sigma(\theta + fzM). \tag{4.29}$$

According to equation (4.29), the expected return on this $fzM$ extra position is

$$E_1[fzM'(P_2 - P_1)] = \alpha fzM'\Sigma\theta + \alpha f^2z^2M'\Sigma M, \tag{4.30}$$

which means that liquidity providers' unconditional expected return is

$$E_0[R] = E_0\big[E_1[fzM'(P_2 - P_1)]\big] = \alpha f^2\sigma_z^2M'\Sigma M. \tag{4.31}$$

**Proposition 3:** This $fzM$ extra units of the risky assets that liquidity suppliers buy has the variance of

$$Var_1[fzM'(P_2 - P_1)] = f^2z^2M'\Sigma M. \tag{4.32}$$

From equation (4.30) and (4.32), we can conclude that the unconditional expected Sharpe ratio of the liquidity suppliers is

$$E_0[SR] = E_0\Big[\frac{\alpha fzM'\Sigma\theta + \alpha f^2z^2M'\Sigma M}{\sqrt{f^2z^2M'\Sigma M}}\Big] = \alpha f\sigma_z\sqrt{\frac{2M'\Sigma M}{\pi}}. \tag{4.33}$$

**Proposition 4:** We know that for all investors, the wealth at time 1 is equal to their wealth from time 0 ($W_0$), plus their capital gain from investing in the risky assets ($\theta_0'(P_1 - P_0)$). Thus

$$W_1 = W_0 + \theta_0'(P_1 - P_0). \tag{4.34}$$

By replacing $P_1$ from equation (4.27) into equation (4.34), we have

$$W_1 = W_0 + \theta_0'\Big(\bar{P} - P_0 - \Sigma(\alpha\theta + \alpha f z M)\Big). \tag{4.35}$$

Moreover from equation (4.23) and (4.27), we have

$$\theta_1^d = \theta + (f-1)zM. \tag{4.36}$$

If we insert (4.35) and (4.36) into (4.21), we get the liquidity demanders' expected utility at time 1 as

$$U_1^d = -exp\Bigg(\overbrace{-\alpha W_0 - \alpha\theta_0'\Big(\bar{P} - P_0 - \Sigma(\alpha\theta + \alpha f z M)\Big)}^{-\alpha W_1} \overbrace{- \alpha^2\Big(\theta + (f-1)zM\Big)'\Sigma(\theta + fzM) +}^{-\alpha\theta_1^{d\prime}(P_1 - \bar{P})}$$
$$\overbrace{\frac{\alpha^2}{2}\Big(\theta + (f-1)zM + zM\Big)'\Sigma\Big(\theta + (f-1)zM + zM\Big)}^{\frac{\alpha^2}{2}(\theta_1^d + zM)'\Sigma(\theta_1^d + zM)}\Bigg). \tag{4.37}$$

At time 0 investors are identical, and thus, they all hold the market portfolio. Therefore, we replace the value of $\theta_0$ from equation (4.3), and define

$$A^d = W_0 + \theta'\bar{P} - \theta' P_0 - \frac{\alpha}{2}\theta'\Sigma\theta, \tag{4.38}$$

$$B^d = -\alpha\theta'\Sigma M, \tag{4.39}$$

$$C^d = \alpha(f^2 - 2f)M'\Sigma M. \tag{4.40}$$

Then we can rewrite $U_1^d$ in equation (4.37) as

$$U_1^d = -exp\Big(-\alpha(A^d + B^d z + \frac{1}{2}C^d z^2)\Big). \tag{4.41}$$

Then the expected utility of the liquidity demanders at time 0 (i.e. $U_0^d$) is

$$U_0^d = E[U_1^d] = \frac{-exp\Big(-\alpha\overbrace{\Big(A^d - \frac{\alpha {B^d}^2\sigma_z^2}{2\times(1+\alpha C^d\sigma_z^2)}\Big)}^{F_d}\Big)}{\sqrt{1+\alpha C^d\sigma_z^2}}, \tag{4.42}$$

such that

$$F_d = W_0 + \theta'\bar{P} - \theta' P_0 - \frac{\alpha}{2}\theta'\Sigma\theta - \frac{\alpha^3\sigma_z^2(\theta'\Sigma M)^2}{2\times\Big(1+\alpha^2\sigma_z^2(f^2-2f)M'\Sigma M\Big)}, \tag{4.43}$$

$$\frac{\partial F_d}{\partial\theta} = \bar{P} - P_0 - \alpha\Sigma\theta - \frac{\alpha^3\sigma_z^2(\theta'\Sigma M)(\Sigma M)}{2\times\Big(1+\alpha^2\sigma_z^2(f^2-2f)M'\Sigma M\Big)}. \tag{4.44}$$

Inserting equation (4.35) and (4.28), into equation (4.24) yields

$$U_1^s = -exp\Bigg(\overbrace{-\alpha W_0 - \alpha\theta_0'\Big(\bar{P} - P_0 - \Sigma(\alpha\theta + \alpha f z M)\Big)}^{-\alpha W_1} - \overbrace{\alpha^2(\theta + fzM)'\Sigma(\theta + fzM)}^{-\alpha{\theta_1^s}'(P_1-\bar{P})} + \overbrace{\frac{\alpha^2}{2}(\theta + fzM)'\Sigma(\theta + fzM)}^{\frac{\alpha^2}{2}{\theta_1^s}'\Sigma\theta_1^s}\Bigg). \tag{4.45}$$

At time 0 investors are identical, and thus, they all hold the market portfolio. Therefore, we replace the value of $\theta_0$ from equation (4.3), and define

$$A^s = W_0 + \theta'\bar{P} - \theta' P_0 - \frac{\alpha}{2}\theta'\Sigma\theta, \tag{4.46}$$

$$B^s = 0, \tag{4.47}$$

$$C^s = \alpha f^2 M'\Sigma M, \tag{4.48}$$

to get

$$U_1^s = -exp\Big(-\alpha(A^s + B^s z + \frac{1}{2}C^s z^2)\Big). \tag{4.49}$$

Then the expected utility of the liquidity supplier at time 0 (i.e. $U_0^s$) is

$$U_0^s = E[U_1^s] = \frac{-exp\Big(-\alpha\overbrace{\Big(A^s - \frac{\alpha {B^s}^2\sigma_z^2}{2\times(1+\alpha C^s\sigma_z^2)}\Big)}^{F_s}\Big)}{\sqrt{1+\alpha C^s\sigma_z^2}}. \tag{4.50}$$

such that

$$F_s = W_0 + \theta' \bar{P} - \theta' P_0 - \frac{\alpha}{2} \theta' \Sigma \theta, \tag{4.51}$$

$$\frac{\partial F_s}{\partial \theta} = \bar{P} - P_0 - \alpha \Sigma \theta. \tag{4.52}$$

Before a liquidity shock happens, we know that a population $f$ of the investors will be liquidity demanders and the remainder will be liquidity suppliers. Therefore, the expectation of the aggregate utility at time 0 is

$$U_0 = f U_0^d + (1-f) U_0^s. \tag{4.53}$$

The expectation of the aggregate utility is maximum when

$$\frac{\partial U_0}{\partial \theta} = f \frac{\partial U_0^d}{\partial \theta} + (1-f) \frac{\partial U_0^s}{\partial \theta} = 0. \tag{4.54}$$

By inserting the values of $\frac{\partial U_0^d}{\partial \theta}$ and $\frac{\partial U_0^s}{\partial \theta}$ from equation (4.42) and (4.50), into equation (4.54), we get

$$\frac{\alpha f}{\sqrt{1 + \alpha C^d \sigma_z^2}} exp(-\alpha F_d) \frac{\partial F_d}{\partial \theta} + \frac{\alpha (1-f)}{\sqrt{1 + \alpha C^s \sigma_z^2}} exp(-\alpha F_s) \frac{\partial F_s}{\partial \theta} = 0. \tag{4.55}$$

We define $\Delta_0 = 1 + \alpha^2 \sigma_z^2 (f^2 - 2f) M' \Sigma M$ and $\Delta_1 = \alpha^2 \sigma_z^2 \theta' \Sigma M$. Thus from equation (4.43) and (4.51), one can show that

$$F_d - F_s = \frac{-\alpha \Delta_1 \theta' \Sigma M}{2 \Delta_0}, \tag{4.56}$$

which transforms equation (4.55) into

$$\frac{f}{1-f} \sqrt{\frac{1 + \alpha C^s \sigma_z^2}{1 + \alpha C^d \sigma_z^2}} exp\Big(\frac{\alpha^2 \Delta_1 \theta' \Sigma M}{2 \Delta_0}\Big) \big(\frac{\partial F_d}{\partial \theta}\big) + \big(\frac{\partial F_s}{\partial \theta}\big) = 0. \tag{4.57}$$

By inserting the values of $\frac{\partial F_d}{\partial \theta}$ and $\frac{\partial F_s}{\partial \theta}$ from equation (4.44) and (4.52), we get

$$\frac{f}{1-f} \sqrt{\frac{1 + \alpha C^s \sigma_z^2}{1 + \alpha C^d \sigma_z^2}} exp\Big(\frac{\alpha^2 \Delta_1 \theta' \Sigma M}{2 \Delta_0}\Big) \Big(\bar{P} - P_0 - \alpha \Sigma \theta - \frac{\alpha \Delta_1 \Sigma M}{\Delta_0}\Big) + (\bar{P} - P_0 - \alpha \Sigma \theta) = 0. \tag{4.58}$$

We define $\kappa = \sqrt{\frac{1 + \alpha C^s \sigma_z^2}{1 + \alpha C^d \sigma_z^2}} exp\Big(\frac{\alpha^2 \Delta_1 \theta' \Sigma M}{2 \Delta_0}\Big) > 0$. In this case, equation (4.58) gives the equilibrium price of the risky assets at time 0 as

$$P_0 = \bar{P} - \alpha \Sigma \theta - \frac{\kappa f}{1 - f + \kappa f} \left( \frac{\alpha \Delta_1}{\Delta_0} \right) \Sigma M, \tag{4.59}$$

## 4.6 Appendix B: Option-Implied Variance and Correlation

We employ the methodology of Carr and Wu (2009) to exploit the variance expectation of each stock in each day from the out-of-the-money [OTM] European options traded on that particular day. The computed variance is under the risk-neutral measure. According to this method, the annualized expected variance of a stock between time $t$ and $t + \tau$ is computed as

$$\sigma_{i,t}^2 = \frac{2}{\tau} \int_0^\infty \exp(-R_{F,t} \times \tau) \frac{\Phi_i(K,\tau)}{K^2} dK, \tag{4.60}$$

where, $\Phi_i(K,\tau)$ is the price of a European out-of-the-money (OTM) option on day $t$, written on stock $i$ that has a strike price of $K$ and time to maturity of $\tau$. In this equation, $R_{F,t}$ stands for the risk-free rate on day $t$.

According to equation (4.60), in order to calculate the expected variance on each day, we need a continuum of OTM options with different strike prices. Thus for each day from January 1996 to December 2015, we obtain the volatility smile of the S&P 100 stocks from the Standardized Options file of the OptionMetrics database. This database provides us with the implied volatility and the strike price of synthetic OTM European put and call options, with delta values ranging from -0.80 to 0.80, in 0.05 intervals.

On each day, we fit a cubic spline to the volatility smile of the synthetic options with 30 days to maturity. Thus, we can estimate the implied volatility of 200 uniformly-spaced options on this spline that have moneyness values ($P(t)/K$) between 0.01 and 3.00. If a moneyness value exceeds the domain of the cubic spline, we set its implied volatility equal to the implied volatility of the closest point on the spline. The prices of the OTM options with moneyness values beyond [0.01, 3.00] are negligible.

Using the Black and Scholes formula, we convert the estimated implied volatilities to option prices and use equation (4.60) to estimate the expected variances of the stocks in the S&P 100 index.

Having estimated the daily time series of expected variance for all stocks in the S&P 100 index ($\sigma_{i,t}^2$), we calculate the average option-implied correlation of the S&P 100 stocks from equation (4.17).

In order to calculate stock weights ($w_{i,t}$) accurately, we get the dates of stocks inclusion to and exclusion from the S&P 100 index, from the Compustat database. We also obtain stocks' daily market capitalization from the OptionMetrics database. For each trading day over our sample, at least, we can compute $w_{i,t}$ and $\sigma_{i,t}^2$ for 97 of the S&P 100 stocks. More details about our implementation are available upon request.

## 4.7 Appendix C: Robustness Tests

### 4.7.1 C.1: Robustness Tests with More Lagged Returns

By using the reversal strategy of equation (4.11), we have implicitly assumed that the time required for price reversal is one day. However, Hansch, Naik and Viswanathan (1998) show that especially for illiquid stocks, the price reversion might take more than one day. Also, Hendershott and Menkveld (2014) find that the half-life of the short-term price reversal ranges from 0.54 to 2.11 days for different market capitalization quintiles. To capture delayed price reversals, in this section, we construct a new reversal strategy portfolio in which the weight of stock $i$ on day $t$ depends on its $\tau = 1, ..., 5$ days lagged returns

$$w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}. \tag{4.61}$$

Next we repeat the regression analyses of table (4.2) to (4.4). Table (4.5) to (4.7) report the results of our regression analysis for the reversal strategy of equation (4.61).

Table 4.5: (C.1) Regression Analysis for Return with 5 Days Lags

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | -0.0006 | 0.0003 | -0.0010 | -0.0009 | 0.0005 | -0.0014 |
| | (-4.50) | (2.58) | (-5.41) | (-5.64) | (3.03) | (-5.63) |
| Decimalization Dummy | 0.0023 | 0.0021 | 0.0025 | 0.0020 | 0.0024 | 0.0022 |
| | (15.59) | (13.07) | (17.31) | (11.31) | (10.91) | (10.58) |
| VIX Index | 0.0095 | | | 0.0108 | | |
| | (12.85) | | | (13.25) | | |
| Risk Aversion | | 0.0313 | 0.0520 | | 0.0532 | 0.0641 |
| | | (2.53) | (3.88) | | (3.10) | (3.70) |
| S&P500 Realized Volatility | | 0.0081 | | | 0.0085 | |
| | | (10.23) | | | (9.12) | |
| S&P 100 Average Variance | | | 0.0058 | | | 0.0070 |
| | | | (6.01) | | | (7.00) |
| S&P 100 Average Correlation | | | 0.0037 | | | 0.0044 |
| | | | (7.95) | | | (8.56) |
| 1M-LIBOR | | | | 0.0112 | -0.0061 | 0.0111 |
| | | | | (3.39) | (-1.69) | (2.82) |
| Ted-Spread | | | | -0.0457 | -0.0310 | -0.0724 |
| | | | | (-1.95) | (-1.49) | (-2.86) |
| R-Squared | 0.19 | 0.18 | 0.20 | 0.19 | 0.19 | 0.20 |

*Note:* We regress the return of our reversal strategy portfolio on investors' risk aversion, proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock $i$ on day $t$. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The time series frequency is daily and they range from January 1996 to December 2015. The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

Table 4.6: (C.1) Regression Analysis for Sharpe Ratio with 5 Days Lags

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | 2.51 | 4.22 | 0.64 | 0.82 | 3.96 | -1.88 |
| | (4.28) | (9.56) | (0.80) | (1.02) | (5.96) | (-1.66) |
| Decimalization Dummy | 4.57 | 3.96 | 5.38 | 2.63 | 3.36 | 3.34 |
| | (9.72) | (7.81) | (11.33) | (3.65) | (3.91) | (3.87) |
| VIX Index | 21.21 | | | 26.50 | | |
| | (8.25) | | | (8.32) | | |
| Risk Aversion | | 90.41 | 215.88 | | 110.02 | 208.67 |
| | | (1.72) | (3.47) | | (1.72) | (2.97) |
| S&P500 Realized Volatility | | 20.20 | | | 23.27 | |
| | | (7.08) | | | (6.71) | |
| S&P 100 Average Variance | | | 8.32 | | | 12.89 |
| | | | (2.64) | | | (3.84) |
| S&P 100 Average Correlation | | | 11.51 | | | 14.88 |
| | | | (6.44) | | | (7.41) |
| 1M-LIBOR | | | | 60.74 | 22.70 | 71.18 |
| | | | | (3.45) | (1.24) | (3.48) |
| Ted-Spread | | | | -170.63 | -152.28 | -251.03 |
| | | | | (-2.17) | (-2.07) | (-2.98) |
| R-Squared | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |

*Note:* We regress the daily conditional Sharpe Ratio of our reversal strategy portfolio on investors' risk aversion, proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock $i$ on day $t$. The return of this portfolio is then orthogonalized with respect to the market fluctuations. We set the Sharpe ratio of each day equal to the ratio of return to volatility in that particular day. The time series frequency is daily and they range from January 1996 to December 2015. The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

Table 4.7: (C.1) Liquidity Premium in the Cross section of Stocks with 5 Days Lags

| Asset-specific Liquidity | Lowest | | | Middle | | | Highest | | |
|---|---|---|---|---|---|---|---|---|---|
| Variance | Lowest | Middle | Highest | Lowest | Middle | Highest | Lowest | Middle | Highest |
| Panel A: Summary Statistics | | | | | | | | | |
| 5th Percentile | -0.57% | -0.69% | -1.38% | -0.47% | -0.57% | -0.99% | -0.53% | -0.57% | -1.00% |
| 25th Percentile | -0.12% | -0.16% | -0.26% | -0.09% | -0.11% | -0.07% | -0.12% | -0.10% | -0.02% |
| Median | 0.05% | 0.10% | 0.32% | 0.07% | 0.14% | 0.46% | 0.07% | 0.15% | 0.53% |
| 75th Percentile | 0.22% | 0.40% | 1.02% | 0.25% | 0.43% | 1.07% | 0.27% | 0.45% | 1.19% |
| 95th Percentile | 0.69% | 1.14% | 2.45% | 0.70% | 1.11% | 2.37% | 0.76% | 1.16% | 2.53% |
| Average | 0.05% | 0.14% | 0.40% | 0.09% | 0.19% | 0.54% | 0.09% | 0.20% | 0.62% |
| St. Dev. | 0.38% | 0.58% | 1.17% | 0.36% | 0.53% | 1.04% | 0.41% | 0.52% | 1.09% |
| Ann. Sharpe Ratio | 2.25 | 3.94 | 5.47 | 3.83 | 5.61 | 8.31 | 3.37 | 6.04 | 9.02 |
| Panel B: Regression Analysis | | | | | | | | | |
| Intercept | -0.0001 | -0.0002 | -0.0021 | -0.0002 | -0.0003 | -0.0015 | -0.0005 | -0.0005 | -0.0016 |
| | (-0.28) | (-0.67) | (-3.66) | (-0.78) | (-0.86) | (-2.81) | (-2.22) | (-1.88) | (-2.76) |
| Decimalization Dummy | 0.0003 | 0.0019 | 0.0065 | 0.0003 | 0.0019 | 0.0054 | 0.0001 | 0.0020 | 0.0051 |
| | (2.29) | (8.35) | (15.23) | (2.02) | (9.52) | (14.77) | (0.91) | (10.55) | (12.56) |
| Risk Aversion | -0.0098 | 0.0210 | 0.0656 | 0.0121 | 0.0136 | 0.1128 | 0.0023 | 0.0472 | 0.0879 |
| | (-0.59) | (0.90) | (1.49) | (0.81) | (0.62) | (2.72) | (0.13) | (2.32) | (2.07) |
| Average Variance | 0.0034 | 0.0063 | 0.0081 | 0.0042 | 0.0106 | 0.0168 | 0.0070 | 0.0100 | 0.0226 |
| | (2.69) | (3.41) | (2.61) | (3.39) | (5.98) | (6.51) | (4.54) | (6.18) | (8.47) |
| Average Correlation | 0.0003 | 0.0010 | 0.0077 | 0.0011 | 0.0010 | 0.0080 | 0.0013 | 0.0020 | 0.0086 |
| | (0.62) | (1.35) | (5.81) | (2.42) | (1.56) | (6.30) | (2.49) | (3.19) | (6.22) |
| R-Squared | 0.01 | 0.04 | 0.08 | 0.02 | 0.07 | 0.10 | 0.03 | 0.08 | 0.11 |

*Note:* This table reports the summary statistics and the regression results of the reversal strategy portfolios, constructed for 3-by-3 categories of stocks. In each year stocks are categorized into terciles, based on their variance and their exposure to asset-specific liquidity shocks. From the intersection of these terciles, we get nine stock categories. Using the return of these stock categories over the subsequent year, we construct reversal strategy portfolios such that the weight of stock $i$ on day $t$ is $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. By rolling the window one year ahead and repeating the same procedure, we obtain the time series of nine reversal strategy portfolios. The return of these portfolios are then orthogonalized with respect to the market fluctuations. The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

### 4.7.2 C.2: Robustness Tests with Other Weighting Strategies

This section provides robustness tests, based on some alternative short-term reversal strategies. Table (4.8) and (4.9) correspond to the weighting strategy proposed by Lo and MacKinlay (1988) and table (4.10) and (4.11) show the results for a reversal strategy introduced by Nagel (2012).

Table 4.8: (C.2) Robustness Test of the Regression Analysis for Return with Alternative Portfolio Weighting (1)

| | Panel A: Reversal Strategy with 1-day Lagged Returns | | | | | | Panel B: Reversal Strategy with 5-days Lagged Returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | -0.1770 | -0.0465 | -0.1380 | -0.2095 | -0.0201 | -0.1616 | -0.0302 | -0.0092 | -0.0222 | -0.0353 | -0.0049 | -0.0252 |
| | (-10.34) | (-3.83) | (-7.38) | (-12.30) | (-1.22) | (-6.86) | (-8.87) | (-3.85) | (-6.52) | (-11.04) | (-1.48) | (-5.83) |
| Decimalization Dummy | 0.2428 | 0.2075 | 0.2366 | 0.1985 | 0.2517 | 0.2220 | 0.0368 | 0.0309 | 0.0352 | 0.0292 | 0.0383 | 0.0333 |
| | (16.62) | (12.76) | (17.06) | (11.70) | (10.77) | (10.47) | (13.43) | (10.02) | (13.96) | (9.28) | (8.28) | (8.25) |
| VIX Index | 1.4368 | | | 1.4915 | | | 0.2365 | | | 0.2398 | | |
| | (14.89) | | | (16.09) | | | (12.44) | | | (14.50) | | |
| Risk Aversion | | 5.6070 | 3.7777 | | 7.4324 | 4.3655 | | 1.0715 | 0.6666 | | 1.3516 | 0.7434 |
| | | (4.12) | (3.00) | | (4.06) | (2.49) | | (3.96) | (2.91) | | (3.71) | (2.23) |
| S&P500 Realized Volatility | | 1.2552 | | | 1.2330 | | | 0.2098 | | | 0.2047 | |
| | | (11.87) | | | (11.21) | | | (10.23) | | | (10.25) | |
| S&P 100 Average Variance | | | 1.2272 | | | 1.2919 | | | 0.2110 | | | 0.2193 |
| | | | (10.58) | | | (11.36) | | | (9.22) | | | (10.14) |
| S&P 100 Average Correlation | | | 0.2863 | | | 0.3278 | | | 0.0417 | | | 0.0470 |
| | | | (5.83) | | | (6.09) | | | (4.61) | | | (4.71) |
| 1M-LIBOR | | | | 1.2375 | -1.1077 | 0.6621 | | | | 0.1997 | -0.1884 | 0.0851 |
| | | | | (3.94) | (-3.19) | (1.86) | | | | (3.39) | (-2.85) | (1.26) |
| Ted-Spread | | | | -1.3275 | 0.0441 | -3.9760 | | | | 0.0113 | 0.0880 | -0.5140 |
| | | | | (-0.44) | (0.02) | (-1.36) | | | | (0.02) | (0.18) | (-0.90) |
| R-Squared | 0.30 | 0.30 | 0.32 | 0.31 | 0.30 | 0.33 | 0.23 | 0.23 | 0.25 | 0.23 | 0.23 | 0.25 |

*Note:* To test the robustness of our results, in this table, we repeat the regression analysis of table (4.2) with the short-term reversal strategy portfolios, proposed by Lo and MacKinlay (1988). Panel A shows the results for a portfolio, in which the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = 1000 \times \frac{R_{m,t-1} - R_{i,t-1}}{N}$. Panel B corresponds to a portfolio, in which the weight of stock $i$ on day $t$ is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} 1000 \times \frac{R_{m,t-\tau} - R_{i,t-\tau}}{N}$. Here, $N$ is the number of stocks in the market on day $t$. Also, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock $i$ on day $t$. Both of these portfolios are orthogonalized to the market return, using equation (4.12). The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

Table 4.9: (C.2) Robustness Test of the Regression Analysis for Sharpe Ratio with Alternative Portfolio Weighting (1)

| | Panel A: Reversal Strategy with 1-day Lagged Returns | | | | | | Panel B: Reversal Strategy with 5-days Lagged Returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 2.47 | 4.16 | 0.70 | 0.82 | 3.89 | -1.83 | 1.49 | 3.00 | -0.51 | -0.01 | 2.87 | -2.82 |
| | (4.04) | (8.91) | (0.85) | (0.98) | (5.63) | (-1.54) | (2.35) | (5.88) | (-0.59) | (-0.01) | (3.87) | (-2.23) |
| Decimalization Dummy | 4.89 | 4.05 | 5.67 | 2.96 | 3.43 | 3.57 | 4.95 | 4.07 | 5.78 | 3.22 | 3.68 | 3.93 |
| | (10.78) | (8.26) | (12.28) | (4.05) | (3.96) | (4.07) | (9.67) | (7.41) | (11.04) | (4.08) | (3.96) | (4.20) |
| VIX Index | 24.27 | | | 29.23 | | | 23.63 | | | 28.22 | | |
| | (8.74) | | | (8.53) | | | (8.06) | | | (7.66) | | |
| Risk Aversion | | 72.42 | 204.62 | | 92.81 | 189.68 | | 71.29 | 217.88 | | 104.78 | 212.87 |
| | | (1.33) | (3.14) | | (1.45) | (2.66) | | (1.20) | (3.13) | | (1.50) | (2.77) |
| S&P500 Realized Volatility | | 25.25 | | | 28.41 | | | 25.63 | | | 28.93 | |
| | | (7.94) | | | (7.57) | | | (7.18) | | | (6.77) | |
| S&P 100 Average Variance | | | 11.15 | | | 15.46 | | | 10.13 | | | 14.37 |
| | | | (3.33) | | | (4.38) | | | (2.81) | | | (3.76) |
| S&P 100 Average Correlation | | | 12.04 | | | 15.30 | | | 12.46 | | | 15.57 |
| | | | (6.46) | | | (7.25) | | | (6.13) | | | (6.72) |
| 1M-LIBOR | | | | 59.61 | 23.26 | 71.22 | | | | 53.73 | 18.39 | 65.08 |
| | | | | (3.23) | (1.22) | (3.28) | | | | (2.79) | (0.92) | (2.88) |
| Ted-Spread | | | | -157.90 | -156.78 | -231.85 | | | | -147.02 | -170.05 | -233.51 |
| | | | | (-1.77) | (-1.97) | (-2.55) | | | | (-1.53) | (-1.95) | (-2.35) |
| R-Squared | 0.05 | 0.06 | 0.05 | 0.05 | 0.06 | 0.06 | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |

*Note:* To test the robustness of our results, in this table, we repeat the regression analysis of table (4.3) with the short-term reversal strategy portfolios, proposed by Lo and MacKinlay (1988). Panel A shows the results for a portfolio, in which the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = 1000 \times \frac{R_{m,t-1} - R_{i,t-1}}{N}$. Panel B corresponds to a portfolio, in which the weight of stock $i$ on day $t$ is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} 1000 \times \frac{R_{m,t-\tau} - R_{i,t-\tau}}{N}$. Here, $N$ is the number of stocks in the market on day $t$. Also, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock $i$ on day $t$. Both of these portfolios are orthogonalized to the market return, using equation (4.12). The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

Table 4.10: (C.2) Robustness Test of the Regression Analysis for Return with Alternative Portfolio Weighting (2)

| | Panel A: Reversal Strategy with 1-day Lagged Returns | | | | | | Panel B: Reversal Strategy with 5-days Lagged Returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0143 | 0.0324 | -0.0168 | 0.0037 | 0.0357 | -0.0356 | 0.0020 | 0.0049 | -0.0035 | 0.0001 | 0.0054 | -0.0068 |
| | (3.71) | (11.23) | (-3.19) | (0.74) | (8.27) | (-4.96) | (2.62) | (8.47) | (-3.46) | (0.06) | (6.30) | (-4.91) |
| Decimalization Dummy | 0.0723 | 0.0672 | 0.0841 | 0.0637 | 0.0712 | 0.0715 | 0.0121 | 0.0112 | 0.0142 | 0.0104 | 0.0117 | 0.0119 |
| | (16.10) | (14.41) | (19.94) | (11.83) | (11.40) | (11.48) | (14.63) | (12.90) | (17.95) | (10.26) | (9.94) | (10.08) |
| VIX Index | 0.1975 | | | 0.2542 | | | 0.0337 | | | 0.0431 | | |
| | (10.33) | | | (11.19) | | | (9.07) | | | (9.88) | | |
| Risk Aversion | | 0.2686 | 2.0855 | | 0.8705 | 2.3978 | | 0.0715 | 0.3927 | | 0.1761 | 0.4447 |
| | | (0.78) | (5.06) | | (1.83) | (4.84) | | (1.05) | (4.95) | | (1.93) | (4.64) |
| S&P500 Realized Volatility | | 0.1719 | | | 0.1972 | | | 0.0307 | | | 0.0354 | |
| | | (8.22) | | | (7.58) | | | (7.33) | | | (6.96) | |
| S&P 100 Average Variance | | | 0.0288 | | | 0.0750 | | | 0.0048 | | | 0.0128 |
| | | | (1.14) | | | (2.85) | | | (0.98) | | | (2.56) |
| S&P 100 Average Correlation | | | 0.1467 | | | 0.1773 | | | 0.0253 | | | 0.0307 |
| | | | (11.30) | | | (12.05) | | | (10.42) | | | (11.00) |
| 1M-LIBOR | | | | 0.3441 | -0.0247 | 0.5263 | | | | 0.0633 | -0.0005 | 0.0932 |
| | | | | (3.32) | (-0.23) | (4.27) | | | | (3.14) | (-0.02) | (3.92) |
| Ted-Spread | | | | -2.0471 | -1.4886 | -2.7724 | | | | -0.3347 | -0.2755 | -0.4827 |
| | | | | (-3.46) | (-2.67) | (-3.95) | | | | (-2.89) | (-2.55) | (-3.55) |
| R-Squared | 0.19 | 0.18 | 0.21 | 0.19 | 0.18 | 0.22 | 0.14 | 0.14 | 0.16 | 0.14 | 0.14 | 0.17 |

*Note:* To test the robustness of our results, in this table, we repeat the regression analysis of table (4.2) with the short-term reversal strategy portfolios, proposed by Nagel (2012). Panel A shows the results for a portfolio, in which the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N}(R_{m,t-1} - R_{i,t-1})^2}$. Panel B corresponds to a portfolio, in which the weight of stock $i$ on day $t$ is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\sum_{i=0}^{N}(R_{m,t-\tau} - R_{i,t-\tau})^2}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock $i$ on day $t$. Both of these portfolios are orthogonalized to the market return, using equation (4.12). The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

Table 4.11: (C.2) Robustness Test of the Regression Analysis for Sharpe Ratio with Alternative Portfolio Weighting (2)

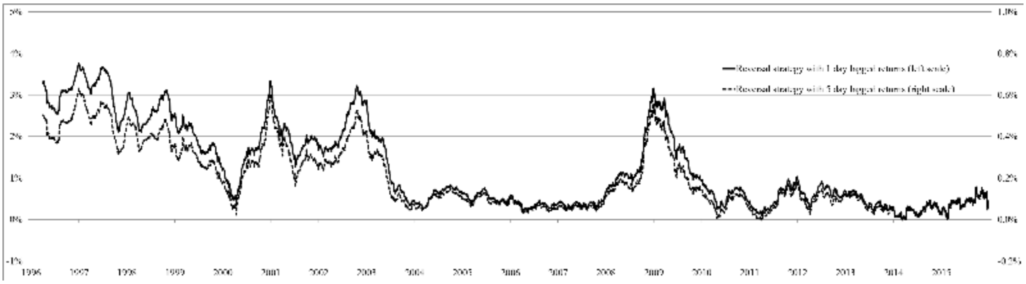
| | Panel A: Reversal Strategy with 1-day Lagged Returns | | | | | | Panel B: Reversal Strategy with 5-days Lagged Returns | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 4.63 | 6.45 | 2.68 | 2.64 | 6.15 | -0.11 | 3.40 | 5.07 | 1.21 | 1.44 | 4.84 | -1.54 |
| | (8.32) | (15.88) | (3.59) | (3.63) | (10.32) | (-0.11) | (5.78) | (11.49) | (1.54) | (1.87) | (7.49) | (-1.44) |
| Decimalization Dummy | 4.53 | 4.04 | 5.44 | 2.38 | 3.33 | 3.28 | 4.96 | 4.43 | 5.95 | 2.83 | 3.81 | 3.85 |
| | (10.89) | (9.14) | (13.18) | (3.62) | (4.34) | (4.24) | (10.67) | (8.94) | (12.96) | (3.98) | (4.56) | (4.59) |
| VIX Index | 20.23 | | | 27.32 | | | 20.02 | | | 26.92 | | |
| | (8.32) | | | (9.77) | | | (7.61) | | | (8.68) | | |
| Risk Aversion | | 96.71 | 230.53 | | 125.26 | 236.01 | | 105.62 | 254.66 | | 142.96 | 265.92 |
| | | (2.02) | (4.05) | | (2.18) | (3.72) | | (2.03) | (4.16) | | (2.26) | (3.83) |
| S&P500 Realized Volatility | | 17.84 | | | 21.78 | | | 18.59 | | | 22.83 | |
| | | (6.90) | | | (7.05) | | | (6.40) | | | (6.56) | |
| S&P 100 Average Variance | | | 6.09 | | | 11.60 | | | 5.35 | | | 10.98 |
| | | | (2.14) | | | (3.94) | | | (1.69) | | | (3.33) |
| S&P 100 Average Correlation | | | 11.71 | | | 15.64 | | | 12.28 | | | 16.25 |
| | | | (7.14) | | | (8.58) | | | (6.99) | | | (8.24) |
| 1M-LIBOR | | | | 70.04 | 27.52 | 78.65 | | | | 69.11 | 26.35 | 77.57 |
| | | | | (4.26) | (1.62) | (4.22) | | | | (3.99) | (1.47) | (3.94) |
| Ted-Spread | | | | -236.51 | -197.26 | -311.09 | | | | -229.72 | -215.45 | -321.49 |
| | | | | (-3.38) | (-2.99) | (-4.11) | | | | (-2.94) | (-2.95) | (-3.76) |
| R-Squared | 0.05 | 0.05 | 0.06 | 0.06 | 0.05 | 0.07 | 0.05 | 0.05 | 0.06 | 0.05 | 0.05 | 0.06 |

*Note:* To test the robustness of our results, in this table, we repeat the regression analysis of table (4.3) with the short-term reversal strategy portfolios, proposed by Lo and MacKinlay (1988). Panel A shows the results for a portfolio, in which the weight of stock $i$ on day $t$ is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N}(R_{m,t-1} - R_{i,t-1})^2}$. Panel B corresponds to a portfolio, in which the weight of stock $i$ on day $t$ is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\sum_{i=0}^{N}(R_{m,t-\tau} - R_{i,t-\tau})^2}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock $i$ on day $t$. Both of these portfolios are orthogonalized to the market return, using equation (4.12). The t-statistics, reported in parentheses, are adjusted with the Newey and West (1987) technique with 5-days lag.

## 4.8 Appendix D: Average Return Plot

Figure (4.2) plots the three-month moving-average return of the reversal strategy of equation (4.11) and (4.61).

Figure 4.2: (D) Three-month Moving-Average Return of the Reversal Strategy Portfolios



## 4.9 Appendix E: Reversal Strategy Portfolio Constructed with Mid-quote Prices

To test the robustness of our results, we construct our reversal strategy portfolio of equation (4.11) based on mid-quote prices, i.e. the average of the best closing-bid and the best closing-ask on each day, rather than actual closing price. Then we repeat the regressions of table (4.2) and (4.3) for the new portfolio. The results displayed in table (4.12) and (4.13), again, show that investors' risk aversion, stocks' average variance and stocks' average correlation are positively linked to the return and the Sharpe ratio of the liquidity providers.

In the CRSP database, closing-bid and closing-ask quotes are only available for NASDAQ stocks. Therefore for the construction of this portfolio we exclude all AMEX and NYSE stocks from our sample and compute the end-of-the-day mid-quote prices only for the NASDAQ stocks. Furthermore, following Nagel (2012), to avoid micros-structural anomalies we exclude stocks with prices below 1 dollar or above 1000 dollars. Also if in a particular day the ratio of bid-quote to mid-quote of a stock is less than 0.5, we exclude that stock from the sample in that particular day.

Table 4.12: (E) Regression Analysis for Return with Mid-quote Prices

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | -0.0017 | 0.0003 | -0.0027 | 0.0004 | 0.0018 | 0.0003 |
| | (-2.97) | (0.70) | (-4.05) | (0.80) | (4.04) | (0.37) |
| VIX Index | 0.0232 | | | 0.0145 | | |
| | (7.91) | | | (5.21) | | |
| Risk Aversion | | 0.1197 | 0.1830 | | 0.1061 | 0.1108 |
| | | (2.36) | (3.35) | | (2.38) | (2.27) |
| S&P500 Realized Volatility | | 0.0197 | | | 0.0174 | |
| | | (6.27) | | | (5.42) | |
| S&P 100 Average Variance | | | 0.0127 | | | 0.0109 |
| | | | (3.87) | | | (3.34) |
| S&P 100 Average Correlation | | | 0.0098 | | | 0.0049 |
| | | | (6.56) | | | (3.08) |
| 1M-LIBOR | | | | -0.0642 | -0.0795 | -0.0619 |
| | | | | (-5.53) | (-7.41) | (-5.07) |
| Ted-Spread | | | | 0.3485 | 0.2830 | 0.2922 |
| | | | | (3.04) | (2.66) | (2.55) |
| R-Squared | 0.03 | 0.03 | 0.03 | 0.04 | 0.05 | 0.04 |

*Note:* To test the robustness of our results, in this table, we repeat the regression analysis of table (4.2) with the short-term reversal strategy portfolios that are constructed based on the mid-quote prices, i.e. the average of closing-bid and closing-ask on each day, rather than the actual closing price.

Table 4.13: (E) Regression Analysis for Sharpe Ratio with Mid-quote Prices

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Intercept | -0.04 | 1.81 | -1.92 | 2.33 | 3.78 | 1.29 |
| | (-0.07) | (3.97) | (-2.47) | (3.51) | (7.30) | (1.35) |
| VIX Index | 19.29 | | | 13.34 | | |
| | (6.82) | | | (4.01) | | |
| Risk Aversion | | 137.23 | 258.65 | | 180.87 | 231.89 |
| | | (2.18) | (3.80) | | (3.09) | (3.71) |
| S&P500 Realized Volatility | | 15.30 | | | 16.17 | |
| | | (5.09) | | | (4.38) | |
| S&P 100 Average Variance | | | 5.04 | | | 6.05 |
| | | | (1.69) | | | (1.78) |
| S&P 100 Average Correlation | | | 11.90 | | | 7.43 |
| | | | (6.78) | | | (3.88) |
| 1M-LIBOR | | | | -72.94 | -88.14 | -64.00 |
| | | | | (-5.43) | (-7.09) | (-4.53) |
| Ted-Spread | | | | 245.79 | 144.29 | 150.24 |
| | | | | (2.03) | (1.21) | (1.24) |
| R-Squared | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 |

*Note:* To test the robustness of our results, in this table, we repeat the regression analysis of table (4.3) with the short-term reversal strategy portfolios that are constructed based on the mid-quote prices, i.e. the average of closing-bid and closing-ask on each day, rather than the actual closing price.

# Chapter 5

# Summary and Conclusion

In this dissertation, we investigated the impacts of the VIX index on stock prices from different angles. The VIX index, at any point in time, is derived from the value of the S&P 500 index and the options, traded on that. Therefore, the VIX index is a conditional measure. Moreover, since option prices depend on investors' expectation about the future path of the market, the VIX index is a forward-looking measure. This index reflects the investors' conditional expectation about the market volatility, and thus, it is considered as a barometer for investors' anxiety and fear.

## Chapter 2: From Time Varying Risk-Aversion to Anomalies in Market Moments' Risk Premia

When investors are anxious about market future, they treat different assets, differently. For example, stocks that tend to have a good return when the VIX spikes up (stocks with positive loadings on the changes of VIX index) are extremely desirable. This attractiveness, compared to stocks that tend to perform poorly when the VIX increases, raises their prices and reduces their expected return. In fact the difference between the return of stocks with positive exposure and stocks with negative exposure to the changes of the VIX index is the premium that investors pay to protect themselves against an economic state with a high level of the VIX. In chapter 2, we show that the magnitude of this premium depends on investors' risk aversion. If investors are more risk averse, they accept to pay a higher premium to buy this insurance against the high levels of the VIX.

In this chapter, furthermore we show that the signs of prices of insurance against the market skewness and market kurtosis are both against the inter-temporal capital asset printing model of Merton (1973). However, the magnitude of these anomalies decline with investors' risk aversion.

## Chapter 3: Does Oil and Gold Price Uncertainty Matter for the Stock Market?

By estimating investors' uncertainty with the wedge between volatility under the risk-neutral and the physical measures, we find that not all types of uncertainty matter. Our empirical analysis in this chapter shows that only the uncertainty that originates from the stock market is significantly priced risk factor in the entire cross section of stock prices; Stock market uncertainty affects the time series and the cross section of all stocks.

The uncertainty that comes from the oil market is a sector-specific factor and it is only important for oil-relevant industries. Specialized investors in oil-relevant industries process and incorporate oil-uncertainty shocks in stock prices of these industries, quickly and efficiently. However, we do not observe any significant evidence for the spillover of oil-uncertainty news to other industries. Furthermore, we identify the gold uncertainty risk as an idiosyncratic factor. It can be diversified aways, and therefore, exposure to this factor is not compensated.

These findings imply that for pricing any stock, investors must consider its exposure to the stock market uncertainty rik, because this is a systematically priced factor that affects the risk premium and the expected return of every stock. The investors in oil-relevant industries, in addition, must consider oil price uncertainty risk because as a sector-specific factor, it affects the risk premium and the expected return of the stocks in those industries. The investors, who hold sufficiently diversified portfolios, can ignore gold price uncertainty, as this type of uncertainty is asset-specific and it has negligible impact on diversified portfolios.

## Chapter 4: Why is the VIX index related to the liquidity premium?

Compensation for liquidity provision depends on short-term price reversal. Existing studies find that the intensity of short-term price reversal in stock prices is highly correlated with the VIX index; when the VIX goes up, the intensity of short-term price reversal is larger and liquidity becomes more expensive.

In this chapter, we develop a 3-period economic model and explain why this is the case. In this model, there are two types of investors. Investors are initially identical and indistinguishable. Therefore, they all hold the market portfolio beside the riskless bond.

However after a while, a proportion of investors receive a risky endowment. Receiving the endowment persuades these investors to trade with the others and makes them *liquidity demanders*, as it departs their portfolio from optimality. The other investors, however, do not have any incentive to trade because they do not receive any endowment. Only if they receive sufficient price discount, they will trade and act as *liquidity suppliers*.

When liquidity demanders are more risk averse, even a small departure from optimality has a large impact on their utility. Consequently, after a liquidity shock they will be desperate to trade and they accept to pay a higher liquidity premium so that they can convince the liquidity supplier to trade with them. Moreover when assets are extremely volatile, due to the higher uncertainty about future payoffs, identical liquidity shocks create a stronger trade motivation in liquidity demanders, which urges them to pay a higher liquidity premium and trade immediately. Finally, when asset correlations are high liquidity shocks spread amongst assets more efficiently, and thereby, liquidity suppliers demand a larger premium for their service. Since the VIX index encapsulates these three factors, an escalated level of the VIX raises the expected return and the Sharpe ratio of liquidity providers.

To empirically test these theoretical findings, we construct a portfolio that proxies for liquidity providers' return. This trading strategy on average yields to 1.27% return per day. When investors' risk aversion or their expectations about stock variances and correlations increase by one standard deviation, the average daily return on this portfolio increases by 0.16%, 0.36% and 0.39%, respectively. Also while the annualized Sharpe ratio of this portfolio is 11.76, one standard deviation increase in each of these factors contribute to 0.84, 1.20 and 2.02 higher Sharpe ratio for liquidity suppliers.

# Valorization

The three essays of this dissertation extend our knowledge in the field of asset pricing, which in turn results into more efficient deployment of capital in financial markets and increases the aggregate utility of investors.

From an investor's perspective, at any point in time, it is crucial to know (1) what are the risk factors that can negatively affect her portfolio, and (2) what is the dynamics of the compensation that she should expect for taking each particular type of risk (risk premium). By knowing the important risk factors that might affect her portfolio, the investor can use hedging instruments and transfer the risk to another party or at least she can get prepared to act, once a known risk factor negatively affects her investment. Moreover, knowing the dynamics of the compensation for each type of risk enables the investor to improve the risk and return profile of her portfolio; the investor can "time" a risk factor by getting more exposure to it when she expects a huge compensation for taking risk, and similarly, reduce her loading on a risk factor when she sees no compensation for taking a particular type of risk. This dissertation broadens our knowledge on these two important aspects of investment by exploring the nature of some of the most important risk factors and the dynamics of the compensation for taking them.

Chapter 2 critically investigates the robustness of the compensation that previous studies find for exposure to the risk of higher market moments. The novel results of this chapter show that the counter-intuitive negative compensation that investors receive for taking the market skewness risk is only restricted to the periods when the investors have a very low level of risk aversion or when they have a very high level of sentiment. In other times, when investors are more rational, the size of this irrational premium becomes insignificant.

Chapter 3 investigates the characteristics of the uncertainty that exists in prices of stocks, oil and gold, and shows that stock market uncertainty is an important factor that affects the entire cross-section of expected stock returns. Investors in the stock market must always consider their exposure to stock market uncertainty, because this is a systematically priced risk factor that affects the risk premium and the expected return of every stock. This chapter also identifies oil price uncertainty as a factor that affects the risk and return of the stocks in oil-relevant industries and therefore industry-specialized investors in oil-relevant sectors must consider their exposure to this factor. Finally, this chapter finds that gold price uncertainty is an idiosyncratic risk factor that can be diversified away and thus it does not carry a risk premium.

Chapter 4 of this dissertation provides deep insights in the risk and return dynamics of an important trading strategy, i.e. the liquidity provision. Interestingly, as the theory and the empirical analyses show, this strategy is more profitable when the investors are more risk averse or when the market is extremely volatile. This finding signals when an active investor should enter this strategy and when she should stop providing liquidity.

Moreover as previous studies show, many conventional investment strategies - such as passively holding the market portfolio or actively engaging in a momentum strategy - have a very low return when the market is volatile. In other words, the returns on these strategies are negatively correlated with the return on liquidity provision. Hence, the findings of chapter 4 show that following the liquidity provision strategy, besides the aforementioned conventional investment strategies, reduces the volatility and increases the Sharpe ratio of the overall portfolio.

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# Curriculum Vitae

Iman Honarvar Gheysary was born on 25th of July 1988 in Mashhad, Iran. In 2010, he obtained his bachelor's degree in Industrial Engineering from Sharif University of Technology (Tehran, Iran). During his bachelor's studies, Iman was elected to run the poem and literature community of the university and he obtained the award of "Exceptional Talented Student". With a dissertation on "Hedge Funds Stress Testing", Iman obtained his Master's degree in Financial Engineering from the Swiss Finance Institute at the École Polytechnique Fédérale (Lausanne, Switzerland) in 2012. During this Master's program, Iman was elected as the vice-president of Finance Association at the EPFL.

In February 2012, Iman joined FinLab Solutions (Geneva, Switzerland) as an intern, and later he was promoted to a R&D associate. In July 2013, he started his PhD studies in Finance in the School of Business and Economics at Maastricht University. Over the 4 years of PhD, he continued his collaboration with industry with various part-time positions at FinLab Solutions and Montesquieu Consulting (Maastricht, The Netherlands). In fall 2016, Iman visited the finance department of Rotman School of Management (Toronto, Canada). Iman's field of research is empirical asset pricing and risk management, and his academic papers have been presented in various conferences such as the American Finance Association Conference (Chicago 2017), European Economics Association Conference (Geneva 2016 and Lisbon 2017), French Finance Association Conference (Liege 2016), Italian Economic Association Conference (Milan 2016), Australasian Finance and Banking Conference (Sydney 2014), Conference on Financial Econometrics and Applications (Melbourne 2014), Auckland Finance Meeting (Auckland 2014), and European Financial Management Association Conference (Amsterdam 2015). Iman has also been invited to present in various external seminars such as in University of Toronto (2016), University of Luxembourg (2014), Radboud University (2016), University of Münster (2017) and Robeco (2017).

Besides his PhD studies at Maastricht University, Iman organized the PhD colloquial of the finance department for two years and taught Finance and Risk Management, for which he was awarded "Prof Eichholtz Trophy" as the best teacher of the department in 2014.

As of November 2017, Iman is working in the Quant Selection Research department of Robeco (Rotterdam, The Netherlands) as a medior quantitative researcher.