

Is Liquidity the Trigger for Stock Returns? A Double Take and the Role of Investors' Risk Aversion

Jian Chen^a, Taufiq Choudhry^b, Jing-Ming Kuo^{c,*} and Qingjing Zhang^d

^a *Fujian Key Laboratory of Statistical Sciences & Department of Finance, School of Economics, Xiamen University, China.*

^{b,c,d} *Southampton Business School, University of Southampton, UK.*

Abstract

This study investigates the interrelationships among variance risk premium (VRP), stock returns and liquidity using monthly US data. We find that the innovation of VRP reflecting investors' risk aversion causes variations in stock returns, and in turns leads to the movement of market liquidity. Our results further show that VRP has a strong predictive power for stock returns, while liquidity does not. Finally, we further find supportive evidence that VRP affects stock returns via the systematic risk factors, namely market risk premium and value and momentum factors. This implies that investors' risk aversion affects stock returns via these risk factors.

JEL classification: C22; C53; G12; G13; G14

Key words: Variance risk premium; Illiquidity; Fama-French factors; Granger causality; Impulse response function

I. Introduction

Market risks play a prominent role in modern financial theory and are closely related to future stock returns (Merton, 1973). Although a growing body of literature shows that investors' risk aversion and (il)liquidity have strong explanatory power for stock returns, it is still inconclusive whether investors' risk aversion and liquidity triggers stock returns, or vice versa. Variance risk premium is defined as the difference between implied volatility and realized volatility, in that it contains information on both conventional risk measures and also reflects exclusive information of investors' risk aversion.¹ Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011) investigate the variance risk premium for the US stock market, and find that it has strong stock return predictability at monthly, quarterly and annual horizons. Bollerslev, Marrone, Xu, and Zhou (2014) extend the study of the predictive power of variance risk premium to the international stock markets, and show similar evidence as for the US market.

Jones (2002) and Lesmond, Ogden, and Trzcinka (1999) document that liquidity can predict future stock returns. However, Chordia, Huh, and Subrahmanyam (2006) argue that past returns can trigger the need for portfolio rebalancing which in turns leads to the fluctuations in liquidity. Some studies find further supportive evidence that past stock returns can affect future market liquidity. For instance, Chordia, Roll, and Subrahmanyam et al. (2002) document that stock returns are able to forecast future market liquidity rather than vice versa for the US market. Similarly, using a large sample from 46 countries, Griffin et al. (2007) provide international evidence that stock liquidity follows past returns and further indicate that this positive association between past returns and stock liquidity is economically significant as an increase of

¹ See Bakshi and Madan (2006) and Bollerslev, Gibson, and Zhou (2011) for details.

0.46 standard deviation in liquidity after 10 weeks can be triggered by a shock of one standard deviation of stock returns.

If stock returns can affect future stock liquidity, variance risk premium may also do so as it captures the risk aversion attitude of investors to risk exposure. Failure to recognize that liquidity is not the causal variable may lead to misjudgements in the interplay among liquidity, stock return, and variance risk premium. Also, if liquidity responds to past returns or past variance risk premium, it is intuitive to include these variables to supplement any forecasting tests of liquidity. By doing so it is likely that the overestimation of the true forecasting power of liquidity can be avoided. In this paper, we investigate the interrelationships among investors' risk aversion, indicated by variance risk premium, liquidity, and stock returns, and examine how these factors affect stock returns. This clarification regarding the causal relationships among variance risk premium, liquidity, and stock returns is essential for advancing our understanding of the determinants of liquidity and stock returns and, consequently, it also holds crucial implications for the development of trading strategies, the forecast of trading activities and the enhancement of financial market liquidity and efficiency. More importantly, the intention is to shed light on the fundamental question about whether variance risk premium and liquidity should be considered and employed as predictive variables for future stock returns.

This paper tests the relation between variance risk premium and stock returns, and between variance risk premium and illiquidity. To the best of our knowledge, this is the first study that examines the relationship between variance risk premium and illiquidity. If illiquidity responds to stock returns, then it is also possible that illiquidity responds to the variance risk premium if variance risk premium is a forecasting variable for stock returns. Our empirical results show that the variance risk premium can Granger-cause stock returns and also illiquidity,

rather than vice versa. This finding is robust for different sub-sample periods and when controlling for conventional economic variables. The results indicate that there is a need to add variance risk premium in the forecasting tests of liquidity. Furthermore, the result clarifies the interrelationships among illiquidity, stock returns and variance risk premium by confirming that variance risk premium affects stock returns and illiquidity, and that there is a causal relationship running from stock returns to liquidity. However, illiquidity affects neither variance risk premium nor stock returns; therefore, the traditional view that illiquidity is a useful forecasting variable for future stock returns can be serendipitous.

We also investigate whether past stock liquidity can drive future stock returns, or whether past stock returns can affect liquidity. Amihud (2002) and other related papers have shown that stock returns also reflect compensation for market illiquidity.² However, if we step away from this traditional view on the liquidity-return relation, and ask how the liquidity might be generated, it is intuitive to expect that stock returns could affect future liquidity due to the need for portfolio rebalancing. This is empirically confirmed by Chordia et al. (2002) using daily data, and by Griffin et al. (2007) using weekly data. Thus, there is mixed evidence as to the return-liquidity relation, and to date there is no generally agreed-upon explanation for it; nor has it been subject to a comprehensive examination. This study adopts Amihud's (2002) illiquidity ratio which has been widely used in the literature as the liquidity measure and employs a large sample of monthly US data over the period 1992-2010. We comprehensively investigate the direction and magnitude of the return-liquidity relation using the Granger-causality test and impulse response function. We find that illiquidity does not Granger-cause stock returns, while stock returns can Granger-cause illiquidity. This result is further confirmed by the impulse response function

² Amihud et al. (2005) provide a good review of the development of illiquidity theory.

graphs, as there is no evidence that stock returns respond to changes in stock illiquidity. Our results imply that the liquidity measured by the illiquidity ratio follows past stock returns, rather than vice versa, for the US market over the period 1992-2010. This indicates that research that seeks to exploit the potential impact of liquidity is unlikely to be successful for returns forecasting. Moreover, it implies that we should include the stock returns to supplement the forecasting test of liquidity instead.

This study further investigates the forecasting power of variance risk premium and illiquidity for excess stock market returns. Our results show that variance risk premium, rather than illiquidity, has statistically and significantly predictive power for stock returns. That is, the variance risk premium rather than illiquidity contains useful information for forecasting future stock returns. Moreover, our results of impulse response functions also show that there is impulse response of stock returns to variance risk premium rather than illiquidity, and both stock returns and variance risk premium can significantly affect illiquidity. However, it is intriguing that the impulse responses of variance risk premium to both stock returns and illiquidity cannot be observed.

Finally, we examine how variance risk premium and illiquidity are related to the US stock returns, by looking at the casual relationships between variance risk premium and risk factors and between illiquidity and risk factors, including the Fama-French three-factor and the momentum factor. The results of Granger-causality tests show that variance risk premium Granger-causes the market risk premium, value factor and momentum factor. In other words, variance risk premium affects stock returns via these systematic risk factors. The test for the Granger-causality relationship between illiquidity and systematic risk factors shows that market illiquidity cannot cause movement in the four risk factors, but that the market risk premium and

momentum factor affect variations in illiquidity. These confirm our conjecture that investors' risk aversion, measured by variance risk premium, is a predictive variable for both stock returns and illiquidity while illiquidity has no predictive power for investors' risk aversion or stock returns.

The paper proceeds as follows. Section 2 provides a review of the related literature. Section 3 presents models, data and summary statistics, and section 4 discusses our empirical results. While section 5 carries out robustness checks, section 6 summarizes our conclusions.

II. Related Literature

A. Variance Risk Premium

Variance risk premium is defined as the difference between the variance under *risk-neutral* probability and that under the *physical* probability and reflects investors' risk aversion (Bakshi & Madan, 2006; Bollerslev et al., 2009; Rosenberg & Engle, 2002). Bollerslev et al. (2009) and Drechsler and Yaron (2011) show that this variance risk premium is induced by the uncertainty of consumption related to macroeconomic uncertainty through a recursive utility framework. The classical intertemporal CAPM model of Drechsler and Yaron (2011) demonstrates that the aggregate equity risk premium is determined by the uncertainty of underlying returns, quantified by the return variance. When holding the market portfolio, however, an investor is also bearing the uncertainty of the variance itself (Drechsler & Yaron, 2011). Just as equity risk premium demanded by investors is a result of fear of the uncertainty of future returns, variance risk premium is required to compensate for the uncertain variance.

Theoretically, Bollerslev et al. (2009) propose that variance risk premium effectively

isolates the factor associated with the volatility of consumption growth volatility and, as a result, it serves as an useful predictor for the returns over horizons for which that risk factor is relatively more important. Also, Drechsler and Yaron (2011) argue that the variance risk premium is particularly relevant for unravelling the connections among uncertainty, the dynamics of the economy, preferences, and prices, and they identify conditions under which it predicts future stock returns. In addition, since the variance risk premium is required by investors for bearing the volatility risk, many papers directly extract the risk aversion from the variance risk premium (Bakshi & Madan, 2006; Bollerslev et al., 2009).

There is a close relation between the variance risk premium and the risk aversion of a representative agent.³ Assuming a stochastic volatility process for stock returns, Bollerslev et al. (2011) find that the variance risk premium is related to the risk aversion. Under the general equilibrium framework, Drechsler (2013) specifically shows that the variance risk premium is controlled by the representative agent's risk preference, which comprises the risk aversion and model uncertainty aversion. Also, Bakshi and Madan (2006) posit that variance risk premium could be expressed as a nonlinear function of the aggregate degree of risk aversion in a simple representative agent setting, and Bollerslev et al. (2009) conclude that variance risk premium can be considered as a proxy for the aggregate degree of risk aversion. As a consequence, according to the aforementioned discussion, we employ variance risk premium to capture the dynamics of risk aversion of a representative agent.

³ Bakshi and Madan (2006) show that the variance risk premium is determined by the higher moments of stock return distribution and the degree of risk aversion.

B. Market Liquidity

It is generally acknowledged that liquidity has predictability over stock returns. Many papers investigate the relation between liquidity and stock returns by testing the impact of liquidity on contemporaneous stock returns. In the first study to focus on this relationship, Amihud and Mendelson (1986) adopt the quoted bid-ask spread as a proxy for illiquidity and discover that expected stock return is an increasing and concave function of illiquidity. Subsequent studies use alternative measures of liquidity, such as the marginal cost of trading, dollar trading volume, and turnover ratio, and present consistent conclusions (Brennan & Subrahmanyam, 1996). A number of theories and empirical results suggest that liquidity has substantial predictive power for future stock returns, at both the firm level and the aggregate stock market level (Amihud & Mendelson, 1986; Baker & Stein, 2004; Jones, 2002). These studies argue that increases in liquidity, such as higher turnover ratio, lower illiquidity ratio, lower price impact of trade, or lower bid-ask spread, all forecast lower future returns.

The predictability of liquidity over stock returns can be deduced from the fact that investors anticipate selling the stocks in the future with transactions costs. Transaction costs may come from the issues of adverse selection or the consideration of professional market-makers (Stoll, 1978; Glosten & Milgrom, 1985; Easley & O'Hara, 1987; Grossman & Miller, 1988; Jones, 2002). If transaction costs are high, investors discount the asset by a higher rate and consequently require higher stock returns. As a result, the stocks are observed to have lower liquidity. In other words, higher transaction costs, lower turnover and higher illiquidity ratio are expected to generate higher future returns (Amihud & Mendelson, 1986; Baker & Stein, 2004; Bekaert, Harvey, & Lundblad, 2007); Glosten & Milgrom, 1985; Lesmond et al., 1999). This

theory fits well with a cross section of individual stocks and is empirically supported by cross-sectional results by Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996).

An alternative possible explanation for the cross-sectional relation between lagged liquidity and returns is from the perspective of behavioral finance. Against the behavioral finance framework, investors are prone to over-optimism and over-pessimism. When irrational investors are excessively optimistic about the market, they will trade more actively and thus boost the liquidity. Conversely, when such investors are over-pessimistic, they avoid trading and holding equity, and thus reduce the market turnover. In both cases, stock prices will eventually revert to the fundamental values. Hence, this behavioral theory implies that liquidity and future stock returns are negatively related (Jones, 2002). On the basis of two assumptions - the short-sale constraints, and the existence of irrational overconfident investors - the supportive time-series results of this predictive power of aggregate liquidity for market returns was further documented by Baker and Stein (2004).⁴

A number of papers investigate the relation between liquidity and stock market returns by looking at the components of liquidity - the expected liquidity and the unexpected liquidity. Amihud (2002) proposes that liquidity predicts future stock returns due to the positive relation between expected illiquidity and *ex ante* stock returns. Investors estimate the expected illiquidity based on the information available in one preceding year, and then use the forecast to set prices that generate desired expected returns; that is, if investors anticipate higher market illiquidity based on the one-preceding-year illiquidity information, this will generate higher expected return to compensate for the higher expected market illiquidity. Similarly, Bali, Cakici, Yan, and Zhang (2005) find that the expected liquidity is significantly related to the expected stock market

⁴ Baker and Stein (2004) argue that the magnitude of the decrease in stock returns related to the increase in liquidity seems extremely large to be explained by theoretical models where the cost of trading influences expected returns.

returns. This indicates that past liquidity information could impact the future market price movement. In addition, they argue that after controlling for the expected illiquidity and contemporaneous unexpected illiquidity, the explanatory power of volatility for the market return disappears.

C. Returns and the Predictability for Liquidity

Contrary to the aforementioned theories and evidence indicating the predictability of liquidity over future stock returns, there is some empirical evidence showing the relation between past stock returns and future illiquidity. Lakonishok and Smidt (1986) show that higher daily positive price movement leads to higher level of liquidity for individual stocks. Similarly, Smirlock and Starks (1988) investigate the association between daily stock returns and trading volume for individual stocks in the US market. They document that trading volume is caused by the variability of stock returns, and that this relation tends to be stronger in the periods surrounding earnings announcement. The results imply that delivery of information to investors follows a sequential rather than simultaneous process as past stock returns can provide information to improve volume forecasts. For the aggregate market, Chordia, Roll, and Subrahmanyam (2001) document that market liquidity varies with market trends. That is, market liquidity increases in down markets and decreases in up markets, as rising markets attract more investors and, additionally, stock price movement could prompt changes in optimal portfolio compositions. Also, Chordia et al. (2001) show that past returns could trigger the movements in market liquidity. They argue that various technique analysis strategies such as momentum or

contrarian strategies involve past market movements, which create a link between market liquidity and past returns.

Chordia et al. (2002) employ Stoll's (1978) inventory model to explain the relation between past stock return and liquidity. This model states that the level of liquidity is driven by the inventory holding cost, which arises from financing constraints and risk. More specifically, the fluctuation in liquidity follows previous market performance - it declines following past stock market return falls and increases after past market return rises. This inventory model is supported by the empirical results of Chordia et al. (2002), who document that stock market returns predict liquidity for the US market, rather than vice versa. Furthermore, inventory cost theory offers a plausible explanation for the observed phenomenon of liquidity drying up in falling markets (Chordia et al., 2001; Hameed, Kang, and Viswanathan, 2010). First, the influence of financial constraints is asymmetric; for example, the short-sales restriction significantly affects the trading activities in down markets.

Second, market makers are more risk-averse when stock prices decrease, and the fear of future liquidity shocks causes them to be unwilling to provide liquidity at the current time (Bernardo & Welch, 2004). Furthermore, using an asymmetric VAR, Griffin et al. (2007) show a symmetric reaction of liquidity to past stock returns.

Behavior finance theories also provide plausible explanations for the association between past stock returns and liquidity. According to the disposition effect proposed by Shefrin and Statman (1985), investors are reluctant to trade in down markets and wish to realize the gains in up markets. This implies that past stock returns affect investors' trading activities and, in turn, affect liquidity. Odean (1998) draws on overconfidence bias theory to claim that overconfidence causes investors to trade more frequently and thus increases liquidity. In addition, Gervais and

Odean (2001) argue that overconfidence grows with past success in the market; hence, liquidity increases following positive market returns. Statman, Thorley, and Vorkink (2006) find that overconfidence bias at the market level and the disposition effect at the stock level could explain the positive relation between past stock return and liquidity for the developed markets. As a consequence, both disposition effect and overconfidence theory show a positive return-liquidity relationship. An alternative explanation for the positive association between past return and liquidity is the cost of participation (Griffin et al., 2007). Orosel's (1998) participation model assumes the existence of sidelined investors. Such investors could but do not invest in the stock market because of the participation costs, such as trading and information costs. High stock market returns will induce these investors to increase their estimates of profitability of the market and thus be more willing to participate. As a result, market participation rises following high past returns and falls following low past returns. With a large sample of weekly data from 46 countries over the period 1983-2003, Griffin et al. (2007) find a positive relationship between past stock returns and future trading activities. Their results show that an up market predicts higher liquidity, with approximately the same magnitude of effect as for a previous down market. Bekaert et al. (2007) adopt monthly data from 19 emerging markets and the US market over the period 1987-2003 and study the return-liquidity relation. They employ a VAR analysis with relative number of zero trading days as illiquidity proxy and discover a positive association between past returns and future liquidity in emerging markets⁵.

Consequently, the literature on the return-liquidity relation has not arrived at a general conclusion; nor has there been a comprehensive examination of that relation. Therefore, it is important to comprehensively examine the causality and magnitude of the return-liquidity

⁵ However, in contrast to the finding of Chordia et al. (2002), Bekaert et al.'s (2007) results reveal that the effect of past stock returns on future liquidity is not significant in the US.

relation. Another crucial point is that different liquidity measures capture different dimensions of market liquidity. Chordia et al. (2002) employ bid-ask spread and Bekaert et al. (2007) use the proportion of zero daily returns to capture the trading cost dimension; Griffin et al. (2007) adopt turnover ratio to capture the trading quantity dimension. Adopting a different approach, Amihud's (2002) liquidity measure captures the price impact dimension of the market liquidity. Moreover, unlike the other liquidity measures, Amihud's (2002) illiquidity ratio does not rely on the microstructure data and thus allows the study on the return-liquidity relation to cover long periods of time (Amihud, 2002). Finally, the association between the variance risk premium and market liquidity has not yet been investigated in the literature. If stock market returns have a substantial influence on market liquidity, it is plausible that the variance risk premium also has an impact on liquidity as variance risk premium drives market returns. If this is the case, we could expect to observe a link between variance risk premium, market returns, and liquidity, and thus it is essential to examine the direction of causality.

III. Data and methodology

A. Variance Risk Premium (VRP)

Following Bollerslev et al. (2009), Carr and Wu (2009) and Drechsler and Yaron (2011), we define the variance risk premium (*VRP*) as the difference between risk-neutral and physical expected variances,

$$VRP_t = E_t^Q(Var_{t,t+1}) - E_t^P(Var_{t,t+1}), \quad (1)$$

where Q and P represent the risk-neutral and physical probability measures, respectively, and $E(\cdot)$ is the expectation operator. Variance risk premium reflects investors' risk aversion (Bakshi & Madan, 2006; Bollerslev et al., 2009, 2011). Bollerslev et al. (2009) and Drechsler and Yaron (2011) suggest that the variance risk premium is induced by the uncertainty of consumption related to macroeconomic uncertainty through a recursive utility framework, and hence it shows a strong predictive power for stock market returns. However, both terms are unobservable, and we need to choose their empirical counterparts.

1. Model-free Implied Volatility

Implied volatility is regarded as the expected future volatility as extracted from relevant option prices. It is equal to the volatility parameter, σ , the value of which can be revealed when the option price is equal to its theoretical price according to the pricing formula. The Black-Scholes (Black & Scholes, 1973) option pricing formula is commonly used to calculate the implied volatility. However, the studies that employ this formula suffer from misspecification errors and there is inconsistency stemming from the constant volatility assumption of the Black-Scholes model. Britten-Jones and Neuberger (2000) derive the model-free implied volatility from no-arbitrage conditions. In particular, all consistent processes for the prices of underlying securities generate a common expectation of integrated variance under the risk-neutral measure over a specified horizon, and therefore imply the same forecast of volatility. Britten-Jones and Neuberger (2000) suggest that the common risk-neutral expectation of squared price volatility between the current date and the future date is given by the set of prices of options that expire on

the two dates. Thus, they derive the forecast of volatility from the current option price via the risk-neutral integrated return variance.

Unlike traditional implied volatility measures, model-free implied volatility is independent of option pricing models and requires only current option price. Therefore, it is be subject to misspecification errors. Since it does not rely on the Black-Scholes pricing model or any variant, the model-free implied volatility does not require a constant volatility assumption and consequently bypasses the criticisms of the inconsistency of previous implied volatility measures. The information efficiency of Britten-Jones and Neuberger's (2000) model-free implied volatility is examined by Jiang and Tian (2005). They find that model-free implied volatility from the S&P 500 index options subsumes all the information incorporated in historical realized volatility and in the Black-Scholes implied volatility. Consequently, they suggest that model-free volatility is a more efficient and unbiased predictor for future volatility, compared with previous volatility measures.

According to Carr and Madan (1998) and Britten-Jones and Neuberger (2000), the expectation of integrated variance under the risk-neutral measure can be calculated from a complete set of call option prices,

$$\sigma_{MF}^2(T_1, T_2) = E^Q \left[\int_{T_1}^{T_2} \sigma_t^2 dt \right] = 2 \int_0^\infty \frac{c(T_2, K) - c(T_1, K)}{K^2} dK, \quad (2)$$

where $\sigma_{MF}^2(T_1, T_2)$ is the model-free implied volatility over the period from T_1 to T_2 ; $c(T_1; K)$ and $c(T_2; K)$ are the European-type call option prices with strike price K and time to maturity T_1 and T_2 , respectively; and $E^Q \left[\int_{T_1}^{T_2} \sigma_t^2 dt \right]$ denotes the expectation operator under the risk-neutral measure. Under the assumption of zero dividend yield and interest rate, it can be implied that the

model-free implied volatility measure from T_1 to T_2 is determined by a series of option prices with time to maturity at these two days. Because no assumption of underlying process or specific option pricing model is imposed, this measure is considered to be model-free. For the US market, we follow previous studies to employ the VIX index (constructed through the model-free implied volatility approach) as the measure of $E_t^Q(\text{Var}_{t,t+1})$, which is observable at time t .

2. Realised Volatility

The daily realized variance, RV , of market returns is traditionally measured by the squared (absolute) daily index returns, where the market return is defined as the natural logarithm of the ratio of consecutive daily closing index levels. Andersen and Bollerslev (1998a, 1998b) indicate that these traditional measures are poor estimators of day-by-day movements in volatility, as the idiosyncratic component of daily returns is large. They demonstrate that the realized volatility measures based on intraday data provide a dramatic reduction in noise and a radical improvement in temporal stability relative to realized volatility measures based on daily returns. Therefore, numerous studies suggest using high frequency intraday returns to calculate the daily realized variance. In this study, we also adopt high-frequency intraday data and define the daily realized variance ($\sigma_{RV}^2(t)$) for day t as the summation of intraday squared returns,

$$\sigma_{RV}^2(t) = \sum_{j=1}^N r^2(t, j), \quad (3)$$

where t is the t -th day, which is divided into N sub-periods, and $r(t; j)$ denotes the j -th intraday return in day t . σ_{RV} represents the realized volatility. This measure is used in several high-

frequency studies (Zhou, 1996, Taylor & Xu, 1997; Andersen et al., 2003). Following the literature, we employ the five-minute high frequency intraday returns to construct the realized volatility.⁶

The literature, however, diverges on the choice of measure for expected realized volatility. For example, Bollerslev et al. (2009) use the *ex post* realized return variation over the $[t-1, t]$ time interval, which is the lagged realized variance over $[t, t+1]$. The method is valid under the assumption that realized volatility is a martingale process. Under this assumption, the realized volatility would behave like a unit root process with the first-order autocorrelation coefficient almost equal to one, which is usually not true in practise. Empirically, Bollerslev et al. (2009) find that the estimated slope coefficient of variance risk premium is significant in time horizons of less than or equal to six months and the R^2 shows a hump-shaped pattern.

On the other hand, Drechsler and Yaron (2011) argue that high-frequency S&P 500 cash index returns may be subject to the autocorrelation existing in the “stable” index when summing up 500 separate individual stock prices. Instead, they consider the high frequency S&P 500 futures realized variance forecasts by projecting futures realized variance on VIX and lagged index realized variance. Their slope coefficients are statistically significant and slightly larger than those in Bollerslev et al. (2009), with an increasing pattern from monthly horizon to quarterly horizon.

Following the usual practise in the variance swap market, Carr and Wu (2009) use *ex post* forward realized variance from daily price as the measure of expected realized variance. Although they do not directly consider an asset return predictability regression in their paper, they demonstrate a highly significant negative relationship between log difference of realized

⁶ In application, Andersen et al. (2001) and Areal and Taylor (2002) use the summation of 79 five-minute squared intraday returns to calculate realized volatility, while Andersen et al. (2003) use 30-minute data. Andersen, Bollerslev, Diebold, and Labys (2000), Ebens (1999), and Areal and Taylor (2002) also use the five-minute returns.

variance and implied variance (which is the opposite of the variance premium used above), and future excess return for the stock index and many of the individual stocks considered on a monthly basis.

Due to the advantages and disadvantages of the measures aforementioned, we construct all the measures of variance risk premium by using the respective methods of Bollerslev et al. (2009), Carr and Wu (2009) and Drechsler and Yaron (2011). The variance premium of Bollerslev et al. (2009) is denoted by VRP^{BTZ} , that of Carr and Wu (2009) is denoted by VRP^{CW} and that of Drechsler and Yaron (2011) is denoted by VRP^{DY} .

B. Illiquidity

A number of illiquidity proxies have been advanced, including quoted bid-ask spread (Amihud & Mendelson, 1986), marginal cost of trading (Brennan & Subrahmanyam, 1996), and the probability of information-based trading (Easley, Hvidkjaer, & O'Hara, 2002). These illiquidity measures, however, are computed from microstructure data on quotes and transactions, which are unavailable for the long periods required by most studies of the return-liquidity relation (Amihud, 2002). Therefore, in this study, we employ Amihud's (2002) illiquidity ratio, which is based on readily available data (daily volumes and daily returns) and which captures the price impact dimension of liquidity. This illiquidity measure, denoted by $AILLIQ$, is the average ratio of absolute stock return to the trading volume in dollars on the same day.

$$AILLIQ_i = \frac{1}{D_i} \sum_{d=1}^{D_i} \frac{|R_{i,d}|}{VOLD_{i,d}}, \quad (4)$$

where $R_{i,d}$ is the return on stock i on day d , $VOLD_{i,d}$ is the corresponding daily volume in dollars, and D_i is the number of days with data available for stock i during the pre- and post-addition measurement periods. Following Oded (2009), our analysis is performed using the natural logarithm of $AILLIQ$ (henceforth $ILLIQ$), rather than $AILLIQ$.⁷ This illiquidity proxy has been widely used over many decades in the liquidity literature and has a strong theoretical appeal. It is argued that Amihud's (2002) illiquidity ratio outperforms other commonly used illiquidity proxies in capturing Kyle's lambda (Miralles & Miralles, 2006).

C. Data and Sample

For empirical investigation, we employ monthly observations of variance risk premium, illiquidity, and excess stock returns for the US market over the period extending from January 1992 to December 2010. In our empirical investigations, we divide the full sample into three sub-samples - 1992 to 2006, 1994 to 2008, and 1996 to 2010; consequently we can have the same length for each sample period and have the periods with and without financial crisis. First, we use five-minute intraday returns of the S&P 500 index obtained from the Institute for Financial Markets to construct the monthly realized volatility, and employ the monthly-end VIX index as a proxy for model-free implied volatility. The VIX index is obtained from the CBOE

⁷ This paper uses the natural logarithm of $AILLIQ$ as several firms in our sample have extreme values of $AILLIQ$. The qualitative results are similar when $AILLIQ$ is used.

(Chicago Board of Options Exchange). According to the white papers published by the CBOE, the VIX index is the risk-neutral expectation of future 30- day return variance inferred from daily option trading data. VIX has been widely used in the literature as a proxy for the risk-neutral expected volatility (e.g., Bollerslev et al., 2009 and Drechsler and Yaron, 2011). According to Eq.(1), using the methods of Bollerslev et al. (2009), Carr and Wu (2009) and Drechsler and Yaron (2011) to construct the expected realized variance, we obtain three measures of variance risk premium, denoted by VRP^{BTZ} , VRP^{CW} and VRP^{DY} , respectively.

Second, we consider the illiquidity for the S&P 500 index and the aggregate stock market (NYSE), respectively. We obtain the daily returns, prices, and trading volumes of stocks from CRSP. According to Eq. (6), we construct the monthly illiquidity ratio for the NYSE ($ILLIQ^{NYSE}$), and that for the S&P 500 index ($ILLIQ^{SP500}$). Third, we also consider two stock return measures: the monthly excess returns on a value-weighted market portfolio (denoted by VW), and the S&P 500 index excess return (denoted by $INDEX$). We download the monthly value-weighted return, the S&P 500 index return and the risk-free rate from CRSP. We obtain the monthly data during our sample period for the Fama-French factors ($R_m - R_f$, SMB , and HML) and the momentum factor (MOM) from Ken French's website.

Finally, following Welch and Goyal (2008) and Bollerslev et al. (2009), our forecasting analysis considers a number of economic predictors; specifically, we use price-earnings ratio (PE), price-dividend ratio (PD)⁸, default spread ($DFSP$), term spread ($TMSP$), and the stochastically de-trended risk-free rate ($RREL$), defined as the one-month T-bill rate minus its backward 12-month moving averages. The monthly price-earnings ratio and price-dividend ratio

⁸ Following Bollerslev et al. (2009), we use the logarithms of price-earnings ratio and price-dividend ratio.

for the S&P 500 are obtained from Standard & Poor's, and the other economic data are downloaded from the public website of the Federal Reserve Bank of St. Louis.

Table 1 reports the summary statistics for all variables - namely, variance risk premium (VRP^{BTZ} , VRP^{CW} and VRP^{DY}), illiquidity ratio ($ILLIQ^{NYSE}$ and $ILLIQ^{SP500}$), stock return (VW and $INDEX$), and economic variables (PD , PE , $DFSP$, $TMSP$, and $RREL$). All variables are reported in percentage form whenever appropriate. As shown in the table, the mean values of VRP^{BTZ} , VRP^{CW} and VRP^{DY} are 17.93, 17.92 and 18.51, respectively, while their standard deviations are 20.95, 32.80 and 22.83, respectively. This implies that, compared with Bollerslev et al.'s (2009) variance risk premium measure, the measures of Carr and Wu (2009) and Drechsler and Yaron (2011) are more volatile. Table 1 also illustrates that the illiquidity of the aggregate stock market is higher in both the mean and the standard deviation than those of the S&P 500 index. As for the portfolio return measures, the aggregate stock market return and S&P 500 index return present similar means and standard deviations. More specifically, the mean values of VW and $INDEX$ are 0.50 and 0.39, respectively, while the standard deviations for VW and $INDEX$ are 4.32 and 4.38, respectively. Furthermore, we also conduct the Jarque-Bera test to examine the distribution of the time-series variables, and the Null hypothesis of normal distribution is statistically rejected for all the variables listed in Table 1. All the return and VRP variables display a distribution with higher kurtosis than the normal distribution. Finally, we report the Ljung-Box Q-statistics for testing the autocorrelation of the variables at the bottom of Table 1 and these show that the Q-statistics are all statistically significant, except for the stock returns. This is consistent with the results given by Durand et al. (2011).

[Insert Table 1 around here]

We also compute the correlation matrix of those variables employed in this study. High correlation is shown between the illiquidity of the NYSE and the S&P 500 index, and the two portfolio return measures. These imply that the measures are representative and consistent and can be substituted with each other. Also, we find that the illiquidity of the NYSE is negatively related to contemporaneous market portfolio returns, while the illiquidity of the S&P 500 is positively related to contemporaneous portfolio returns. However, both of the correlations are statistically insignificant. For the variance risk premium, we find that VRP^{BTZ} and VRP^{CW} positively correlate with contemporaneous illiquidity, while in the case of VRP^{DY} , the relationship is negative although, again, the correlations are not significant.

[Insert Table 2 around here]

IV. Empirical Results

A. Granger-causality Test

To analyze the interrelation among variance risk premium, return and illiquidity, we apply the Granger-causality test to investigate the existence of Granger-causality relationship among them. We test the causal relationship between variance risk premium and index returns by the application of bivariate vector autoregression (VAR) models, and the lag length of the VAR model is chosen by optimizing the Akaike Information Criterion. As a consequence, we test two-

way relations; that is, we examine whether variance risk premium could Granger-cause index returns, and whether index returns could Granger-cause variance risk premium. We also investigate the Ganger-causality relations between illiquidity and index returns, and between variance risk premium and illiquidity.

We seek to answer whether or not the variation of variance risk premium could cause the changes in index returns using one unrestricted model and one restricted model. The unrestricted model is the regression of returns on the lagged returns and lagged variance risk premium, and the restricted model is the regression of returns solely on the lagged returns. We employ a standard likelihood ratio to determine whether the restricted form of the model should be statistically rejected. If the restricted form is rejected, this implies that we have significant evidence to reject the null hypothesis that variance risk premium does not cause index returns. An identical method is used to test whether index returns Granger-causes variance risk premium. The same methodology is also adopted for testing the causal relations between illiquidity and index return, and between variance risk premium and illiquidity.

We present the p-values of the chi-square statistics for the Granger-causality tests between illiquidity and stock returns, between variance risk premium and stock returns, and between variance risk premium and illiquidity in Table 3. For the Granger-causality relation between variance risk premium and stock returns on the aggregate stock market and S&P 500 index portfolios, there is compelling evidence that the variance risk premium Granger-causes stock returns. Table 3 provides strong evidence of causality running from the variance risk premium for all measures to the stock market returns. For both VRP^{BTZ} and VRP^{CW} , the likelihood ratio statistics are significant at the 1% level for the full period and the sub-periods. Meanwhile, VRP^{DY} can significantly cause the variation in aggregate stock market returns for the

full period 1992-2010, and for the sub-periods 1992-2006 and 1996-2010. Nevertheless, there is no evidence that returns are causal variables as we cannot reject the null hypothesis that stock returns do not cause the variance risk premium. These results imply that variance risk premium causes stock market returns but rather than vice versa. With respect to the causal relationship between illiquidity and stock returns, there is insufficient evidence that illiquidity can have an impact on the future stock returns. However, the results in Table 3 indicate that illiquidity, both for the aggregate market and the S&P 500 index portfolios, can be statistically and significantly Granger-caused by stock returns. The significance is at the 1% level for the full sample and all sub-samples. Therefore, there exists unidirectional causality running from stock return to illiquidity, which is consistent with the finding of Chordia et al. (2002).

[Insert Table 3 around here]

If the variation in variance risk premium can lead to the changes in stock returns and, in turn, to that in stock liquidity, we may expect to find supportive evidence of the impact of variance risk premium on stock liquidity. Panel B of Table 3 shows the causal relationship between illiquidity and variance risk premium. As presented in the table, the variance risk premium Granger-causes illiquidity rather than vice versa. All the likelihood ratios are significant except for the causal relation from VRP^{BTZ} to illiquidity of the S&P 500 index for the full period and the sub-period 1996-2010. In other words, we can reject the null hypothesis that variance risk premium does not cause stock liquidity. However, we cannot reject the null hypothesis that the illiquidity measures do not cause variance risk premium. In sum, firstly, our results suggest that stock returns do not cause variance risk premium, but that variance risk

premium does cause the stock returns. Secondly, stock returns Granger-cause illiquidity, while illiquidity does not statistically affect stock returns. Thirdly, illiquidity does not Granger-cause the variance risk premium, while there is significant evidence that the changes in variance risk premium can lead to the fluctuations in the market liquidity. These further confirm our conjecture that the fluctuation in variance risk premium can lead to the changes in stock return and, in turn, to those in stock liquidity.

To avoid the possibility that these results are driven by other factors, we further incorporate some exogenous variables with the VAR models, including P/E ratio, dividends yields, default spread (between Moody's BAA and AAA corporate bond spreads), term spread (between the 10-year T-bond and the three-month T-bill yields), and the stochastically de-trended risk-free rate (the one-month T-bill rate minus its backward 12-month moving averages) following the regression model used by Bollerslev et al. (2009). This procedure motivates us to look into the interrelations among variance risk premium, return, and illiquidity by controlling for the impact of these exogenous variables. We report the results of the Granger-causality tests for the relationship between illiquidity and stock market return, between variance risk premium and stock market return, and between illiquidity and variance risk premium, by controlling for a number of economic variables as shown in Table 4. The control variables are price-earnings ratio, price-dividend ratio, default spread, term spread, and the stochastically de-trended risk-free rate included in Table 1. The results for the Granger-causality tests in Table 4 are consistent with those presented in Table 3. More specifically, after controlling for the economic variables, the variance risk premium still Granger-causes stock returns across the full sample period and all sub-sample periods, and also causes illiquidity. Therefore, we can reach the conclusion that even after controlling for these economic variables, there is strong evidence for causality running from

variance risk premium to stock returns and market illiquidity, while stock returns and illiquidity do not cause the variance risk premium. Moreover, stock returns Granger-cause illiquidity but rather than vice versa. In other words, our results confirm that the variation in variance risk premium can lead to the changes in stock return and, in turn, to stock liquidity.

[Insert Table 4 around here]

B. Impulse Response Functions

Although the Granger-causality test facilitates the analysis of whether the changes in variance risk premium can cause the variations in stock returns, it does not help to reveal whether the sign of the impact is positive or negative and how long it will take for the impact to work through the VAR system. To answer these questions, we apply the impulse response function derived from the VAR models. Furthermore, the impulse response functions can be employed to predict the responses from variance risk premium to stock returns. The figure of the impulse response presents the responsiveness of returns to a 1% exogenous change in the variance risk premium. Therefore, from the impulse responses figures, we can know the sign of the impact and whether the impact is long-run persistence or just a temporary jump.

Figure 1 depicts the estimated impulse response functions for variance risk premium, stock returns, and illiquidity for 24 months, while Figure 2 plots the estimated cumulative impulse response functions. Both Figure 1 and Figure 2 are plotted according to the VAR models for the full sample period from January 1992 to December 2010. The estimated response is

represented by the solid line, with the confidence intervals (two standard errors) represented by the dashed lines. If the dashed lines contain zero (that is, cross the horizontal axis), this implies that the effect is statistically insignificant. In each impulse response function graph, the horizontal axis represents the months relative to the shock. Month 1 is the month of the shock; Month 2 is the first month after the shock. The vertical axis in Figure 1 refers to the percentage change in each variable in the months following a one-standard-deviation increase in another variable. The vertical axis in Figure 2 records the magnitude of the accumulated response, measured as a percentage change, from the month of innovation.

In the analysis of impulse response functions, we focus on how variance risk premium affects stock returns and, in turn, how stock returns impact stock liquidity as variance risk premium can capture investors' attitude of risk aversion and consequently allows us to examine how the movement of investors' risk aversion affect stock turns and in turn stock liquidity. In Panel A of Figure 1, we depict how the aggregate stock returns respond to a one-standard-deviation innovation in illiquidity and variance risk premium. The first two figures in Panel A illustrate how a one-standard-deviation increase in illiquidity affects the aggregate stock market returns, and they show that there is no impulse response for stock returns in reaction to illiquidity. This is consistent with our results from the Granger-causality tests - that illiquidity measures for both the aggregate stock market and S&P 500 index portfolios do not cause stock returns. In contrast, the third figure in Panel A shows that the variance risk premium significantly and positively affects stock returns. In response to a one-standard-deviation disturbance in VRP^{BTZ} , stock return starts increasing in the first month, then reaches 1% in the third month, and declines gradually from the fourth month. For the first five months, the impulse response function is above the horizontal line and the standard error lines do not contain zero. This implies that

VRP^{BTZ} has lasting positive effects on stock market returns using conventional confidence intervals. It also indicates that it takes about six months after a shock to variance risk premium on stock returns for the relationships between the two variables to fully play out while all the other variables remain constant. Similar patterns of impulse response are shown for the other two variance risk premium measures, VRP^{CW} and VRP^{DY} . In addition, our results are robust for S&P 500 index returns, as shown in Panel B.

[Insert Figure 1 around here]

Panels C and D of Figure 1 display the response of illiquidity to a one-standard-deviation innovation in stock returns and variance risk premium. We find that a one-standard-deviation disturbance originating from VW and $INDEX$ results in around 1% decrease in stock illiquidity for the first two months, and this decrease starts reducing gradually from the sixth month and then becomes insignificant. However, the impulse response of illiquidity to the variance risk premium measures displays different patterns. The significant impulse response to VRP^{BTZ} cannot be observed in the long run using conventional levels of confidence. The third figure in Panel C shows that one-standard-deviation disturbance originating from VRP^{CW} results in around 1% decrease in illiquidity for the NYSE stocks in the first two months, followed by a long-term impact of VRP^{CW} . The impulse response of illiquidity to VRP^{DY} is significantly positive over the first three months and then becomes insignificant. Panel D reports the results for the illiquidity of the S&P 500 index. Compared with the results in Panel C, the response of illiquidity for the S&P 500 index to the variance risk premium has similar patterns. The response to stock returns is also significant and negative in the first four months and then disappears.

Together, Panels C and D show that stock market returns have a considerable impact on the illiquidity in the short term. In addition, it can be seen that different variance risk premium measures display significant impacts on illiquidity using conventional confidence intervals. Overall, in the short run, both stock returns and most variance risk premium measures can significantly affect illiquidity.

The impulse responses of variance risk premium to illiquidity and stock returns are depicted in Panels E, F, and G, respectively, of Figure 1. It is worth noting that the statistically significant impulse responses of variance risk premium measures to both stock returns and illiquidity cannot be observed. Therefore, it appears that neither stock market returns nor illiquidity affects investors' attitude of risk aversion, measured by variance risk premium.

The cumulative impulse response functions are presented in Figure 2 and confirm the conclusions drawn from Figure 1 that 1) stock returns significantly and positively respond to variance risk premium; 2) illiquidity negatively responds to stock returns and significantly respond to variance risk premium; and 3) however, stock returns and illiquidity do not affect variance risk premium. For example, the third figure in Panel A of Figure 2 illustrates the accumulated response of the aggregate stock market returns to VRP^{BTZ} , and the accumulated impulse response increases to 3% in the first 5 months, which is consistent with the positive impulse response over the same period shown in Panel A of Figure 1.

[Insert Figure 2 around here]

C. Predictability of Variance Risk Premium and Illiquidity

The specification used in the return forecast is presented in equation (5), which regresses excess stock market returns on lagged predictors.

$$R_{t+1} = \alpha + \beta x_t + \varepsilon_t, \quad (5)$$

where R_{t+1} is the excess stock market return at time $t+1$, x_t is the vector of predictors at time t , and the significance of coefficients, β , are used to test the predictive power of predictors over the excess stock returns. In order to test whether illiquidity and variance risk premium are able to predict future excess stock returns, we estimate the regressive model (5) with illiquidity, variance risk premium, a number of economic variables and financial crisis dummy variable as the independent variables. Following Lettau and Ludvigson (2001), Ang and Bekaert (2007), and Bollerslev, Tauchen and Zhou (2009), we consider a set of conventional economic predictors which include price-earnings ratio (PE), price-dividend ratio (PD), default spread ($DFSP$), term spread ($TMSP$), and the stochastically de-trended risk-free rate ($RREL$). Therefore, model (5) can be regarded as a benchmark model when x_t represents financial crisis dummy (FC) and the set of conventional economic predictors. This is expressed as the following equation:

$$R_{t+1} = \alpha + \beta_1 PE_t + \beta_2 PD_t + \beta_3 DFSP_t + \beta_4 TMSP_t + \beta_5 RREL_t + \beta_6 FC_t + \varepsilon_t . \quad (6)$$

To investigate the predictability of variance risk premium and illiquidity (i.e. whether variance risk premium and/or illiquidity can a useful predictor variable), we examine the significance of the coefficients on these two variables by estimating the following multivariate regression models in which the economic predictors, financial crisis dummy and variance risk premium/illiquidity are all incorporated:

$$R_{t+1} = \alpha + \beta_1 VRP_t + \beta_2 PE_t + \beta_3 PD_t + \beta_4 DFSP_t + \beta_5 TMSP_t + \beta_6 RREL_t + \beta_7 FC_t + \beta_8 FC * VRP_t + \varepsilon_t \quad (7)$$

$$R_{t+1} = \alpha + \beta_1 ILLIQ_t + \beta_2 PE_t + \beta_3 PD_t + \beta_4 DFSP_t + \beta_5 TMSP_t + \beta_6 RREL_t + \beta_7 FC_t + \beta_8 FC * VRP_t + \varepsilon_t \quad (8)$$

If variance risk premium or illiquidity has forecasting power for stock returns, we would expect their corresponding coefficients to be statistically significant. Table 5 reports the results for the benchmark model (Panel A) and those for the forecasting power of variance risk premium (Panel B and Panel D) and illiquidity (Panel C and Panel E). We report the estimates and the Newey-West *t*-statistic for coefficients of all the predictors used in the forecasting regressions. The results for the S&P 500 index returns are reported in Panel B and Panel C, and the results for the aggregate stock market returns are presented in Panel D and Panel E.

According to the results in Panel B of Table 5, it appears that the predictability of economic variables in the benchmark model can be enhanced by the incorporation of variance risk premium as the coefficients on all three variance risk premium variables are statistically

positive and significant at the 1% or 5% levels. Moreover, although the coefficients on the financial crisis dummy variable are insignificant, its interaction terms with variance risk premium are all significant at the 1% level for VRP^{CW} and VRP^{DY} . These indicate that the variance risk premium manifests different impact on the forecasting of stock returns. As the coefficient on the financial crisis dummy variable is negative, the increase in stock returns caused by the positive changes in variance risk premium tends to be smaller during the financial crisis period. However, in Panel C of Table 5, the results indicate that the two measures of stock illiquidity except the illiquidity measure of S&P 500 index are not useful for forecasting the aggregate stock market returns of NYSE during the sub-sample period over 1994-2008. These observations are consistent with our previous results in Tables 3 and 5; that variance risk premium can Granger-cause stock returns rather than illiquidity. Similar results can be observed in Panels D and E when S&P 500 index returns are considered for the dependent variable. Table 5 also shows that among the coefficients of economic variables, only the PE ratio shows predictive power for stock return, and this is consistent with the empirical findings of Welch and Goyal (2008) and Bollerslev et al. (2009); that these economic variables show limited predictive power for the excess stock returns. However, it is worth noting that when the variance risk premium is incorporated into the regressions, the value of F-statistic increases remarkably and all coefficients of variance risk premium measures are significant. In contrast, when the illiquidity is incorporated, its coefficient is still insignificant. This implies that there is insufficient evidence for us to reject the null hypothesis that illiquidity can forecast the future excess stock market returns.

[Insert Table 5 around here]

V. Robustness Tests

Previous studies also show that variance risk premium and illiquidity are highly related with equity returns (Smirlock & Starks, 1988; Amihud, 2002; Carr and Wu, 2009). However, we still do not have the detail about whether the significant relation is quasi-rational behavior, or simply serendipitous, or a function of economically rational expectation. In the recent decades, researchers have devoted their efforts to discovering risk factors which can drive the changes in stock returns. Fama and French (1993) and Carhart (1997) demonstrate four key risk factors - market risk premium ($R_m - R_f$), size factor (*SMB*), value factor (*HML*), and the momentum factor (*MOM*). In our main tests, we examine the interrelationships among variance risk premium, stock returns and illiquidity. It is of interest to learn whether the same casual relationships can be found when stock returns are replaced by these risk factors, and we use these tests as the robustness tests for our main findings. In other words, here, we investigate the interrelationships among risk factors (instead of stock returns), variance risk premium and illiquidity if these risk factors are truly the drivers of stock returns. Following the findings in Tables 3, 4 and 5, we conjecture that variance risk premium Granger-causes stock returns via the risk factors and, in turn, stock illiquidity; and the risk factors also cause stock illiquidity rather than vice versa. More specifically, we investigate whether the variance risk premium and illiquidity have a systematic and interrelationship with the Fama-French three factors, (i.e. market risk premium ($R_m - R_f$), size factor (*SMB*), value factor (*HML*), and the momentum factor (*MOM*)). To implement the investigation, we apply the Granger-causality test again between variance risk premium (illiquidity) and the four risk factors ($R_m - R_f$, *SMB*, *HML* and *MOM*). We present the results of the Granger-causality tests without conventional economic predictors in

Table 6. On the one hand, Panel A of Table 6 shows that the changes in variance risk premium affect the variation in the market risk premium, value factor and momentum factor for the full sample period and most of the sub-sample periods but not the size factor. More specifically, nine out of 12 likelihood ratio statistics for testing the hypothesis that variance risk premium does not cause market risk premium are statistically significant. Similarly, for value factor and momentum factor, there are nine significant statistics out of 12, while only five out of 12 statistics are significant for the size factor. On the other hand, there is limited evidence to reject the null hypothesis that the four risk factors do not cause variance risk premium as most of the likelihood ratio statistics are insignificant. Panel B of Table 6 demonstrates that there is one-way causality running from market risk premium and momentum to illiquidity. In other words, the fluctuation in stock returns drives the changes in liquidity via these two factors - the market risk premium and momentum. For the causal relationships between illiquidity and the size and value factors, scant supportive evidence can be found in Table 6. More importantly, consistent with the results of stock returns, there is no evidence showing the casual relationship running from illiquidity to any of the risk factors.

[Insert Table 6 around here]

Table 7 reports the results for the Granger-causality test with conventional economic predictors including price-earnings ratio, price-dividend ratio, default spread, term spread, and the stochastically de-trended risk-free rate. The results are similar to those reported in Table 6. In Table 7, we find significant one-way Granger-causality relationship running from the variance risk premium to market risk premium, value factor and momentum factors in all the periods.

Similar results can also be found for testing the interrelationships between illiquidity and the four risk factors. The only difference is that the value factor can cause the changes in illiquidity which is not found in Panel A and Table 6, and this further supports our main findings in Tables 3, 4 and 5.

To summarise, consistent with our conjecture that variance risk premium Granger-causes market risk premium, value factor and momentum factor, and in turns affects stock returns and illiquidity. In particular, this result is remarkable for the market risk premium and the momentum factor. This indicates that the variance risk premium affects stock returns as its changes are driven systematically by time-varying market risk premium, value factor and momentum factor. The results show that illiquidity does not Granger-cause any of the risk factors. This implies that illiquidity does not affect stock returns through the risk factors included in the augmented Fama and French (1993) model. Conversely, market risk premium, value factor and momentum factor can Granger-cause the illiquidity.

[Insert Table 7 around here]

VI. Conclusion

Researchers, investment managers and regulators have paid much attention and regularly devote their great efforts to forecasting future stock returns. In the literature, both variance risk premium (an indicator of investors' attitude of risk aversion) and stock illiquidity can be useful variables to explain the innovation in stock returns. However, the interrelationships among them

and their predictive powers to stock returns are still inconclusive. This study has addressed this research gap, by investigating the interrelationships among variance risk premium, liquidity, and stock returns using the US monthly data from January 1992 to December 2010. We find that the variance risk premium can Granger-cause stock returns and, in turn, illiquidity, but this conclusion does not hold if reversed. Similarly, our results also indicate that there is a casual relationship running from stock returns to illiquidity rather than vice versa. More importantly, stock illiquidity does not affect variance risk premium or stock returns. Our results are robust for the whole sample period and different sub-sample periods.

The impulse response function graphs show that 1) stock returns significantly and positively respond to the changes in investors' attitude of risk aversion measured by variance risk premium in the short run of four to six months; 2) illiquidity statistically and significantly responds to the innovations in both stock returns and variance risk premium; and 3) stock returns and illiquidity do not affect variance risk premium in both short- and long-run periods. More importantly, according to the findings in the Granger causality test and the impulse response function graphs, we further examine the forecasting power of variance risk premium and stock illiquidity on stock returns. Following previous forecasting literature (Lettau and Ludvigson, 2001, Ang and Bekaert, 2007, and Bollerslev, Tauchen, and Zhou, 2009), we incorporate a set of conventional economic predictors including price-earnings ratio (PE), price-dividend ratio (PD), default spread ($DFSP$), term spread ($TMSP$), and the stochastically de-trended risk-free rate ($RREL$). In line with the results of Granger causality tests and impulse response functions, it is apparent that investors' attitude of risk aversion, proxied by variance risk premium, shows a strong predictive power for future excess stock returns, while such evidence for illiquidity is scant. These results further confirm our contention that investors' attitude of risk aversion, in the

form of variance risk premium, is a useful predictive variable for stock returns but not stock illiquidity.

Finally, we examine the channels along which variance risk premium and stock illiquidity can affect stock returns by investigating the Granger-causality relationships between variance risk premium and systematic risk factors and between illiquidity and systematic risk factors contained in the augmented Fama and French (1993) model. It is intriguing that changes in variance risk premium trigger variations in the market risk premium, value factor and momentum factor statistically; and also there is a causal relationship running from these four systematic risk factors to stock illiquidity. Nevertheless, no supportive evidence is found for the causal relationships running from the four systematic risk factors to variance risk premium and from stock illiquidity to the four systematic risk factors. These findings imply that variance risk premium mainly drives stock returns via time-varying market risk premium, value and momentum factors. Finally, illiquidity cannot affect stock returns by acting on the risk factors included in the Carhart (1997) four-factor model.

TABLE 1**Summary Statistics**

This table shows the summary statistics of the variables used in this study. The variables are liquidity measures ($ILLIQ^{NYSE}$ and $ILLIQ^{SP500}$), variance risk premium (VRP^{BTZ} , VRP^{CW} and VRP^{DY}), return proxies (VW and $INDEX$) and control variables (PD , PE , $DFSP$, $TMSP$ and $RREL$). The analysis uses monthly data from January 1992 to December 2010.

	$ILLIQ^{NYSE}$	$ILLIQ^{SP500}$	VW	$INDEX$	VRP^{BTZ}	VRP^{CW}	VRP^{DY}	PD	PE	$DFSP$	$TMSP$	$RREL$
Mean	-2.39	-7.25	0.50	0.39	17.93	17.92	18.51	3.97	3.19	0.94	1.86	-0.15
Median	-2.05	-7.10	0.97	0.94	13.79	14.94	12.44	4.01	3.12	0.83	1.78	-0.05
Maximum	0.06	-4.99	9.59	9.07	116.52	124.45	206.57	4.49	4.81	3.38	3.76	1.86
Minimum	-4.71	-9.24	-16.86	-18.58	-180.68	-350.28	-41.73	3.38	2.71	0.55	-0.53	-2.51
Std. Dev.	1.20	1.15	4.32	4.38	20.95	32.80	22.83	0.28	0.41	0.45	1.23	0.90
Skewness	-0.16	0.09	-0.70	-0.90	-2.77	-6.07	3.84	-0.12	2.00	3.13	-0.13	-0.58
Kurtosis	2.03	1.90	4.17	4.76	39.57	72.55	27.03	2.19	7.91	14.49	1.72	3.04
Jarque-Bera	9.88	11.93	31.50	60.11	12993.74	47146.38	6044.01	6.80	381.29	1627.72	16.26	12.60
Probability	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00
Autocorrelation												
Q-statistics (1 lag)	189.82	191.83	1.67	2.06	18.66	18.02	20.08	185.62	177.39	160.75	181.05	170.00
P-value	0.00	0.00	0.20	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

TABLE 2

Correlation Matrix

This table shows the correlations among the variables used in this study. The variables are liquidity measures ($ILLIQ^{NYSE}$ and $ILLIQ^{SP500}$), variance risk premium (VRP^{BTZ} , VRP^{CW} and VRP^{DY}), return proxies (VW and $INDEX$) and control variables (PD , PE , $DFSP$, $TMSP$ and $RREL$). The analysis uses monthly data from January 1992 to December 2010. The 1%, 5% and 10% significance levels are denoted by ***, ** and * respectively.

	$ILLIQ^{NYSE}$	$ILLIQ^{SP500}$	VW	$INDEX$	VRP^{BTZ}	VRP^{CW}	VRP^{DY}	PD	PE	$DFSP$	$TMSP$	$RREL$
$ILLIQ^{NYSE}$	1.000											
$ILLIQ^{SP500}$	0.954*** (48.023)	1.000										
VW	-0.015 (-0.229)	0.020 (0.297)	1.000									
$INDEX$	-0.016 (-0.238)	0.020 (0.308)	0.999*** (333.060)	1.000								
VRP^{BTZ}	0.045 (0.672)	0.008 (0.113)	0.001 (0.016)	0.004 (0.054)	1.000							
VRP^{CW}	0.102 (1.543)	0.070 (1.056)	0.009 (0.134)	0.006 (0.097)	0.283*** (4.420)	1.000						
VRP^{DY}	-0.007 (-0.099)	-0.045 (-0.680)	-0.558*** (-10.106)	-0.582*** (-10.761)	0.085 (1.276)	0.097 (1.466)	1.000					
PD	-0.253*** (-3.937)	-0.339*** (-5.416)	0.089 (1.345)	0.087 (1.314)	0.161** (2.450)	0.047 (0.713)	0.035 (0.528)	1.000				
PE	0.129* (1.954)	-0.010 (-0.156)	-0.052 (-0.778)	-0.065 (-0.973)	0.231*** (3.565)	0.296*** (4.643)	0.296*** (4.662)	0.044 (0.662)	1.000			
$DFSP$	-0.214*** (-3.285)	-0.312*** (-4.938)	-0.154** (-2.344)	-0.168** (-2.556)	0.025 (0.383)	0.192*** (2.936)	0.237*** (3.670)	-0.287*** (-4.508)	0.690*** (14.327)	1.000		
$TMSP$	0.259*** (4.031)	0.179*** (2.727)	-0.049 (-0.736)	-0.048 (-0.719)	-0.009 (-0.133)	0.032 (0.485)	0.017 (0.249)	-0.505*** (-8.804)	0.216*** (3.329)	0.294*** (4.631)	1.000	
$RREL$	-0.159** (-2.426)	-0.013 (-0.190)	0.096 (1.457)	0.100 (1.507)	-0.258*** (-4.011)	-0.183*** (-2.799)	-0.122* (-1.851)	0.123* (1.864)	-0.611*** (-11.612)	-0.492*** (-8.485)	-0.369*** (-5.965)	1.000

TABLE 3

Granger-Causality Test without Control Variables

This table presents the p-value of the chi-square statistics for the Granger-causality tests between variance risk premium and stock returns (reported in Panel A), between illiquidity and stock returns (reported in Panel A), and between variance risk premium and illiquidity (reported in Panel B). The analysis uses monthly data from the full sample period January 1992 to December 2010, sub-period January 1992-December 2006, sub-period January 1994-December 2008, and sub-period January 1996-December 2010.

Panel A. *VRP* & Stock Return, *ILLIQ* & Stock Return

X2	X1	VW		INDEX	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1
<i>VRP^{BTZ}</i>	1992-2010	0.634	0.000	0.612	0.000
	1992-2006	0.328	0.001	0.190	0.001
	1994-2008	0.305	0.005	0.443	0.007
	1996-2010	0.187	0.001	0.203	0.000
<i>VRP^{CW}</i>	1992-2010	0.164	0.000	0.110	0.000
	1992-2006	0.476	0.000	0.388	0.000
	1994-2008	0.729	0.000	0.643	0.000
	1996-2010	0.029	0.000	0.018	0.000
<i>VRP^{DY}</i>	1992-2010	0.421	0.007	0.428	0.006
	1992-2006	0.181	0.071	0.195	0.098
	1994-2008	0.388	0.658	0.414	0.599
	1996-2010	0.428	0.015	0.427	0.022
<i>ILLIQ^{NYSE}</i>	1992-2010	0.000	0.470	0.000	0.467
	1992-2006	0.000	0.974	0.000	0.940
	1994-2008	0.000	0.168	0.000	0.192
	1996-2010	0.000	0.463	0.000	0.520
<i>ILLIQ^{SP500}</i>	1992-2010	0.000	0.287	0.000	0.278
	1992-2006	0.000	0.408	0.000	0.413
	1994-2008	0.000	0.044	0.000	0.052
	1996-2010	0.000	0.213	0.000	0.249

Panel B. *VRP* & *ILLIQ*

X2	X1	<i>VRP^{BTZ}</i>		<i>VRP^{CW}</i>		<i>VRP^{DY}</i>	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1	X1->X2	X2->X1
<i>ILLIQ^{NYSE}</i>	1992-2010	0.036	0.685	0.000	0.409	0.000	0.802
	1992-2006	0.002	0.444	0.084	0.464	0.000	0.880
	1994-2008	0.087	0.271	0.000	0.018	0.000	0.886
	1996-2010	0.035	0.004	0.000	0.032	0.000	0.620
<i>ILLIQ^{SP500}</i>	1992-2010	0.158	0.768	0.000	0.574	0.000	0.179
	1992-2006	0.000	0.446	0.000	0.674	0.000	0.651
	1994-2008	0.082	0.354	0.000	0.048	0.000	0.536
	1996-2010	0.900	0.005	0.000	0.050	0.000	0.246

TABLE 4

Granger-Causality Test with Control Variables

This table presents the p-value of the chi-square statistics for the Granger-causality tests with control variables (*PD*, *PE*, *DFSP*, *TMSP* and *RREL*) between variance risk premium and stock return (reported in Panel A), between illiquidity and stock return (reported in Panel A), and between variance risk premium and illiquidity (reported in Panel B). The analysis uses monthly data from full sample period January 1992 to December 2010, sub-period January 1992-December 2006, sub-period January 1994-December 2008, and sub-period January 1996-December 2010.

Panel A. *VRP* & Stock Return, *ILLIQ* & Stock Return,

X2	X1	VW		INDEX	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1
<i>VRP^{BTZ}</i>	1992-2010	0.205	0.000	0.216	0.000
	1992-2006	0.255	0.000	0.249	0.000
	1994-2008	0.231	0.043	0.182	0.060
	1996-2010	0.224	0.000	0.237	0.000
<i>VRP^{CW}</i>	1992-2010	0.596	0.000	0.504	0.000
	1992-2006	0.432	0.000	0.359	0.000
	1994-2008	0.911	0.000	0.870	0.000
	1996-2010	0.615	0.000	0.532	0.000
<i>VRP^{DY}</i>	1992-2010	0.339	0.000	0.354	0.000
	1992-2006	0.732	0.001	0.763	0.002
	1994-2008	0.173	0.000	0.179	0.000
	1996-2010	0.447	0.002	0.466	0.002
<i>ILLIQ^{NYSE}</i>	1992-2010	0.000	0.967	0.000	0.984
	1992-2006	0.000	0.275	0.000	0.319
	1994-2008	0.000	0.147	0.000	0.143
	1996-2010	0.000	0.943	0.000	0.868
<i>ILLIQ^{SP500}</i>	1992-2010	0.000	0.684	0.000	0.734
	1992-2006	0.000	0.128	0.000	0.258
	1994-2008	0.000	0.012	0.000	0.012
	1996-2010	0.000	0.654	0.000	0.730

Panel B. *VRP* & *ILLIQ*

X2	X1	<i>VRP^{BTZ}</i>		<i>VRP^{CW}</i>		<i>VRP^{DY}</i>	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1	X1->X2	X2->X1
<i>ILLIQ^{NYSE}</i>	1992-2010	0.086	0.920	0.000	0.606	0.000	0.944
	1992-2006	0.002	0.475	0.003	0.832	0.000	0.541
	1994-2008	0.009	0.068	0.000	0.837	0.000	0.136
	1996-2010	0.114	0.255	0.000	0.364	0.000	0.282
<i>ILLIQ^{SP500}</i>	1992-2010	0.837	0.681	0.000	0.576	0.000	0.353
	1992-2006	0.000	0.323	0.001	0.608	0.000	0.380
	1994-2008	0.013	0.020	0.000	0.832	0.000	0.145
	1996-2010	0.837	0.681	0.000	0.289	0.000	0.173

TABLE 5

Stock Return Predictive Power of Variance Risk Premium and Illiquidity

This table presents the results for the predictive power of variance risk premium (Panel B and Panel D) and illiquidity (Panel C and Panel E). Panel A reports the estimation of the benchmark model. The dependent variable is market excess return (*VW* and *INDEX*), the independent variables are the lagged (once) VRP (*VRP^{BTZ}*, *VRP^{CW}* and *VRP^{DV}*), ILLIQ (*ILLIQ^{NYSE}* and *ILLIQ^{SP500}*), control variables (*PE*, *PD*, *DFSP*, *TMSP* and *RREL*), 2007-2008 financial crisis dummy and the slope dummy (interaction term between financial crisis dummy and VRP, ILLIQ). The corresponding Newey-West *t*-values are reported in parentheses and the F statistics are reported in the last column. The significance levels of 1%, 5% and 10% are denoted by ***, ** and * respectively.

Panel A. Benchmark model

	<i>Dep.</i>	Cons	<i>PD</i>	<i>PE</i>	<i>DFSP</i>	<i>TMSP</i>	<i>RREL</i>	<i>FC</i>	<i>F</i>
1992-2010	<i>VW</i>	3.772 (0.69)	-0.714 (-0.55)	0.062 (0.04)	0.281 (0.19)	-0.276 (-0.72)	0.136 (0.26)	-2.827* (-1.81)	1.144
1992-2006	<i>VW</i>	2.647 (0.50)	0.610 (0.36)	-1.136 (-0.42)	-1.139 (-0.53)	0.035 (0.10)	0.190 (0.30)		0.494
1994-2008	<i>VW</i>	3.088 (0.53)	1.712 (0.91)	-2.807 (-1.21)	-0.462 (-0.25)	-0.094 (-0.26)	-0.182 (-0.34)	-2.019 (-1.48)	1.442
1996-2010	<i>VW</i>	8.647 (0.96)	-2.079 (-0.93)	0.493 (0.31)	-0.593 (-0.33)	-0.168 (-0.38)	0.165 (0.25)	-2.759 (-1.65)	1.135
1992-2010	<i>INDEX</i>	4.075 (0.75)	-0.794 (-0.61)	0.061 (0.04)	0.170 (0.11)	-0.267 (-0.68)	0.148 (0.28)	-2.878* (-1.77)	1.143
1992-2006	<i>INDEX</i>	3.235 (0.62)	0.690 (0.40)	-1.479 (-0.54)	-1.103 (-0.51)	0.062 (0.18)	0.154 (0.24)		0.543
1994-2008	<i>INDEX</i>	3.369 (0.58)	1.865 (0.98)	-3.153 (-1.34)	-0.393 (-0.21)	-0.082 (-0.22)	-0.203 (-0.38)	-2.133 (-1.52)	1.499
1996-2010	<i>INDEX</i>	8.727 (0.97)	-2.108 (-0.94)	0.488 (0.31)	-0.678 (-0.37)	-0.158 (-0.35)	0.188 (0.28)	-2.799 (-1.61)	1.125

Panel B. Predictive Power of *VRP* for *VW*

	<i>Dep.</i>	<i>Cons</i>	<i>PD</i>	<i>PE</i>	<i>DFSP</i>	<i>TMSP</i>	<i>RREL</i>	<i>FC</i>	<i>VRP^{BTZ}</i>	<i>FC_VRP^{BTZ}</i>	<i>VRP^{CW}</i>	<i>FC_VRP^{CW}</i>	<i>VRP^{DY}</i>	<i>FC_VRP^{DY}</i>	<i>F</i>
1992-2010	<i>VW</i>	3.549 (0.65)	-0.904 (-0.70)	-0.078 (-0.05)	0.083 (0.06)	-0.066 (-0.17)	0.654 (1.24)	-1.160 (-0.77)	0.064*** (3.25)	-0.024 (-1.08)					14.661***
1992-2006	<i>VW</i>	5.479 (1.01)	1.133 (0.67)	-3.434 (-1.21)	-0.047 (-0.02)	0.205 (0.62)	0.199 (0.31)		0.065*** (2.90)						2.079*
1994-2008	<i>VW</i>	3.512 (0.60)	2.658 (1.21)	-5.085 (-1.62)	1.230 (0.65)	0.050 (0.14)	0.032 (0.05)	-1.199 (-0.85)	0.070*** (3.02)	-0.057 (-1.64)					9.701***
1996-2010	<i>VW</i>	3.224 (0.38)	-1.102 (-0.51)	0.262 (0.16)	-0.219 (-0.12)	0.084 (0.19)	0.880 (1.27)	-0.784 (-0.48)	0.067*** (3.33)	-0.024 (-1.05)					14.739***
1992-2010	<i>VW</i>	4.731 (0.93)	-0.781 (-0.67)	-0.713 (-0.49)	-1.244 (-0.98)	0.152 (0.44)	0.735 (1.50)	0.807 (0.65)			0.118*** (7.48)	-0.073*** (-4.47)			47.291***
1992-2006	<i>VW</i>	7.387 (1.44)	1.409 (0.94)	-4.841* (-1.95)	0.054 (0.03)	0.384 (1.28)	0.323 (0.59)				0.122*** (6.12)				9.296***
1994-2008	<i>VW</i>	3.505 (0.63)	4.341*** (2.75)	-7.864*** (-3.47)	1.485 (0.93)	0.409 (1.33)	0.142 (0.33)	0.395 (0.38)			0.131*** (6.09)	-0.083*** (-3.82)			21.667***
1996-2010	<i>VW</i>	3.947 (0.49)	-0.888 (-0.43)	-0.361 (-0.22)	-1.570 (-0.97)	0.334 (0.84)	1.006 (1.59)	1.282 (0.91)			0.121*** (7.32)	-0.076*** (-4.44)			45.164***
1992-2010	<i>VW</i>	2.078 (0.38)	-0.986 (-0.76)	0.652 (0.44)	0.007 (0.00)	-0.024 (-0.07)	0.747 (1.58)	0.189 (0.14)					0.039** (2.09)	-0.102*** (-3.30)	1.933*
1992-2006	<i>VW</i>	4.693 (0.86)	0.946 (0.57)	-2.624 (-0.95)	-0.875 (-0.42)	0.196 (0.58)	0.189 (0.30)						0.048*** (2.74)		1.799*
1994-2008	<i>VW</i>	2.284 (0.38)	0.979 (0.49)	-2.094 (-0.74)	0.108 (0.06)	0.025 (0.07)	0.416 (0.72)	0.218 (0.16)					0.048*** (2.66)	-0.098*** (-2.96)	2.295**
1996-2010	<i>VW</i>	4.309 (0.49)	-1.886 (-0.86)	1.215 (0.75)	-0.702 (-0.39)	0.153 (0.36)	0.995 (1.62)	0.630 (0.44)					0.040** (2.11)	-0.107*** (-3.39)	1.915*

Panel C. Predictive Power of *ILLIQ* for *VW*

	<i>Dep.</i>	<i>Cons</i>	<i>PD</i>	<i>PE</i>	<i>DFSP</i>	<i>TMSP</i>	<i>RREL</i>	<i>FC</i>	<i>ILLIQ</i> ^{NYSE}	<i>FC_ILLIQ</i> ^{NYSE}	<i>ILLIQ</i> ^{SP500}	<i>FC_ILLIQ</i> ^{SP500}	<i>F</i>
1992-2010	<i>VW</i>	3.371 (0.59)	-0.939 (-0.58)	0.254 (0.17)	0.618 (0.32)	-0.190 (-0.51)	0.231 (0.45)	-15.066 (-1.37)	-0.104 (-0.27)	-2.989 (-1.17)			0.877
1992-2006	<i>VW</i>	1.554 (0.29)	2.881 (0.94)	-3.591 (-0.88)	-0.108 (-0.04)	0.095 (0.28)	0.149 (0.23)		0.603 (0.98)				0.529
1994-2008	<i>VW</i>	1.651 (0.26)	4.382 (1.09)	-5.649 (-1.29)	0.782 (0.29)	-0.019 (-0.05)	-0.221 (-0.41)	0.568 (0.03)	0.724 (1.12)	0.346 (0.09)			1.529
1996-2010	<i>VW</i>	7.104 (0.73)	-1.920 (-0.84)	0.535 (0.34)	0.062 (0.03)	-0.052 (-0.12)	0.333 (0.47)	-15.750 (-1.37)	0.018 (0.03)	-3.231 (-1.19)			0.827
1992-2010	<i>VW</i>	2.885 (0.53)	-0.398 (-0.23)	-0.069 (-0.04)	1.092 (0.52)	-0.174 (-0.47)	0.271 (0.54)	-34.060 (-1.36)			0.121 (0.30)	-3.612 (-1.28)	0.854
1992-2006	<i>VW</i>	3.736 (0.71)	4.885 (1.47)	-5.441 (-1.33)	1.558 (0.52)	0.185 (0.53)	-0.080 (-0.13)			1.027 (1.63)			0.721
1994-2008	<i>VW</i>	4.045 (0.69)	6.670* (1.74)	-7.579* (-1.91)	2.487 (0.85)	0.098 (0.26)	-0.425 (-0.83)	-0.292 (-0.01)			1.230** (2.01)	0.054 (0.02)	1.968*
1996-2010	<i>VW</i>	11.095 (1.11)	-1.819 (-0.82)	0.116 (0.07)	0.540 (0.25)	0.049 (0.11)	0.433 (0.65)	-39.881 (-1.48)			0.491 (0.88)	-4.337 (-1.43)	0.868

Panel D. Predictive Power of *VRP* for *INDEX*

	<i>Dep.</i>	<i>Cons</i>	<i>PD</i>	<i>PE</i>	<i>DFSP</i>	<i>TMSP</i>	<i>RREL</i>	<i>FC</i>	<i>VRP^{BTZ}</i>	<i>FC_VRP^{BTZ}</i>	<i>VRP^{CW}</i>	<i>FC_VRP^{CW}</i>	<i>VRP^{DY}</i>	<i>FC_VRP^{DY}</i>	<i>F</i>
1992-2010	<i>INDEX</i>	3.821 (0.70)	-0.979 (-0.75)	-0.058 (-0.04)	-0.016 (-0.01)	-0.065 (-0.17)	0.651 (1.22)	-1.282 (-0.81)	0.061*** (3.09)	-0.021 (-0.96)					12.828***
1992-2006	<i>INDEX</i>	5.991 (1.12)	1.199 (0.70)	-3.716 (-1.30)	-0.040 (-0.02)	0.228 (0.68)	0.162 (0.25)		0.063*** (2.84)						2.033*
1994-2008	<i>INDEX</i>	3.830 (0.66)	2.853 (1.26)	-5.477* (-1.71)	1.262 (0.65)	0.062 (0.17)	-0.015 (-0.02)	-1.330 (-0.91)	0.069*** (2.98)	-0.058 (-1.63)					8.538***
1996-2010	<i>INDEX</i>	3.479 (0.41)	-1.177 (-0.55)	0.286 (0.18)	-0.317 (-0.17)	0.087 (0.19)	0.886 (1.26)	-0.899 (-0.52)	0.064*** (3.19)	-0.021 (-0.93)					12.960***
1992-2010	<i>INDEX</i>	4.995 (0.98)	-0.855 (-0.72)	-0.710 (-0.48)	-1.374 (-1.06)	0.169 (0.48)	0.755 (1.53)	0.782 (0.61)			0.118*** (7.50)	-0.069*** (-4.22)			52.829***
1992-2006	<i>INDEX</i>	8.002 (1.58)	1.493 (0.99)	-5.205** (-2.08)	0.097 (0.05)	0.413 (1.35)	0.288 (0.53)				0.123*** (6.17)				9.785***
1994-2008	<i>INDEX</i>	3.705 (0.68)	4.573*** (2.86)	-8.298*** (-3.62)	1.539 (0.96)	0.441 (1.41)	0.129 (0.30)	0.341 (0.33)			0.132*** (6.17)	-0.080*** (-3.69)			24.318***
1996-2010	<i>INDEX</i>	4.110 (0.51)	-0.946 (-0.46)	-0.351 (-0.21)	-1.696 (-1.02)	0.355 (0.87)	1.044 (1.63)	1.276 (0.89)			0.122*** (7.32)	-0.072*** (-4.20)			50.322***
1992-2010	<i>INDEX</i>	2.258 (0.42)	-1.062 (-0.81)	0.691 (0.47)	-0.085 (-0.06)	-0.015 (-0.04)	0.770 (1.62)	0.172 (0.13)					0.037* (1.97)	-0.103*** (-3.08)	1.774*
1992-2006	<i>INDEX</i>	5.234 (0.97)	1.018 (0.61)	-2.933 (-1.05)	-0.845 (-0.40)	0.220 (0.64)	0.153 (0.24)						0.047*** (2.70)		1.783*
1994-2008	<i>INDEX</i>	2.494 (0.42)	1.059 (0.52)	-2.310 (-0.79)	0.156 (0.09)	0.034 (0.09)	0.415 (0.72)	0.149 (0.11)					0.047*** (2.62)	-0.099*** (-2.77)	2.221**
1996-2010	<i>INDEX</i>	4.424 (0.51)	-1.956 (-0.89)	1.264 (0.78)	-0.791 (-0.43)	0.166 (0.39)	1.034* (1.68)	0.633 (0.43)					0.038** (2.00)	-0.108*** (-3.18)	1.759*

Panel E. Predictive Power of *ILLIQ* for *INDEX*

	<i>Dep.</i>	<i>Cons</i>	<i>PD</i>	<i>PE</i>	<i>DFSP</i>	<i>TMSP</i>	<i>RREL</i>	<i>FC</i>	<i>ILLIQ</i> ^{NYSE}	<i>FC_ILLIQ</i> ^{NYSE}	<i>ILLIQ</i> ^{SP500}	<i>FC_ILLIQ</i> ^{SP500}	<i>F</i>
1992-2010	<i>INDEX</i>	3.756 (0.65)	-1.088 (-0.67)	0.299 (0.20)	0.466 (0.23)	-0.179 (-0.47)	0.238 (0.46)	-15.649 (-1.35)	-0.137 (-0.36)	-3.109 (-1.16)			0.874
1992-2006	<i>INDEX</i>	2.220 (0.43)	2.800 (0.90)	-3.761 (-0.91)	-0.145 (-0.05)	0.118 (0.34)	0.116 (0.18)		0.560 (0.90)				0.545
1994-2008	<i>INDEX</i>	2.090 (0.33)	4.245 (1.02)	-5.692 (-1.26)	0.815 (0.30)	-0.018 (-0.04)	-0.226 (-0.42)	-0.493 (-0.03)	0.669 (1.01)	0.142 (0.04)			1.551
1996-2010	<i>INDEX</i>	6.570 (0.67)	-1.881 (-0.82)	0.581 (0.37)	-0.033 (-0.02)	-0.048 (-0.11)	0.331 (0.46)	-16.174 (-1.34)	-0.053 (-0.09)	-3.302 (-1.17)			0.822
1992-2010	<i>INDEX</i>	3.207 (0.59)	-0.574 (-0.33)	-0.018 (-0.01)	0.917 (0.43)	-0.167 (-0.44)	0.281 (0.55)	-34.920 (-1.33)			0.086 (0.21)	-3.701 (-1.26)	0.847
1992-2006	<i>INDEX</i>	4.298 (0.82)	4.862 (1.44)	-5.682 (-1.36)	1.529 (0.50)	0.209 (0.59)	-0.110 (-0.17)			1.002 (1.58)			0.729
1994-2008	<i>INDEX</i>	4.327 (0.75)	6.640* (1.71)	-7.748* (-1.91)	2.502 (0.84)	0.102 (0.26)	-0.434 (-0.84)	-1.360 (-0.04)		1.196* (1.93)	-0.050 (-0.01)		1.958*
1996-2010	<i>INDEX</i>	10.515 (1.05)	-1.856 (-0.83)	0.175 (0.11)	0.401 (0.18)	0.047 (0.10)	0.442 (0.65)	-40.256 (-1.44)		0.418 (0.74)	-4.368 (-1.38)		0.842

TABLE 6

Variance Risk Premium, Illiquidity, and Risk Factors

This table presents the p-value of the chi-square statistics for the Granger-causality tests between *VRP* and risk factors ($R_m - R_f$, *SMB*, *HML* and *MOM*) (reported in Panel A), and between illiquidity and risk factors ($R_m - R_f$, *SMB*, *HML* and *MOM*) (reported in Panel B). The analysis uses monthly data from the full sample period January 1992 to December 2010, sub-period January 1992-December 2006, sub-period January 1994-December 2008, and sub-period January 1996-December 2010.

Panel A. *VRP* & Risk Factors ($R_m - R_f$, *SMB*, *HML* and *MOM*)

X2	X1	<i>VRP</i> ^{BTZ}		<i>VRP</i> ^{CW}		<i>VRP</i> ^{DY}	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1	X1->X2	X2->X1
$R_m - R_f$	1992-2010	0.000	0.597	0.000	0.110	0.007	0.523
	1992-2006	0.004	0.284	0.000	0.064	0.061	0.249
	1994-2008	0.007	0.534	0.000	0.539	0.693	0.554
	1996-2010	0.000	0.207	0.000	0.018	0.015	0.542
<i>SMB</i>	1992-2010	0.428	0.389	0.076	0.137	0.088	0.769
	1992-2006	0.781	0.200	0.062	0.014	0.253	0.784
	1994-2008	0.510	0.147	0.116	0.100	0.067	0.713
	1996-2010	0.504	0.365	0.112	0.143	0.075	0.887
<i>HML</i>	1992-2010	0.048	0.024	0.004	0.416	0.001	0.984
	1992-2006	0.004	0.190	0.001	0.689	0.006	0.373
	1994-2008	0.469	0.438	0.202	0.730	0.003	0.978
	1996-2010	0.581	0.011	0.006	0.388	0.001	0.882
<i>MOM</i>	1992-2010	0.001	0.328	0.003	0.219	0.000	0.596
	1992-2006	0.000	0.669	0.287	0.396	0.019	0.277
	1994-2008	0.266	0.049	0.145	0.112	0.039	0.501
	1996-2010	0.007	0.410	0.011	0.311	0.002	0.602

Panel B: *ILLIQ* & Risk Factors ($R_m - R_f$, *SMB*, *HML* and *MOM*)

X2	X1	<i>ILLIQ</i> ^{NYSE}		<i>ILLIQ</i> ^{SP500}	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1
$R_m - R_f$	1992-2010	0.501	0.000	0.373	0.000
	1992-2006	0.917	0.000	0.454	0.000
	1994-2008	0.203	0.000	0.231	0.000
	1996-2010	0.550	0.000	0.348	0.000
<i>SMB</i>	1992-2010	0.121	0.161	0.265	0.115
	1992-2006	0.639	0.037	0.354	0.782
	1994-2008	0.275	0.254	0.732	0.617
	1996-2010	0.610	0.129	0.776	0.818
<i>HML</i>	1992-2010	0.475	0.080	0.812	0.133
	1992-2006	0.998	0.002	0.605	0.016
	1994-2008	0.798	0.008	0.362	0.079
	1996-2010	0.951	0.188	0.524	0.322
<i>MOM</i>	1992-2010	0.951	0.000	0.929	0.000
	1992-2006	0.796	0.000	0.874	0.000
	1994-2008	0.715	0.000	0.709	0.000
	1996-2010	0.712	0.000	0.837	0.000

TABLE 7

Variance Risk Premium, Illiquidity, and Risk Factors with Control Variables

This table presents the p-value of the chi-square statistics for the Granger-causality tests with control variables (*PD*, *PE*, *DFSP*, *TMSP* and *RREL*) between *VRP* and risk factors ($R_m - R_f$, *SMB*, *HML* and *MOM*) (reported in Panel A), and between illiquidity and risk factors ($R_m - R_f$, *SMB*, *HML* and *MOM*) (reported in Panel B). The analysis uses monthly data from the full sample period January 1992 to December 2010, sub-period January 1992-December 2006, sub-period January 1994-December 2008, and sub-period January 1996-December 2010.

Panel A. *VRP* & Risk Factors ($R_m - R_f$, *SMB*, *HML* and *MOM*)

X2	X1	<i>VRP</i> ^{BTZ}		<i>VRP</i> ^{CW}		<i>VRP</i> ^{DY}	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1	X1->X2	X2->X1
$R_m - R_f$	1992-2010	0.000	0.223	0.000	0.444	0.001	0.427
	1992-2006	0.000	0.354	0.000	0.167	0.008	0.862
	1994-2008	0.054	0.211	0.000	0.775	0.000	0.263
	1996-2010	0.000	0.238	0.000	0.021	0.003	0.531
<i>SMB</i>	1992-2010	0.745	0.274	0.339	0.035	0.037	0.527
	1992-2006	0.638	0.055	0.498	0.009	0.362	0.558
	1994-2008	0.666	0.071	0.404	0.051	0.019	0.802
	1996-2010	0.648	0.471	0.219	0.070	0.069	0.959
<i>HML</i>	1992-2010	0.044	0.002	0.006	0.307	0.000	0.835
	1992-2006	0.003	0.147	0.000	0.830	0.006	0.223
	1994-2008	0.256	0.182	0.043	0.679	0.015	0.967
	1996-2010	0.352	0.005	0.012	0.373	0.000	0.832
<i>MOM</i>	1992-2010	0.000	0.197	0.001	0.191	0.006	0.131
	1992-2006	0.000	0.073	0.052	0.688	0.000	0.286
	1994-2008	0.040	0.112	0.076	0.067	0.003	0.221
	1996-2010	0.001	0.339	0.005	0.432	0.015	0.052

Panel B. *ILLIQ* & Risk Factors ($R_m - R_f$, *SMB*, *HML* and *MOM*)

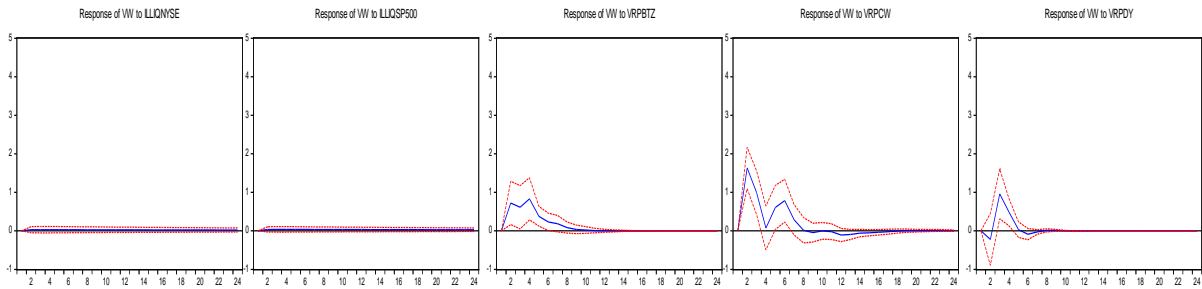
X2	X1	<i>ILLIQ</i> ^{NYSE}		<i>ILLIQ</i> ^{SP500}	
	Sample period	X1->X2	X2->X1	X1->X2	X2->X1
$R_m - R_f$	1992-2010	0.973	0.000	0.731	0.000
	1992-2006	0.300	0.000	0.190	0.000
	1994-2008	0.305	0.000	0.027	0.000
	1996-2010	0.846	0.000	0.791	0.000
<i>SMB</i>	1992-2010	0.845	0.037	0.116	0.023
	1992-2006	0.414	0.041	0.199	0.275
	1994-2008	0.442	0.339	0.246	0.011
	1996-2010	0.128	0.096	0.191	0.027
<i>HML</i>	1992-2010	0.659	0.070	0.240	0.122
	1992-2006	0.788	0.001	0.288	0.012
	1994-2008	0.431	0.001	0.860	0.029
	1996-2010	0.658	0.166	0.154	0.281
<i>MOM</i>	1992-2010	0.841	0.000	0.293	0.000
	1992-2006	0.798	0.000	0.411	0.000
	1994-2008	0.148	0.000	0.136	0.000
	1996-2010	0.652	0.000	0.451	0.000

FIGURE 1

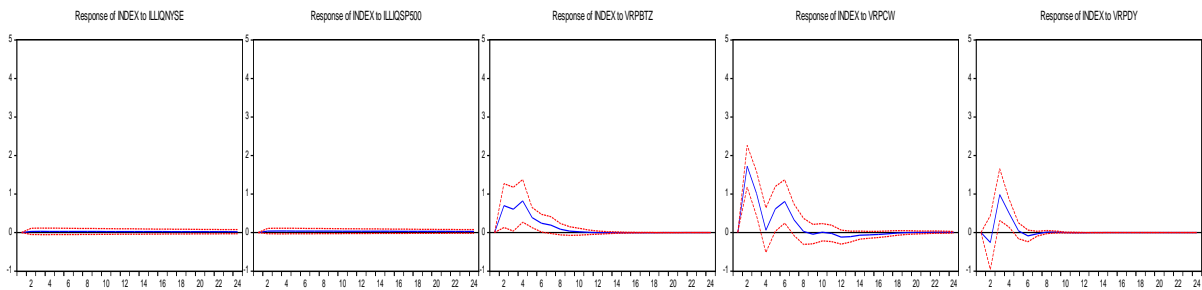
Impulse Response Functions for Stock Return, Illiquidity and Variance Risk Premium

Figure 1 plots the estimated impulse response functions for illiquidity, stock return and variance risk premium for 24 months. These figures are based on the VAR model for the full sample period from January 1992 to December 2010. Panel A presents the impulse response function for *VW* following a one-standard-deviation innovation in illiquidity and variance risk premium. Panel B presents the impulse response function for *INDEX* to illiquidity and variance risk premium. Panel C illustrates the response of illiquidity for NYSE to one unit change in index return and variance risk premium. Panel D reports the response for illiquidity for S&P500 index to the change in stock return and variance risk premium. The impulse response functions for variance risk premium to the illiquidity and stock return are reported in Panel E, Panel F and Panel G, respectively. The solid lines refer to the response of each variable in the month (represented on the horizontal axis of each figure) following one standard deviation in another variable. The magnitude of the response, measured as percentage change, is reported on the vertical axis in each figure. The dashed lines refer to the confidence intervals at two standard errors.

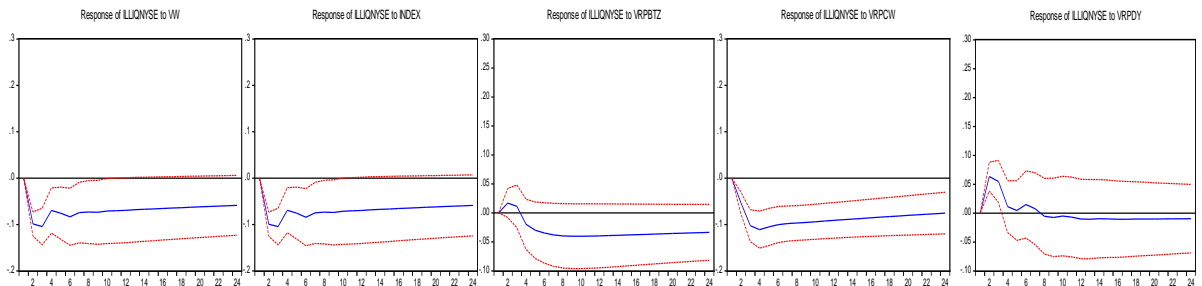
Panel A. The Response of *VW*



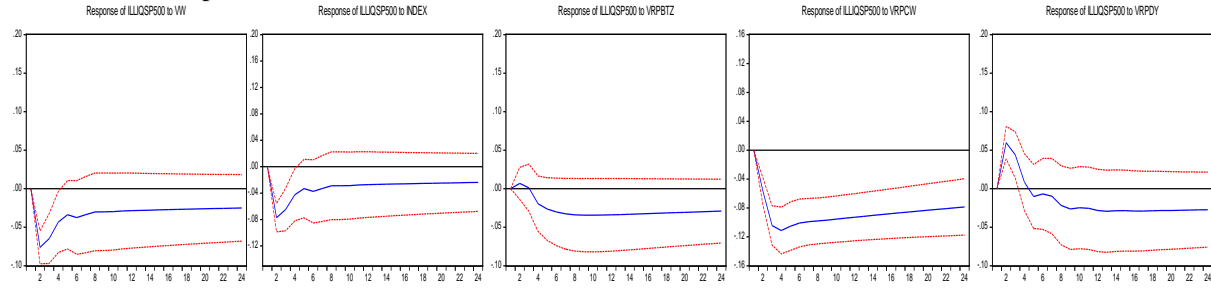
Panel B. The Response of *INDEX*



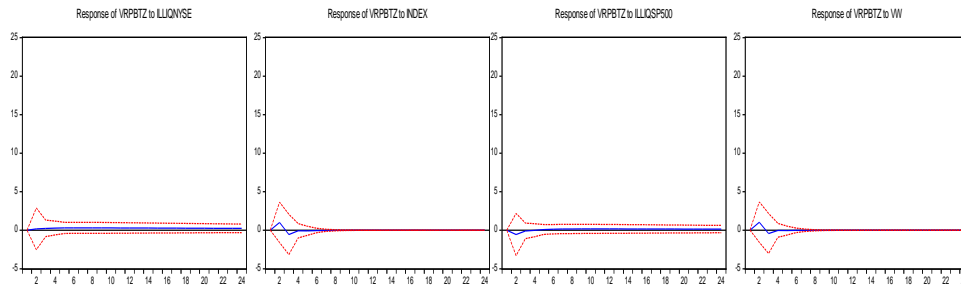
Panel C. The Response of *ILLIQ*^{NYSE}



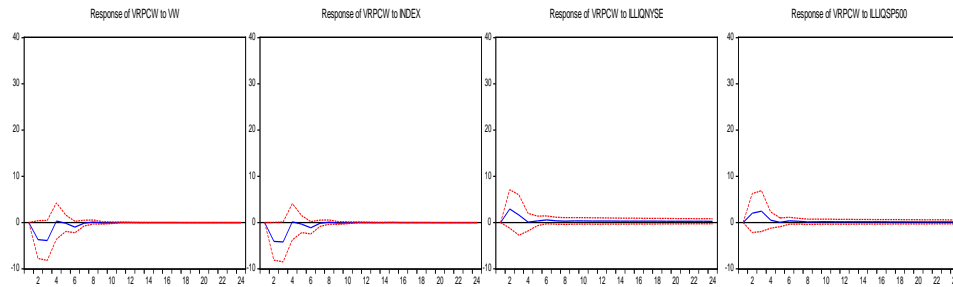
Panel D. The Response of $ILLIQ^{SP500}$



Panel E. The Response of VRP^{BTZ}



Panel F. The Response of VRP^{CW}



Panel G. The Response of VRP^{DY}

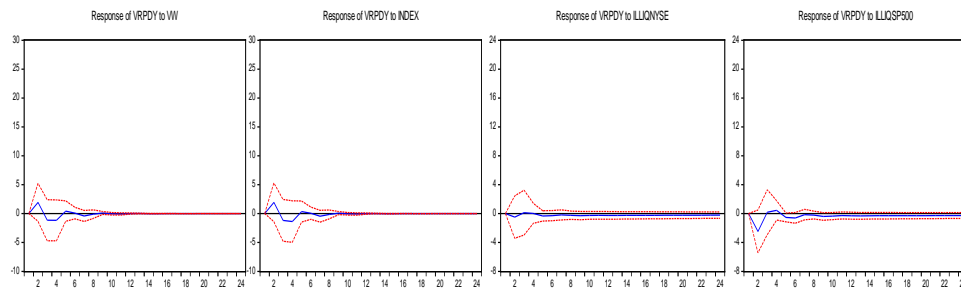
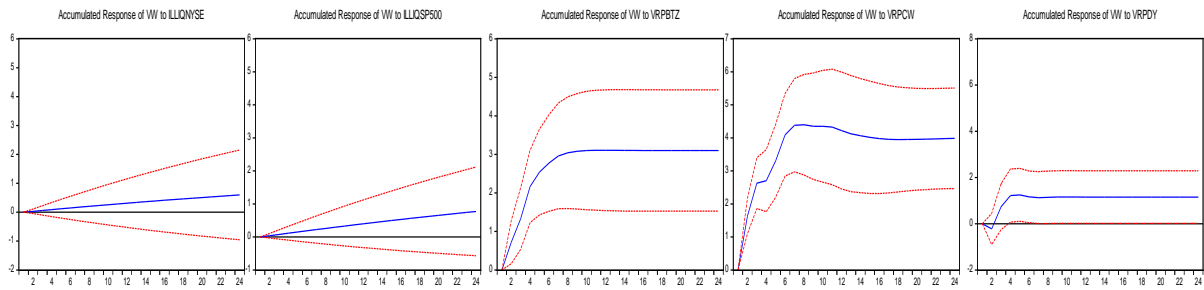


FIGURE 2

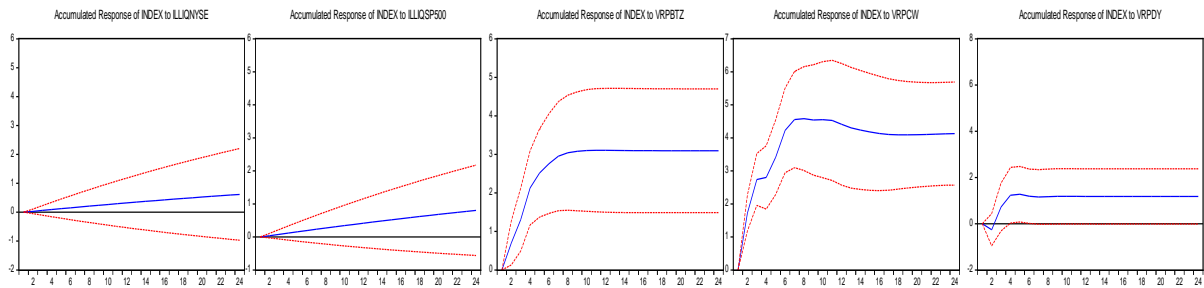
Cumulative Impulse Response Functions for Stock Return, Illiquidity, and Variance Risk Premium

Figure 2 presents the estimated impulse response functions for illiquidity, stock return, and variance risk premium for twenty-four months. The figures are based on the VAR model for the full sample period from January 1992 to December 2010. Panel A presents the cumulative impulse response function for *VW* to illiquidity and variance risk premium. Panel B presents the cumulative impulse response function for *INDEX* to illiquidity and variance risk premium. Panel C illustrates the response of illiquidity for NYSE to one unit change in stock return and variance risk premium. Panel D reports the response of illiquidity for the S&P 500 index to the change in stock return and variance risk premium. The impulse response functions for variance risk premium to the illiquidity and return are reported in Panel E, Panel F and Panel G, respectively. The solid lines refer to the accumulated response for each variable from the month of innovation (represented on the horizontal axis of each figure). The magnitude of the response, measured as percentage change, is reported on the vertical axis in each figure. The dashed lines refer to the confidence intervals at two standard errors.

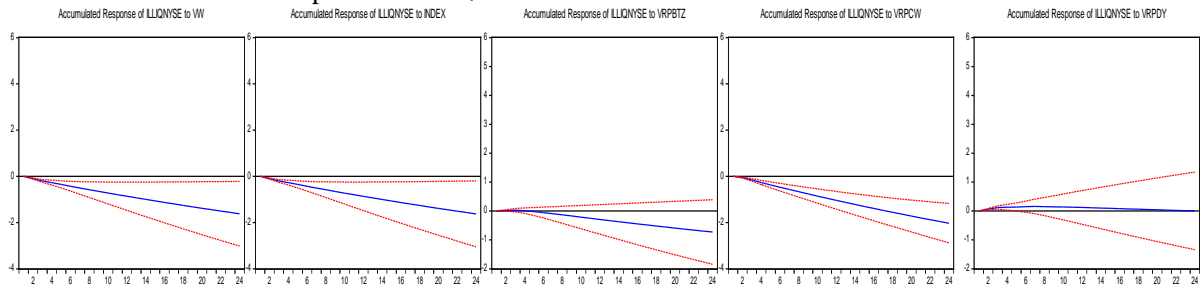
Panel A. Accumulated Response of *VW*



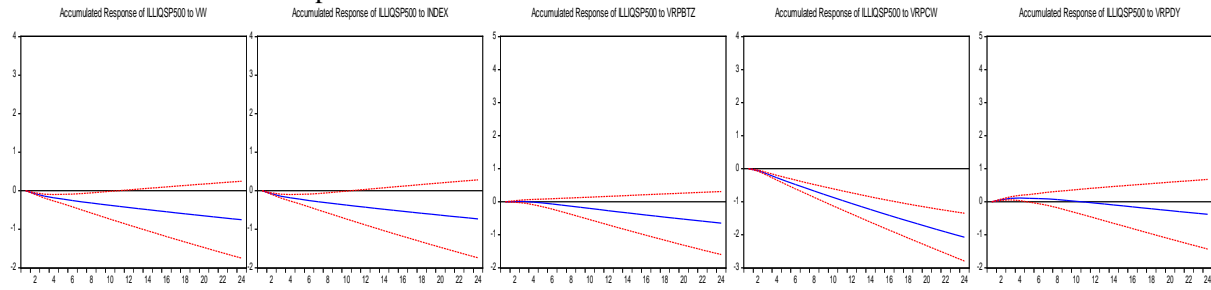
Panel B. Accumulated Response of *INDEX*



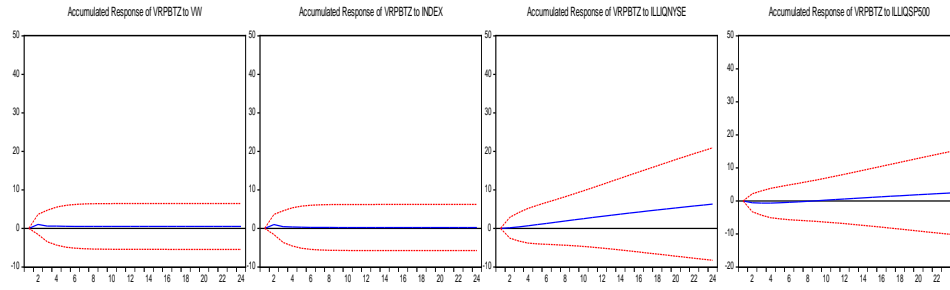
Panel C. Accumulative Response of *ILLIQ*^{NYSE}



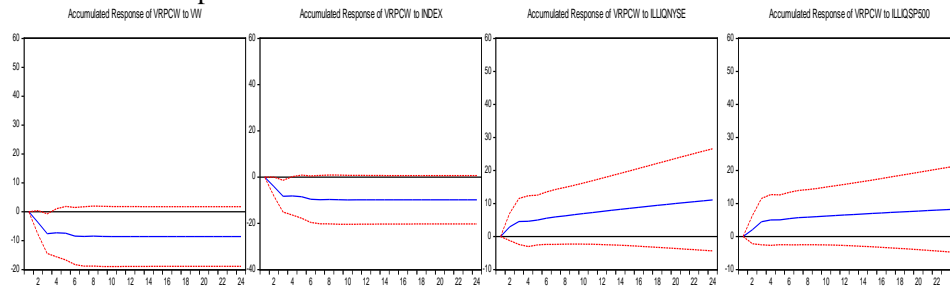
Panel D. Accumulative Response of $ILLIQ^{SP500}$



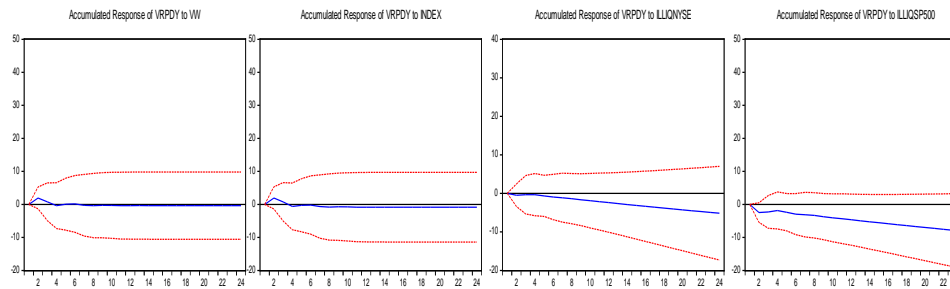
Panel E. Accumulative Response of VRP^{BTZ}



Panel F. The Response of VRP^{CW}



Panel G. Accumulative Response of VRP^{DY}



References

- Amihud, Y. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets*, 5 (2002), 31-56.
- Amihud, Y., and H. Mendelson. "Asset Pricing and the Bid Ask Spread." *Journal of Financial Economics*, 17 (1986), 223-249.
- Amihud, Y.; H. Mendelson; and L. H. Pederson. "Liquidity and Asset Prices." *Foundation and Trends in Finance*, 1 (2005), 1-96.
- Andersen, T. G., and T. Bollerslev. "Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts." *International Economic Review*, 39 (1998a), 885-905.
- Andersen, T. G., and T. Bollerslev. "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies." *Journal of Finance*, 53 (1998b), 219-265.
- Andersen, T. G.; T. Bollerslev; F. X. Diebold; and H. Ebens. "The Distribution of Realized Stock Return Volatility." *Journal of Financial Economics*, 61 (2001), 43-76.
- Andersen, T. G.; T. Bollerslev; F. X. Diebold; and P. Labys. "Exchange Rate Return Standardized by Realized Volatility Are (Nearly) Gaussian." *Multinational Finance Journal*, 4 (2000), 159-179.
- Andersen, T. G.; T. Bollerslev; F. X. Diebold; and P. Labys. "Modeling and Forecasting Realized Volatility." *Econometrica*, 71 (2003), 579-625.
- Ang, A., and G. Bekaert. "Stock Return Predictability: Is It There?" *Review of Financial Studies*, 20 (2007), 651-707.
- Areal, N. M., and S. J. Taylor. "The Realized Volatility of FTSE-100 Futures Prices." *Journal of Futures Markets*, 22 (2002), 627-648.
- Awartani, B.; V. Corradi; and W. Distaso. "Assessing Market Microstructure Effects via Realized Volatility Measures with an Application to the Dow Jones Industrial Average Stocks." *Journal of Business & Economic Statistics*, 27 (2009), 251-265.
- Baker, M., and J. C. Stein. "Market Liquidity as a Sentiment Indicator." *Journal of Financial Markets*, 7 (2004), 271-299.
- Bakshi, G., and D. Madan. "A Theory of Volatility Spreads." *Management Science*, 52 (2006), 1945-1956.
- Bali, T. G.; N. Cakici; X. M. Yan; and Z. Zhang. "Does Idiosyncratic Risk Really Matter?" *Journal of Finance*, 60 (2005), 905-929.
- Bekaert, G.; C. R. Harvey; and C. Lundblad. "Liquidity and Expected Returns: Lessons from Emerging Markets." *Review of Financial Studies*, 20 (2007), 1783-1831.
- Bernardo, A. E., and I. Welch. "Liquidity and Financial Market Runs." *Quarterly Journal of Economics*, 119 (2004), 135-158.
- Black, F., and M. Scholes. "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy*, 81 (1973), 637-654.
- Bollerslev, T.; M. Gibson; and H. Zhou. "Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option-Implied and Realized Volatilities." *Journal of Econometrics*, 160 (2011), 235-245.

- Bollerslev, T.; J. Marrone; L. Xu; and H. Zhou. "Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence." *Journal of Financial and Quantitative Analysis*, 49 (2014), 633-661.
- Bollerslev, T.; G. Tauchen; and H. Zhou. "Expected Stock Returns and Variance Risk Premia." *Review of Financial Studies*, 22 (2009), 4463-4492.
- Brennan, M. J., and A. Subrahmanyam. "Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns." *Journal of Financial Economics*, 41 (1996), 441-464.
- Britten-Jones, M., and A. Neuberger. "Option Prices, Implied Price Processes, and Stochastic Volatility." *Journal of Finance*, 55 (2000), 839-866.
- Carhart, M. M. "On Persistence in Mutual Fund Performance." *Journal of Finance*, 52 (1997), 57-82.
- Carr, P., and L. R. Wu. "Variance Risk Premiums." *Review of Financial Studies*, 22 (2009), 1311-1341.
- Carr, P., and D. Madan. "Towards a Theory of Volatility Trading." In *Volatility: New Estimation Techniques for Pricing Derivatives*, R. Jarrow, ed. London: Risk (1998).
- Chordia, T.; R. Roll; and A. Subrahmanyam. "Commonality in Liquidity." *Journal of Financial Economics*, 56 (2000), 3-28.
- Chordia, T.; R. Roll; and A. Subrahmanyam. "Market Liquidity and Trading Activity." *Journal of Finance*, 56 (2001), 501-530.
- Chordia, T.; R. Roll; and A. Subrahmanyam. "Order Imbalance, Liquidity, and Market Returns." *Journal of Financial Economics*, 65 (2002), 111-130.
- Drechsler, I. "Uncertainty, Time-Varying Fear, and Asset Prices." *Journal of Finance*, 68 (2013), 1843-1889.
- Drechsler, I., and A. Yaron. "What's Vol Got to Do with It." *Review of Financial Studies*, 24 (2011), 1-45.
- Durand, R. B.; D. Lim; and J. K. Zumwalt. "Fear and the Fama - French Factors." *Financial Management*, 40 (2011), 409-426.
- Easley, D.; S. Hvidkjaer; and M. O'Hara. "Is Information Risk a Determinant of Asset Returns?" *Journal of Finance*, 57 (2002), 2185-2221.
- Easley, D., and M. O'hara. "Price, Trade Size, and Information in Securities Markets." *Journal of Financial Economics*, 19 (1987), 69-90.
- Ebens, H. "Realized Stock Volatility." Working Paper, John Hopkins University (1999).
- Fama, E. F., and K. R. French. "Common Risk-Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3-56.
- Gervais, S., and T. Odean. "Learning to be Overconfident." *Review of Financial Studies*, 14 (2001), 1-27.
- Glosten, L. R., and L. E. Harris. "Estimating the Components of the Bid Ask Spread." *Journal of Financial Economics*, 21 (1988), 123-142.
- Glosten, L. R., and P. R. Milgrom. "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." *Journal of Financial Economics*, 14 (1985), 71-100.
- Griffin, J. M.; F., Nardari; and R. M. Stulz. "Do Investors Trade More When Stocks Have Performed Well? Evidence from 46 Countries." *Review of Financial studies*, 20 (2007), 905-951.
- Grossman, S. J., and M. H. Miller. "Liquidity and Market Structure." *Journal of Finance*, 43 (1988), 617-633.

- Hameed, A.; W. Kang; and S. Viswanathan. "Stock Market Declines and Liquidity." *Journal of Finance*, 65 (2010), 257-293.
- Hansen P. R., and A. Lunde. "Realized Variance and Market Microstructure Noise." *Journal of Business and Economic Statistics*, 24 (2006), 127-218.
- Jiang, G. J., and Y. Tian. "The Model-Free Implied Volatility and Its Information Content." *Review of Financial Studies*, 18 (2005), 1305-1342.
- Jones, C. M. "A Century of Stock Market Liquidity and Trading Costs." Working Paper, Columbia University (2002).
- Lakonishok, J., and S. Smidt. "Volume for Winners and Losers: Taxation and Other Motives for Stock Trading." *Journal of Finance*, 41 (1986), 951-974.
- Lesmond, D. A.; J. P. Ogden; and C. A. Trzcinka. "A New Estimate of Transaction Costs." *Review of Financial Studies*, 12 (1999), 1113-1141.
- Lettau, M., and S. Ludvigson. "Consumption, Aggregate Wealth, and Expected Stock Returns." *The Journal of Finance*, 56 (2001), 815-849.
- Li, K. "Long-Memory versus Option-Implied Volatility Prediction." *Journal of Derivatives*, 9 (2002), 9-25.
- Martens, M., and J. Zein. "Predicting Financial Volatility: High-Frequency Time-Series Forecasts vis-a-vis Implied Volatility." *Journal of Futures Markets*, 24 (2004), 1005-1028.
- Merton, R. C. "Intertemporal Capital Asset Pricing Model." *Econometrica*, 41 (1973), 867-887.
- Miralles, J. L., and M. M. Miralles. "The Role of an Illiquidity Risk Factor in Asset Pricing: Empirical Evidence from the Spanish Stock Market." *The Quarterly Review of Economics and Finance*, 46 (2006), 254-267.
- Oded, J. "Optimal Execution of Open-Market Stock Repurchase Programs." *Journal of Financial Markets*, 12 (2009), 832-869.
- Odean, T. "Volume, Volatility, Price, and Profit When All Traders Are Above Average." *Journal of Finance*, 53 (1998), 1887-1934.
- Orosel, G. O. "Participation Costs, Trend Chasing, and Volatility of Stock Prices." *Review of Financial Studies*, 11 (1998), 521-557.
- Ren, F.; G. F. Gu; and W. X. Zhou. "Scaling and Memory in the Return Intervals of Realized Volatility." *Physica A: Statistical Mechanics and its Applications*, 388 (2009), 4787-4796.
- Rosenberg, J. V., and R. F. Engle. "Empirical Pricing Kernels." *Journal of Financial Economics*, 64 (2002), 341-372.
- Shefrin, H., and M. Statman. "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence." *Journal of Finance*, 40(1985), 777-790.
- Smirlock, M., and L. Starks. "An Empirical Analysis of the Stock Price-Volume Relationship." *Journal of Banking & Finance*, 12(1988): 31-41.
- Statman, M.; S. Thorley; and K. Vorkink. "Investor Overconfidence and Trading Volume." *Review of Financial Studies*, 19 (2006), 1531-1565.
- Stoll, H. R. "The Supply of Dealer Services in Securities Markets." *The Journal of Finance*, 33 (1978), 1133-1151.
- Taylor, S. J., and X. Xu. "The Incremental Volatility Information in One Million Foreign Exchange Quotations." *Journal of Empirical Finance*, 4 (1997), 317-340.
- Voev, V., and A. Lunde. "Integrated Covariance Estimation Using High-Frequency Data in the Presence of Noise." *Journal of Financial Econometrics*, 5 (2007), 68-104.

- Welch, I., and A. Goyal. "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction." *Review of Financial Studies*, 21 (2008), 1455-1508.
- Zhou, B. "High-Frequency data and Volatility in Foreign-Exchange Rates." *Journal of Business & Economic Statistics*, 14 (1996), 45-52.