# 國 立 交 通 大 學

## 財務金融研究所

## 博 士 論 文

波動風險溢酬之決定因素及交易波動風險溢酬的影響:

以臺灣指數選擇權市場為例

The determinant of volatility risk premium and the effect of trading volatility risk premium: Evidence from the Taiwan index option market


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中 華 民 國 一0二 年 十一 月

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# 波動風險溢酬之決定因素及交易波動風險溢酬的影響:

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## 中文摘要

本研究主要在探討兩個波動風險溢酬(volatility risk premium)的重要議題。第一個議題分析指數選擇權的需求壓力對波動風險溢酬的影響，因買賣委託單不均衡(order imbalance)是可被觀測且以此作為淨需求測度的結果可應用於選擇權流動性提供者(liquidity providers)的買賣報價上，所以本研究使用買賣委託單不均衡(order imbalance)替代真實選擇權的淨需求，其結果發現指數選擇權需求可以解釋動態的波動風險溢酬，選擇權需求的壓力與波動風險溢酬存在正向的關係。特別的是，當市場價格出現大幅的變動(jump)時，選擇權需求的壓力效果變的更大。

第二個議題則是在探討交易波動風險溢酬對市場波動的影響，大的波動風險溢酬會吸引波動交易者從事波動交易(volatility trading)，本研究主張如此的波動交易會產生一個回饋的效果加劇市場的波動，使用線性及非線性的因果測試(linear and nonlinear Granger causality tests)，結果發現波動風險溢酬與市場波動間存在雙向的因果關係，而其中大的波動風險溢酬伴隨較高的市場波動的證據支持回饋效果的存在。非線性因果測試結果亦發現波動風險溢酬的回饋效果存在於連續波動(continuous volatility)、負波動跳躍 (negative jump volatility)與正波動跳躍(positive jump volatility)，即使控制在會產生波動的訊息的衝擊下，此回饋的效果亦維持顯著。

關鍵字：波動風險溢酬、真實波動、向量異質自我相關迴歸模型、買賣委託單不均衡、非線性因果關係檢測

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ABSTRACT

This dissertation consists of two separate essays on the volatility risk premium (VRP). The first essay is to examine the impact of option demand pressure on the volatility risk premium. The order imbalance in options is used to proxy for option net demand because this measure is easily observable from public order flows and the result based on this demand measure can be applied to the adjustment of the bid-ask quote of options for liquidity providers. Our empirical results show that demand in options can help to explain time-varying VRP. A positive (negative) demand pressure for an index option raises (decreases) the VRP. In particular, this effect of demand pressure on VRP becomes stronger at the arrival of market jumps.

The second essay is to investigate the feedback effect of trading volatility risk premium. Large VRP attracts volatility trading that seeks to benefit from the temporary mispricing in volatility. This study suggests that such trading generates a feedback effect that subsequently raises the market volatility. Using linear and nonlinear Granger causality tests, the bidirectional influence between VRP and market volatility is documented. The finding of higher volatility following large VRP supports the existence of feedback effect. In the nonlinear test, the VRP is found to Granger cause the three volatility components: continuous volatility, negative jump volatility, and positive jump volatility. The feedback effect remains significant after controlling for information shocks that may lead to persistence in volatility.

Keywords: volatility risk premium; realized volatility; vector heterogeneous autoregressive (VecHAR) model; order imbalances; nonlinear Granger causality test

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博士生涯一路走來，得之於人者多，出之於己者少，如今即將畢業，心中不勝感激，期許自己能對國家社會有所貢獻，不辜負所有曾經關心及幫助過我的家人及朋友對我的期望。

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陳清和 謹誌于

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# CHAPTER 1 INTRODUCTION

Volatility risk premium (VRP) is the premium that compensates risk stemming from the fluctuation in volatility or jumps. Empirical research also provides strong evidence that this risk premium is priced in options. One interpretation within the most existing literature is that investors who purchase options need to pay a premium for protection against volatility risk. Along this line, the VRP is linked with expected future volatility, hedging demand, and liquidity provision. However, in practice, to meet the obligation of the liquidity provision, market makers must take on the other side of the end-user net demand. This gives a rise to an interesting but less understood question whether the VRP is determined by the option net demand of end users.

In addition, over the past few years, volatility trading has become increasingly popular. A large volatility risk premium provides opportunities to engage in volatility trading. In real market, the VRP is often substantial and implies large profits for option sellers (Eraker, 2008). Despite the overwhelming evidence that large volatility increases VRP, much is unknown about what happens afterward, in particular how a widened VRP may affect subsequent volatility. Therefore, this dissertation focuses on two important issues regarding the VRP in financial market.

The first issue in this dissertation is to discuss the impact of option demand pressure on volatility risk premium. Instead of using actual but unobserved option net demand, the order imbalance in the options is used because this measure is easily observable from public order flows and the result based on this demand measure allows liquidity providers to quickly adjust their bid-ask quote of options.

This paper calculates two types of order imbalance measures, one in number of trades and the other in traded dollar amount. For each order imbalance measure, three order imbalance variables are calculated separately weighted by three unhedgeable risks for market makers that correspond to aggregate risk, volatility risk, and jump risk. They are proxies for three demand variables for options: all demand, volatility demand, and jump demand. Each of these order imbalances variables is applied to examine the demand pressure effect on VRP.

The VRP is quantified as risk-neutral volatility less expected realized volatility. For the risk-neutral volatility, it is calculated directly from option prices using the approach proposed by Jiang and Tian (2005, 2007). Following Busch, Christensen, and Nielsen (2011) and Bollerslev and Todorov (2011), the expected realized volatility is estimated using a vector heterogeneous autoregressive model. Specifically, the estimate for VRP relies on two recently developed model-free measures: realized volatility and implied volatility. Using these two model-free measures, it is not only to calculate VRP easily but also has the advantages of the unspecified volatility process and pricing kernel.

Our empirical results show that the level of demand for an index option plays a key role in determining the time variation in VRP. In particular, as market jumps occur, the demand pressure leads to a greater impact on VRP for all three demand variables.

The second issue is to investigate the dynamic processes between VRP and volatility while focusing on the afterward effect of a large VRP. This study argues that a large VRP attracts volatility trading and is accompanied by hedging transactions, which could subsequently raise market volatility, resulting in a feedback effect that further enlarges market volatility. The bidirectional causality between VRP and market volatility is tested in 5-minute frequency using OLS regression, linear Granger causality, and nonlinear Granger causality tests. A traditional linear Granger causality model is applied to estimate the dynamic relationship between VRP and the realized volatility. The nonlinear causal test adopts a nonparametric method based on the modified version of the Baek and Brock (1992) nonlinear Granger causality test.

The results in the OLS regressions and the linear and nonlinear Granger causality tests show significant two-way impact between realized volatility and VRP. The causal relation from VRP to the realized volatility suggests that VRP plays an important role in explaining future realized volatility: a large volatility premium could lead to greater realized volatility.

This study further separates the market volatility into three components: continuous volatility, negative jump volatility, and positive jump volatility, and examines the causality between VRP and each volatility component. In the nonlinear test, the VRP is found to Granger cause the three volatility components: continuous volatility, negative jump volatility, and positive jump volatility. This feedback effect that the VRP nonlinearly Granger causes the three volatility components is significant even after controlling for the higher volatility attributed to unexpected information shocks.

In conclusion, the dissertation gives some insights into the issues of the influence of option demand pressure on VRP and the effect of trading the VRP. The research results will offer us with the empirical evidence to comprehend the dynamic relationship between the demand pressure of index option and VRP, and between market volatility and VRP in financial market.

# CHAPTER 2 THE IMPACT OF ORDER IMBALANCE IN OPTIONS ON VOLATILITY RISK PREMIUM: EVIDENCE FROM THE TAIWAN INDEX OPTION MARKET

## 1. INTRODUCTION

Recent literature documents that volatility risk stemming from the fluctuation in volatility is compensated by volatility risk premium (VRP) and priced in options.[1] One economic interpretation within the most literature is that investors who purchase options are willing to pay a premium for protection against volatility risk. Several studies also show that the VRP represents option market makers' willingness to absorb inventory and provide liquidity (Bollen, & Whaley, 2004; Gârleanu, Pedersen, & Poteshman, 2009; Nagel, 2012). Along these lines, the magnitude of VRP depends upon investors' demand for hedging volatility risk and intermediaries' willingness to meet the liquidity demand. Despite the abundant evidence has linked the VRP to liquidity, intermediation, and hedging demand, much less is known about the effect of option net demand of end users on the time-varying VRP.[2]

Gârleanu, Pedersen, and Poteshman (2009) propose a demand-based model in which the equilibrium option price is partly determined by its demand. The model shows that demand pressure for an option increases its price by an amount proportional to option's expensiveness, i.e., the premiums of all unhedgeable risk of options such as discrete-time trading, volatility risk, and jump risk. It also raises the prices of other options on the same underlying proportional to the covariance of the unhedgeable parts. These results suggest that option demand impacts the VRP.

In addition, the demand pressure effect for VRP likely differs when risk aversion of

1 See, for example, Bakshi and Kapadia (2003), Bollerslev and Todorov (2011), ; Buraschi and Jackwerth (2001), Carr and Wu (2009), Chernov and Ghysels (2000), Coval and Shumway (2001), and Jackwerth and Rubinstein (1996).
2 As reported in Bollerslev, Gibson, and Zhoud (2011), Bollerslev and Todorov (2011), and Todorov (2010), volatility risk premium varies over time.

market participants varies because it may affect the willingness of market participants to buy or sell options. Todorov (2010) finds that time-varying risk aversion is mainly driven by large or extreme market moves. A large price shock to stock market increases investors' fears for future jumps because investors view the occurrence of jumps as more likely, thereby raising their willingness to pay more for protection against jumps. At such time, it may result in a greater demand effect on VRP, especially when preceded by recent jumps, even through option demand remains the same or lessens. This matches the pattern of VRP in Todorov (2010): it increases and slowly reverts to its long-run mean after jumps occur. However, price jumps often appear in the most major market indices.[3] This provides us a venue to test the differential effect of demand pressure on VRP with and without jumps.

This study investigates the effect of option demand pressure on VRP and test whether the demand pressure effect is greater when market jumps occur. The order imbalance in options is used instead of actual option net demand to analyze the demand pressure effect because this measure is easily observable from public order flows and the result based on this demand measure can be applied to adjust the bid-ask quote of options for liquidity providers. A finding that the order imbalances positively affect VRP with and without market jumps, with former having a larger impact, provides evidence that option demand pressure influences the VRP. To the best of our knowledge, this study is the first of its kind to investigate the dynamic relation between option demand pressure and VRP. Our study contributes to the existing literature not only by illustrating the importance of demand pressure in determining VRP but also by explicitly linking the demand pressure effect on VRP with time-varying risk aversion.

The Taiwan index options (TXO) written on the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) are analyzed, in which TXO is one of the most liquid index

[3] Indeed, most major market indices appear to contain price jumps (Bakshi, Cao, and Chen, 1997; Bollerslev and Todorov, 2011; Eraker, Johannes, and Polson, 2003; Pan, 2002; Todorov, 2010).

options in the world.[4] The trading volume by individuals far exceeds the levels of trading by domestic or foreign institutional investors.[5] The dominance by individual investors contrasts with the common knowledge that institutional investors dominate the index option market such as the U.S. market. Our study in the Taiwan market sheds light on many other markets at a similar stage of development such as Korea and Poland.

To meet the obligation of the liquidity provision, market makers must take on the other side of the end-user net demand. If market makers can not perfectly hedge their net exposure on the option positions, the option prices that they quote include a component that compensates their risk. In real world, the risks faced by market makers stem from incomplete markets such as transaction costs, discrete-time transaction, unexpected volatility, and sudden jumps in the underlying price. Market makers who accept these unhedgeable risks thus require a premium for providing liquidity on option markets. Gârleanu, Pedersen, and Poteshman (2009) and Bollen and Whaley (2004) find that the option's expensiveness is related to the level of risk taken on by the market makers.

The order imbalances are used to proxy for option net demand. Many studies show that order imbalances between buyers and sellers can reflect nonmarket maker net demand. Chordia, Roll, and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004) use order imbalance to measure both direction and degree of buying or selling pressure. Bollen and Whaley (2004) gauge net demand using order imbalances between the number of buyer-initiated and seller-initiated trades. More important, in contrast to the end-user net demand identified with a unique data set by Gârleanu, Pedersen, and Poteshman (2009) and Ni, Pan, and Poteshman (2008), this demand measure is quickly observed from public order flows.

[4] On a global scale, the TXO is ranked the fifth most frequently traded index option in 2010. The constituent stocks of the underlying spot index are also actively traded.
[5] For example, in 2010 individuals, domestic institutional investors, and foreign institutional investors accounted for 39.6%, 1.5%, and 5.9 % of trades, respectively.

This study follows Chordia, Roll, and Subrahmanyam (2008) to calculate two types of order imbalance measures, one in number of trades and the other in traded dollar amount. For each order imbalance measure, three order imbalance variables are calculated separately weighted by three unhedgeable risks for market makers that correspond to aggregate risk, volatility risk, and jump risk. They are proxies for three demand variables for options: all demand, volatility demand, and jump demand. Each of these order imbalances variables is applied to examine the demand pressure effect on VRP.

The VRP is quantified as risk-neutral volatility less expected realized volatility. For the risk-neutral volatility, it is calculated directly from option prices using the method proposed by Jiang and Tian (2005, 2007). Following Busch, Christensen, and Nielsen (2011) and Bollerslev and Todorov (2011), the expected realized volatility is estimated using a vector heterogeneous autoregressive (VecHAR) model. Specifically, the estimate for VRP relies on two recently developed model-free measures: realized volatility and implied volatility. Using these two model-free measures, it is not only to calculate VRP easily but also has the advantages of the unspecified volatility process and pricing kernel.[6]

Our empirical results show that the level of demand for an index option plays a key role in determining the time variation in VRP. In a time-series test, a positive influence of option demand pressure on VRP is found, similar to the finding of Gârleanu, Pedersen, and Poteshman (2009) that a proportion of an option's expensiveness reflects the effect of demand pressure. The finding of a strong linkage between demand pressure and VRP during the period of recent market-maker losses indicates that demand pressure effect is related to the risk aversion of liquidity providers. In particular, when market jumps occur, the demand pressure leads to a greater impact on VRP for all three demand variables. The result provides evidence to support the finding of Todorov (2010) that time-varying risk aversion is driven

[6] For example, utilizing the joint estimation of the asset returns and prices of its underlying derivatives requires complicated modeling and estimation procedures (Ait-Sahalia & Kimmel, 2007; Bates, 1996; Chernov & Ghysels, 2000; Eraker 2004; Jackwerth, 2000; Jones, 2003; Pan, 2002).

by large, or extreme, market moves.

The remainder of this paper is organized as follows. Section 2 contains the formal development of our method. Section 3 provides a brief description of the empirical data. Section 4 analyzes the empirical results. Section 5 provides the key results of the study and a conclusion.

## 2. METHODOLOGY

### 2.1. Volatility Risk Premium

VRP represents the premium associated with uncertainty in volatility and is often measured by the difference between the statistical and risk-neutral expectations of the forward variation in the asset return. To measure VRP faced by liquidity providers, this study follows Bollerslev and Todorov (2011) and Todorov (2010) and define VRP over the next τ trade days as the risk-neutral volatility less the expected realized volatility, quantified as

$$VRP_t = 1/\sqrt{\tau}.E_t^Q(\sigma_{[t,t+\tau]}) - 1/\sqrt{\tau}.E_t^P(\sigma_{[t,t+\tau]}), \quad (1)$$

where $E^Q(.)$ and $E^P(.)$ indicate the expectations under risk-neutral and statistical measures, respectively.[7]

#### 2.1.1. Estimate of risk-neutral volatility

The risk-neutral volatility at the first term in Equation (1) is calculated directly from option prices. As demonstrated in Bakshi and Madan (2000), Britten-Jones and Neuberger

[7] Note that our VRP measure in Equation (1) is opposite to the definition of Bollerslev and Todorov (2011) and Todorov (2011). They calculate the VRP paid by hedgers, which is negative on average, whereas we measure the VRP earned by option liquidity suppliers, which is positive on average.

(2000), and Jiang and Tian (2005), this risk-neutral volatility is equal to option implied volatility. In this study, the approach proposed by Jiang and Tian (2005, 2007) is adopted to compute the implied volatilities of call and put options directly from option prices. This method corrects the inherent methodological problem in the most widely used Black–Scholes (1973) model for deriving the option-implied volatility, which assumes that the underlying asset's return follows a lognormal distribution that is virtually found to be too fat-tailed to be lognormal.

Britten-Jones and Neuberger (2000) derive a model-free measure of implied volatility under the diffusion asset price process, and Jiang and Tian (2005) further extend their result to the case of jump diffusion. The model-free implied variance is defined as an integral of option prices over an infinite range of exercise prices, denoted as $2\int_0^\infty \frac{C^{\mathbb{F}}(\tau,K)-\max(0,F_0-K)}{K^2}dK$, in which the superscript $\mathbb{F}$ denotes the forward probability measure, K is the exercise price, $\tau$ denotes the time to maturity, $F_0$ and $C^{\mathbb{F}}(\tau,K)$ are the forward asset and option prices.

However, in reality, options are trades in the marketplace only over a finite range of exercise prices. The limited availability of discontinuous exercise prices may lead to truncation and discretization errors in the numerical integration for the model-free implied volatility.[8] To resolve the problem, Jiang and Tian (2005, 2007) develop an interpolation–extrapolation scheme to reduce the influence of truncation and discretization errors.[9]

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[8] The truncation error results from disregarding exercise prices beyond the range of the listed exercise prices in the marketplace, and the discretization error arises from the discontinuous exercise prices. In general, the truncation error is negligible while the truncation points are more than two standard deviations from the forward asset price (Jiang & Tian, 2005).

[9] The steps are specified as follows. At first, a wider range of exercise prices relative to available exercise prices is set up by given left and right truncation points $K_{min}$ and $K_{max}$. Next, to obtain the not-traded option prices between these two truncation points, a cubic splines method is used to interpolate the Black–Scholes implied volatilities per the $\Delta K$ price interval between available exercise prices. Finally, the extracted implied volatilities are translated into option prices by using the Black–Scholes model, and the implied volatility is further computed from these option prices. In addition, for options with exercise prices beyond the available range in option market, Jiang and Tian suggest that the slope of the extrapolated segment (on both sides) should be adjusted to match the corresponding slope of the interior segment at the minimum or maximum available exercise price.

Following the approach of Jiang and Tian (2005, 2007), the model-free implied variance is written as

$$2\int_{K_{\min}}^{K_{\max}} \frac{C^{\mathbb{F}}(\tau,K)-\max(0,F_0-K)}{K^2}dK = \sum_{j=1}^{M}(f(\tau,K_j)+f(\tau,K_{j-1}))\Delta K, \qquad (2)$$

where $f(\tau,K_i)=(C^{\mathbb{F}}(\tau,K)-\max(0,F_0-K_i))/K_i^2$, $\Delta K = (K_{max}-K_{min})/M$, $K_i = K_{min} + i\Delta K$ for $0 \le i \le M$. The truncation interval $[K_{min}, K_{max}]$ denotes the range of available exercise prices, in which $K_{min}$ and $K_{max}$ are referred as left and right truncation points, respectively. In our empirical work, option and asset prices are used instead of forward prices to calculate the implied volatility. Under the assumption of deterministic interest rate, the forward option price and forward asset price at time t are respectively represent as $C^{\mathbb{F}}(\tau,K)=C(\tau,K)/B(t,\tau)$ and $F_t = S_t / B(t,\tau)$, in which $S_t$ is spot price, $C(\tau,K)$ is the option price, and $B(t,\tau)$ is the time *t* price of a zero-coupon bound that pays $1 at time τ.

To avoid the bid–ask bounce problem, the midpoint of the quote rather than the transaction price is used to compute the implied volatility (Bakshi, Cao, and Chen, 1997, 2000). As calculating the implied volatility in Equation (5), this study truncates the integration at the lower and upper bounds of 95% and 140% of the current index price for call options and of 60% and 105% of the current index price for put options. The ΔK in numerical integration scheme of Equation (2) is set as 20 index points.[10]

In each day, the implied volatilities at the nearest two maturities are linearly interpolated to obtain the implied volatility at a fixed 22 trading-day horizon. For the implied volatility at each contract month, the average implied volatility of call and put is

[10] The strike price intervals of TXO stipulated by the TAIFEX are grouped into three categories. First, when a strike price is below 3,000 points, the strike price intervals are 50 points in the nearby month and the next two calendar months and 100 point intervals for all months in excess of two months in distance. Second, when a strike price is between 3,000 and 10,000 points, the strike price intervals are 100 points in the nearby month and the next two calendar months, and 200-point intervals for far months. Third, when a strike price is over 10,000 points, the strike price intervals are 200 points in the nearby month and the next two calendar months, and 400-point intervals for far months.

first calculated every five-minute interval and then averaged across intervals in a day. The five-minute implied volatility of the call (and put) is backed out from call (put) prices by using Equation (2).

### 2.1.2. Estimate of expected realized volatility

The expected realized volatility at the second term in Equation (1) is estimated using a VecHAR model constructed on the volatility components of model-free realized volatility. Andersen, Bollerslev, and Diebold (2007) find that the forecasting to the future realized volatility improves significantly when using continuous volatility (CV) and jump volatility (JV) decomposed from realized volatility as separate regressors. They show that volatility components provide better forecasting than realized volatility itself because of the distinct features associated with the CV series and JV series: CV is strongly serially correlated while JV is less persistent and far less predictable than CV. The different features for the two components indicate separate roles in the forecast of realized volatility. In addition, Barndorff-Nielsen and Shephard (2001), Bollerslev, Kretschmer, Pigorsch, and Tauchen (2009), and Todorov and Tauchen (2006, 2011) find that the future volatility increases more following negative price jumps.

Following the Bollerslev and Todorov (2011), the daily close-to-close realized volatility is decomposed into four parts with different characteristics: overnight volatility (NV), CV, nJV, and pJV. In brief, the daily realized volatility is first calculated using 5-minute intraday returns and then decomposed it into four volatility components. This process produces four daily series, one for each volatility component, CV, nJV, pJV, and NV.

The VecHAR model in Equation (3) proposed by Busch, Christensen, and Nielsen

(2011)[11] is applied to forecast the one-period ahead of volatility components. The model follows Andersen et al. (2007) to contain daily, weekly, and monthly volatility measures in the VecHAR forecasting specifications. The expected realized volatility with a 22-day horizon is the square root of the relevant forecasts' sum for the volatility components. The VecHAR model uses the four-dimensional vector $Z_t$, consisting of the CV, nJV, pJV, and NV estimated previously, as input:

$$\begin{gathered} Z_{t+22} = B_0 + B_1 Z_{t-1} + B_5 Z_{t-5} + B_{22} Z_{t-22} + \varepsilon_{t+22}, \\ Z_t = (CV_t \ nJV_t \ pJV_t \ NV_t)' \end{gathered} \tag{3}$$

where $Z_{t-1}$, $Z_{t-5}$, and $Z_{t-22}$, respectively, denote the vector of lagged daily, weekly, and monthly volatility components. $B_0$ is a vector of the intercept term. $B_1$, $B_5$, and $B_{22}$ are matrices for the regression coefficients, in which the first column, second column, third column, and fourth column in each matrix correspond to the parameters of the four volatility components, respectively. The model uses the past 800 days for the estimation of parameters $B_0$, $B_1$, $B_5$, and $B_{22}$. The one-period-ahead volatility component vector is obtained using the estimated parameters and the past 22 days' volatility components. To produce daily-frequency forecasting, this study rolls forward daily, using the same window length (800 days) for every forecasting.

## 2.2. Option Demand Variables

The option net demand is measured using order imbalance in options. The order imbalance is defined as buyer-initiated trade minus seller-initiated trade, where the Lee and Ready (1991) algorithm is used to classify each option trade into buyer-initiated or seller-initiated trades.[12] Following Chordia, Roll, and Subrahmanyam (2008), two types of

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[11] Busch, Christensen, and Nielsen (2011) introduce a VecHAR model for the joint modeling the separate components of realized volatility to forecast volatility components. This model generalizes the heterogeneous autoregressive approach proposed by Corsi (2004) for realized volatility analysis and extended by Andersen et al. (2007) to include the separate volatility components of past realized volatility as regressors.

[12] According to Lee and Ready (1991), a transaction is regarded as a buyer-initiated trade if it occurs above

order imbalance measures are calculated: one in number of trades and the other in traded dollar amount. The order imbalance in trade #OIB is quantified as the difference between the number of buyer- initiated and seller-initiated trades divided by the total number of trades within every 5-minute interval. Dollar order imbalance $OIB is the total dollars paid by buyer-initiated trades less the total dollars received by seller-initiated trades divided by the dollars for all trades within every 5-minute interval.

For each order imbalance measure, three order imbalance variables are calculated separately weighted by three unhedgeable risks for market makers that correspond to aggregate risk, unexpected volatility, and sudden jumps in underlying price. They serve as proxies for option demand (DdAllRisk), volatility demand (DdVolRisk), and jump demand (DdJpRisk), respectively.

DdAllRisk places equal weights across all options and thus measures the aggregate risk demand. DdVolRisk captures the volatility risk-induced demand by weighting order imbalances across all options according to Black–Scholes's vega. The vega reflects an option's sensitivity to the changes in volatility. A large order imbalance in the high vega options indicates that traders are volatility buyers. Order imbalances averaged across option series using vegas as the weight would, therefore, represent demand due to increased volatility risk as documented in Gârleanu, Pedersen, and Poteshman (2009) and Ni, Pan, and Poteshman (2008). For daily measure of DdAllRisk and DdVolRisk, the variable for every 5-minute interval is first calculated and then averaged across intervals in a day.

DdJpRisk captures the jump risk-induced demand by weighting the 5-minute option demand (DdAllRisk) across all 5-minute intervals in one day using the implied volatility skew. The implied volatility skew for an index option, as documented in Bates (2000) and

the prevailing quote mid-point. Conversely, a transaction is regarded as a seller-initiated trade if it occurs under the prevailing quote mid-point. For trades occur exactly at the midpoint of the quote, a "tick test" is used whereby the trade is classified as buyer-(seller-) initiated if the sign of the last non-zero price change is positive (negative).

Pan (2002), reflects the risk of market jumps. Large implied volatility skew indicates that investors highly anticipate future market jumps. Thus, order imbalances weighted across all 5-minute intervals using implied volatility skew as the weight represent the demand due to increased jump risk. In addition, the implied volatility skew is gauged using the slope of option implied volatility, which is calculated by the out-the-money implied volatility, the average implied volatility of call and put with spot-to-exercise ratio beyond the (1.03, 0.97) range, less the at-the-money implied volatility.

Table 1 provides the averages of daily order imbalances and implied volatilities of calls and puts in the negative and positive returns. A decline in the market price leads to negative order imbalances for near and second calls (C1 and C2, respectively) in each of the three demand variables and every order imbalance measure, and almost positive order imbalances for near and second puts (P1 and P2, respectively). This result indicates that investors have a preference for selling calls and buying puts when market price decreases. Inversely, they are inclined to buy calls and sell puts when market price increases. In addition, positive (negative) average order imbalances are found to increase (decrease) average volatility spread ($IV_d$ – $IV_a$), which is the average difference in implied volatility between negative or positive return period and the entire sample period. The increased (decreased) option price in respond to positive (negative) demand pressure provides evidence for the positive (negative) demand pressure effect on VRP, consistent with Gârleanu, Pedersen, and Poteshman (2009). For example, negative order imbalances in C1 and C2 (P1 and P2) decrease the option's price about the size of 19 and 7 (52 and 10) basis-points, respectively, of implied volatility during the negative (positive) return period.

Table 1 Average order imbalances and option implied volatility

| | Negative returns | | | | Positive returns | | | |
|---|---|---|---|---|---|---|---|---|
| | C1 | C2 | P1 | P2 | C1 | C2 | P1 | P2 |
| #DdAllRisk | –0.0207 | –0.0343 | 0.0003 | 0.0158 | –0.0001 | 0.0032 | –0.0240 | –0.0134 |
| #DdVolRisk | –0.0427 | –0.0462 | –0.0211 | 0.0131 | –0.0207 | 0.0072 | –0.0450 | –0.0177 |
| #DdJpRisk | –0.0197 | –0.0370 | 0.0008 | 0.0184 | 0.0011 | 0.0057 | –0.0242 | –0.0150 |
| $DdAllRisk | –0.0312 | –0.0330 | 0.0040 | 0.0200 | 0.0032 | 0.0064 | –0.0316 | –0.0104 |
| $DdVolRisk | –0.0623 | –0.0440 | –0.0152 | 0.0188 | –0.0113 | 0.0115 | –0.0607 | –0.0131 |
| $DdJpRisk | –0.0299 | –0.0356 | 0.0045 | 0.0226 | 0.0044 | 0.0090 | –0.0319 | –0.0123 |
| $IV_d$ | 0.2040 | 0.1942 | 0.2669 | 0.2530 | 0.2075 | 0.1954 | 0.2557 | 0.2507 |
| $IV_a$ | 0.2058 | 0.1948 | 0.2609 | 0.2518 | 0.2058 | 0.1948 | 0.2609 | 0.2518 |
| $IV_d – IV_a$ | –0.0019 | –0.0007 | 0.0060 | 0.0012 | 0.0016 | 0.0006 | –0.0052 | –0.0010 |

*Notes*. This table reports average order imbalances and implied volatilities of call and put options separately corresponding to negative and positive returns. The data cover the period from January 1, 2005 to December 1, 2009. The order imbalances are measured by both the number of trades (#) and traded dollar amount ($). For each order imbalance measure, we calculate three order imbalance variables which correspond to aggregate risk, volatility risk, and jump risk, respectively. They serve proxies for aggregate demand, volatility demand, and jump demand. #DdAllRisk, #DdVolRisk, and #DdJpRisk ($DdAllRisk, $DdVolRisk, and $DdJpRisk) are the order imbalances measured by the number of trades (traded dollar amount). C1 and P1 (C2 and P2) indicate near-month (second-month) call and put options. $IV_d$ is the average of implied volatility in respond to negative or positive returns; $IV_a$ is the average implied volatility during all the sample period. The difference in implied volatility, $IV_d$ – $IV_a$, indicates the volatility spread.

In addition, to simplify our analysis, we aggregate the demand of call and put options with the same exercise price and maturity in every 5-minute interval. Gârleanu, Pedersen, and Poteshman (2009) argue that linearly dependent derivatives have the same demand effect on option prices. If the put–call parity holds, the prices of a call and a put with the same exercise price and maturity must linearly related. Any demand pressure on the call (price increase) would similarly affect the put, causing the put price to increase.

## 2.3. Model Specifications

### 2.3.1. Testing the effect of option demand pressure on VRP

The regression model of Chan and Fong (2006) and Giot, Laurent, and Petitjean (2010) is adopted to assess the impact of demand pressure on VRP. VRP is regressed against a Monday dummy (MD), twelve lags for VRPs, and two option order imbalances in the near and second months ($OIB_1, OIB_2$, respectively). The *t*-statistics of estimated parameters are calculated using the Newey and West (1987) standard errors.

In addition, two types of order imbalance measures are used to proxy for option net demand: one in number of trades (#OIB) and the other in traded dollar amount ($OIB). For every order imbalance measure, three order imbalance variables are calculated to separately proxy for all demand (DdAllRisk), volatility demand (DdVolRisk), and jump demand (DdJpRisk). The three order imbalance variables are used to test for the demand pressure effect on VRP in the presence of the sources of unhedgeable risk. Each of them is individually included in the regression model of Equation (4):

$$VRP_t = \alpha_0 + \alpha_m MD_t + \phi_1 OIB_{1,t} + \phi_2 OIB_{2,t} + \sum_{j=1}^{12} \omega_j VRP_{t-j} + \varepsilon_t, \tag{4}$$

where MD is a Monday dummy variable that takes 1 for Monday, and zero otherwise. This dummy variable controls for the Monday effect. $OIB_1$ and $OIB_2$ respectively denote the daily option order imbalances in the near and second months. $VRP_{t-j}$s are lagged VRPs to control for serial dependence in the VRP.

Further, this study illustrates whether the linkage between demand pressure and VRP is strong following market-maker losses. In reality, market makers are sensitive to risk due to the capital constraints, tolerance of leverage, and agency. If the risk aversion held by market makers plays a crucial role in determining the compensation for accommodating option demand, then the VRP would be expected to be sensitive to demand during their loss period. Following Gârleanu, Pedersen, and Poteshman (2009), the interaction between the market-maker profits and demand pressure, denoted as IntDdP&L, is used to gauge the demand pressure effect of recent profits and losses of market makers. The other control variables for the daily index return (IR) and daily realized volatility (RV) associated with option price (implied volatility) are also included into the regression model in Equation (5).

$$VRP_t = \alpha_0 + \alpha_m MD_t + \phi_1 OIB_{1,t} + \phi_2 OIB_{2,t} + \beta_1 IntDdP\&L_t + \beta_2 RV_t + \beta_3 IR_t + \sum_{j=1}^{12} \omega_j VRP_{t-j} + \varepsilon_t, \quad (5)$$

The daily IntDdP&L is calculated by the sum of product of lag daily market-maker hedged profits (P&Ls) and daily option net demand (DdAllRisk) in the near and second months. For each of call and put options in the near- and second-month, it is assumed to be sold or bought at the midpoint price of quotes. Further, price risk every 30 minutes is dynamically hedged to keep delta-neutral of option positions until option expiration date by buying or selling |delta| units of the underlying futures in the case of a call (put).[13] In each contract month, the daily hedged profits (P&Ls) for market makers are calculated depending on the sign of order imbalance in a trade day. If the option net demand of end users (order imbalance) is positive, i.e., a sell demand for market makers, the daily P&Ls sum up the 30-minutes delta-hedged gains for all sold option series in a trade day. Similarly, for negative order imbalance, the daily P&Ls are sum of the 30-minutes delta-hedged gains for all bought option series in a trade day. In addition, RV, denotes realized volatility, is measured by the sum of the squared 5-minute returns in a day

2.3.2. Testing the effect of demand pressure with time-varying risk aversion

In addition to empirical evidences in favor of changes in risk aversion (e.g., Brandt and Wang, 2003), Todorov (2010) also finds that market jumps drive time-varying risk aversion. Large or extreme price moves increase both investors' and market makers' fear of future jumps. Immediately after the occurrence of jumps, investors are willing to pay a higher

[13] The delta is calculated by constructing on the Black–Scholes model, in which the implied volatility on day t is used to forecast the realized volatility on day t+1. Moreover, in our study, every TXO can be hedged only by a quarter of TXF contract because the multipliers for the futures and options contracts are NT$200 and NT$50 per index point, respectively.

premium for protection against jumps because they view the possibility of future jumps as more likely. However, most major market indices appear to contain price jumps. If risk aversion is indeed driven by jump activity, the demand pressure effect with jumps should result in a substantial impact on VRP in each of three demand variables.

To link the demand pressure effect with time-varying risk aversion, a jump dummy variable (D) is included in Equation (6). The nonparametric test proposed by Lee and Mykland (2008) is adopted to identify the price jumps. $D_t$ is a dummy variable that is equal to 1 if a price jump occurs during the daily trading time period on day *t*, and zero otherwise. $D_t$*$OIB_t$ captures the demand pressure effect in the occurrence of jumps. Here, it is expected to be larger demand pressure effect for the three demand variables as jumps occur:

$$VRP_t = \alpha_0 + \alpha_m MD_t + \alpha_d D_t + +\phi_1 OIB_{1,t} + \phi_2 OIB_{2,t} + \psi_1 D_t * OIB_{1,t} + \psi_2 D_t * OIB_{2,t} + \beta_1 IntDdP \,\&\, L_t + \beta_2 RV_t + \beta_3 IR_t + \sum_{j=1}^{12} \omega_j VRP_{t-j} + \varepsilon_t. \quad (6)$$

## 3. DATA

This study requires two sets of data. The intraday data on the Taiwan index option (TXO), which is traded on the TAIFEX[14], are obtained from the Taiwan Economic Journal (TEJ) database. The data contain trade and quote files of options. The transaction prices, transaction volumes for every trade are extracted from the trade file and the bid and ask prices are acquired from the quote file for January 1, 2005 through December 31, 2009. The minute-by-minute Taiwan stock index data are also obtained from the TEJ database for January 1, 2002 through December 31, 2009.

Several data filters are applied to select our final sample. First, the options with a quote

[14] The TAIFEX introduced the European style TXO, written on the TAIEX, on December 24, 2001. The contract matures on the third Wednesday of the delivery month. The contract months involve five contracts with different maturities in the nearby month, the next two calendar months, and the following two quarterly months.

price of less than 0.1, the minimum tick size, are excluded. These prices cannot reflect true option value. Second, due to the potential liquidity concerns, the options with less than five trading days remaining to maturity are eliminated. Third, the options violating the put–call parity boundary conditions are deleted. These options are significantly undervalued and have negative Black–Scholes implied volatilities.

Table 2 presents the results of the parameter estimation for the realized volatility forecast based on the VecHAR model in Equation (3). The procedure of a daily rolling window generates 927 estimations for every parameter during the sample period. Table 2 reports the average. The mean coefficients for CV, the first elements in the $B_1$ and $B_{22}$ matrices, are significantly positive, indicating an own persistence in the CV component. There exist dynamically asymmetric dependencies between CV, nJV, pJV, and NV. For instance, CV is lagged to nJV as shown by the significant estimates for the second elements in the $B_1$ matrices whereas nJV is only lagged to nJV. Therefore, all four volatility components are included in the forecasting of realized volatility.

Table 2 Parameter estimates for the VecHAR model

| | CV | | nJV | | pJV | | NV | |
|---|---|---|---|---|---|---|---|---|
| | Coeff. | *t*-value | Coeff. | *t*-value | Coeff. | *t*-value | Coeff. | *t*-value |
| $B_0$ | 0.0068 | $5.18^{***}$ | 0.0002 | $3.85^{***}$ | 0.0003 | $2.98^{***}$ | 0.0096 | $3.02^{***}$ |
| $B_1$ | 0.0700 | $1.76^{*}$ | 0.0005 | 0.24 | –0.0006 | –0.27 | 0.0749 | 1.06 |
| | 0.2106 | $2.06^{**}$ | –0.0023 | –0.74 | 0.0027 | 0.64 | 0.3389 | $1.90^{*}$ |
| | 0.3807 | $2.52^{***}$ | 0.0068 | 1.18 | 0.0041 | –0.14 | 0.1551 | 0.21 |
| | 0.0291 | 0.45 | 0.0004 | 0.03 | 0.0030 | 0.27 | 0.2137 | 0.49 |
| $B_5$ | –0.5322 | –0.52 | –0.0235 | –1.07 | 0.0143 | –0.08 | –0.0272 | 0.28 |
| | 0.4751 | 0.00 | –0.2242 | $–3.22^{***}$ | 0.0195 | –0.24 | 1.1956 | –0.67 |
| | 0.0236 | –0.19 | –0.0027 | –0.63 | 0.0008 | 0.15 | 0.2272 | 0.31 |
| | 0.4727 | 0.34 | –0.0209 | –0.81 | 0.0223 | 0.56 | 1.6656 | 0.52 |
| $B_{22}$ | –2.5681 | $–2.19^{**}$ | 0.1157 | 1.20 | –0.1771 | $–2.31^{**}$ | 1.2893 | $–1.69^{*}$ |
| | 0.0077 | 1.31 | 0.0002 | 0.88 | –0.0002 | –0.35 | 0.0122 | 1.25 |
| | –0.0234 | –1.47 | –0.0010 | –1.09 | –0.0001 | 0.01 | 0.0415 | 0.02 |
| | 0.0509 | $1.82^{*}$ | –0.0009 | –0.24 | –0.0048 | –0.69 | 0.0319 | 1.08 |

*Notes*. This table presents the estimating results of parameters for realized volatility forecast based on a vector autoregressive (VecHAR) model in Equation (3):

$$\begin{aligned} Z_{t+22} &= B_0 + B_1 Z_{t-1} + B_5 Z_{t-5} + B_{22} Z_{t-22} + \varepsilon_{t+22}, \\ Z_t &= (CV_t \; nJV_t \; pJV_t \; NV_t)'. \end{aligned} \tag{3}$$

The expected realized volatility is estimated using the moving window data of past 800 days. The realized variation measures underlying the estimate are based on 5-minute high-frequency data from January 1, 2002 to December 31, 2009 inclusively. The procedure of a daily rolling window generates 927 estimations for each parameter during the sample period. Table 2 reports the average. In Equation (3), $B_0$ is a vector of the intercept term. $B_1$, $B_5$, and $B_{22}$ are matrices for the regression coefficients, in which the first column, second column, third column, and fourth column in each matrix correspond to the parameters of the four volatility components, respectively. A four-dimensional vector is included in the VecHAR model, involving continuous volatility (CV), negative jump volatility (nJV), positive jump volatility (pJV), and overnight volatility (NV). In addition, Newey–West standard errors are used to calculate the *t*-values of the estimated parameters. Coeff. indicates the regression coefficient. ***, **, and * indicate that *t*-values are significant at the 0.01, 0.05, and 0.1 level, respectively.

Figure 1 exhibits the plot of the time-series for model-free implied volatility (IV) and expected realized volatility ($RV_E$) in the top panel and VRP in the bottom panel. A visual inspection reveals that both the implied volatility and expected realized volatility track closely. Overall, the IV is slightly above the $RV_E$ by 162 basis points, indicating a positive VRP (The means of IV and $RV_E$ are 0.2320 and 0.2158, respectively).

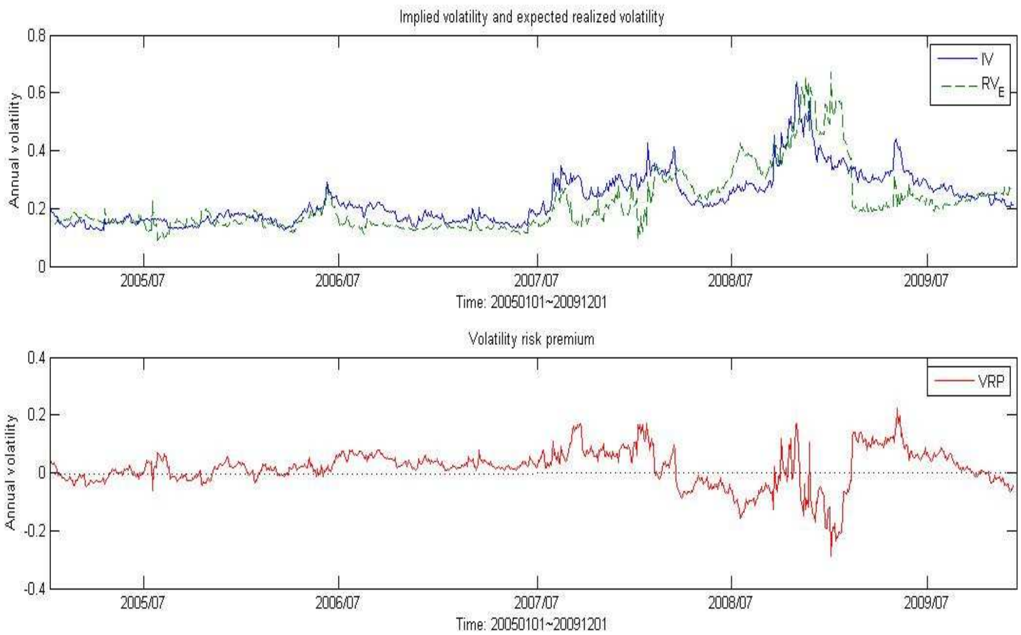


Figure 1. Time series plots of implied volatility, expected realized volatility, and volatility risk premium. The volatility risk premium (VRP) is quantified as the model-free implied volatility (IV) less the expected realized volatility ($RV_E$). The model-free method proposed by Jiang and Tian (2005, 2007) is adopted to extract the implied volatility, and a vector heterogeneous autoregressive (VecHAR) model is used to estimate the expected realized volatility.

The second panel of Figure 1 shows that the time-series VRP ranges from –0.2883 to 0.2245 during the period of 2005–2009 and has a mean 0.0162. The 1.62% volatility spread provides evidence to support the finding of Bollen and Whaley (2004) and Gârleanu et al. (2009) that market makers who provide liquidity to the buy side are compensated for accepting risk. However, when the market is more volatile, market makers also face substantial risk of losses. In the period of financial crisis in 2008, a negative VRP, also shown in Todorov (2010) and Bollerslev, Gibson, Zhou (2011), occurs frequently. That is, market makers providing liquidity to the buy side suffer trading losses. In addition, the VRP is stationary time series according to the results of the Dickey–Fuller test with test statistic of -44.6.

Panels A and B of Table 3 respectively report the summary statistics of option order imbalances measured by the number of trades (#OIB) and traded dollar amount ($OIB). #DdAllRisk$_{1}$, #DdVolRisk$_{1}$, and #DdJpRisk$_{1}$ (#DdAllRisk$_{2}$, #DdVolRisk$_{2}$, and #DdJpRisk$_{2}$) indicate option demand, volatility demand, and jump demand in the near (second) month, in which all are measured by the number of trades. Similarly, $DdAllRisk$_{1}$, $DdVolRisk$_{1}$, and $DdJpRisk$_{1}$ ($DdAllRisk$_{2}$, $DdVolRisk$_{2}$, and $DdJpRisk$_{2}$) are option demands in the near (second) month measured by the dollars $OIB. The results show that all the option order imbalances are slightly negative, negative skewness, and leptokurtic. For instance, the DdAllRisk$_{1}$, DdVolRisk$_{1}$, and DdJpRisk$_{1}$ measured by #OIB ($OIB) in the near month average –0.0058, –0.0284, and –0.0055 (–0.0127, –0.0379, and –0.0125), respectively. In addition, the augmented Dickey–Fuller (ADF) unit root tests significant reject the hypothesis of one unit root for every individual series, indicating that these demand variables are stationary. The correlation coefficients between option order imbalances in near- and second-month for #DdAllRisk, #DdVolRisk, and #DdJpRisk ($DdAllRisk, $DdVolRisk, and $DdJpRisk) are 0.09, 0.06, and 0.09 (0.18, 0.22, and 0.15), respectively. The correlation coefficients range from 0.06 to 0.22, showing a low correlation between these option demand variables in the near- and second-month.

Table 3 Summary statistics for order imbalances

| | obs. | Mean | Std | Min | p5 | p50 | p95 | Max | Skew | Kurt | ADF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Order imbalances measured by number of trades (#OIB) | | | | | | | | | | | |
| #DdAllRisk$_1$ | 927 | –0.0058 | 0.0324 | –0.3271 | –0.0577 | –0.0055 | 0.0451 | 0.0946 | –0.9921 | 13.20 | -569 |
| #DdVolRisk$_1$ | 927 | –0.0284 | 0.0300 | –0.3376 | –0.0778 | –0.0272 | 0.0177 | 0.0717 | –1.2059 | 15.01 | -307 |
| #DdJpRisk$_1$ | 927 | –0.0055 | 0.0334 | –0.3549 | –0.0598 | –0.0049 | 0.0477 | 0.1201 | –1.1050 | 15.73 | -587 |
| #DdAllRisk$_2$ | 927 | –0.0118 | 0.0389 | –0.2435 | –0.0808 | –0.0093 | 0.0487 | 0.1582 | –0.4361 | 4.76 | -477 |
| #DdVolRisk$_2$ | 927 | –0.0166 | 0.0536 | –0.2315 | –0.1120 | –0.0160 | 0.0704 | 0.1504 | –0.0733 | 3.43 | -556 |
| #DdJpRisk$_2$ | 927 | –0.0111 | 0.0409 | –0.2565 | –0.0824 | –0.0092 | 0.0532 | 0.1522 | –0.4527 | 4.66 | -511 |
| Panel B: Order imbalances measured by dollars ($OIB) | | | | | | | | | | | |
| $DdAllRisk$_1$ | 927 | –0.0127 | 0.0348 | –0.3112 | –0.0690 | –0.0114 | 0.0393 | 0.1211 | –0.7107 | 9.13 | -647 |
| $DdVolRisk$_1$ | 927 | –0.0379 | 0.0341 | –0.3226 | –0.0940 | –0.0362 | 0.0155 | 0.0732 | –0.7141 | 8.31 | -401 |
| $DdJpRisk$_1$ | 927 | –0.0125 | 0.0357 | –0.3359 | –0.0712 | –0.0114 | 0.0407 | 0.1300 | –0.8016 | 10.47 | -668 |
| $DdAllRisk$_2$ | 927 | –0.0070 | 0.0396 | –0.2428 | –0.0760 | –0.0055 | 0.0551 | 0.1879 | –0.3370 | 5.08 | -516 |
| $DdVolRisk$_2$ | 927 | –0.0097 | 0.0568 | –0.2301 | –0.1032 | –0.0119 | 0.0827 | 0.1804 | –0.0155 | 3.59 | -626 |
| $DdJpRisk$_2$ | 927 | –0.0064 | 0.0418 | –0.2517 | –0.0796 | –0.0056 | 0.0572 | 0.1726 | –0.3298 | 4.85 | -554 |

*Notes*. This table presents summary statistics for daily option order imbalances in the near and second months. Panel A and Panel B report the statistics of order imbalances measured by number of trades (#OIB) and dollars ($OIB), respectively. #DdAllRisk$_1$, #DdVolRisk$_1$, and #DdJpRisk$_1$ (#DdAllRisk$_2$, #DdVolRisk$_2$, and #DdJpRisk$_2$) indicate option demand, volatility demand, and jump demand in the near (second) month, in which order imbalances are measured by the number of trades. Similarly, $DdAllRisk$_1$, $DdVolRisk$_1$, and $DdJpRisk$_1$ ($DdAllRisk$_2$, $DdVolRisk$_2$, and$DdJpRisk$_2$) are option demands in the near (second) month, in which they are measured by the dollars $OIB. ADF is the augmented Dickey–Fuller unit root test.

## 4. EMPIRICAL RESULTS

### 4.1. Option Demand Pressure on VRP

In practice, the price of the option that market makers sell (buy) includes (excludes) risk premiums that compensate the unhedgeable risk. A positive (buy) demand pressure, which is opposite to the sell demand pressure for market makers, raises VRP, whereas a negative (sell) demand pressure decreases VRP. Thus, if demand pressure in an option affects VRP, it is expected to be a positive effect of demand pressure on VRP.

Panels A and B of Table 4 report the results of the demand effect measured by #OIB and $OIB, respectively. In Panel A, the coefficients for $\phi_1$ and $\phi_2$ in the near and second months are both significant and positive for option demand (DdAllRisk) and jump demand (DdJpRisk). This finding indicates that demand pressure stemming from aggregate option demand and jump demand positively affects VRP. However, the volatility demand (DdVolRisk) pressure has relatively weak influence on VRP due to the positive but insignificant coefficients for $\phi_1$ and $\phi_2$. Panel B reports similar results for the positive effect of demand pressure measured by $OIB. These empirical results support a positive effect of option demand pressure on VRP.

Table 4 The effect of option demand pressure on VRP

| | DdAllRisk | | DdVolRisk | | DdJpRisk | |
|---|---|---|---|---|---|---|
| | Coeff. | *t* | Coeff. | t | Coeff. | *t* |
| Panel A: Demand measured by number of trades (#OIB) | | | | | | |
| $\alpha_m$ | 0.0051 | 3.04*** | 0.0048 | 2.88*** | 0.0052 | 3.04*** |
| $\phi_1$ | 0.0988 | 2.11** | 0.0732 | 1.30 | 0.0980 | 2.10** |
| $\phi_2$ | 0.0464 | 2.08** | 0.0202 | 1.30 | 0.0488 | 2.05** |
| $Adj.R^2$ | 0.8754 | – | 0.8735 | – | 0.8757 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |
| Panel B: Demand measured by traded dollars ($OIB) | | | | | | |
| $\alpha_m$ | 0.0051 | 3.01*** | 0.0047 | 2.86*** | 0.0051 | 3.03*** |
| $\phi_1$ | 0.0903 | 2.41** | 0.0628 | 1.54 | 0.0863 | 2.26** |
| $\phi_2$ | 0.0423 | 1.93* | 0.0150 | 1.11 | 0.0484 | 2.06** |
| $Adj.R^2$ | 0.8754 | – | 0.8735 | – | 0.8757 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |

*Notes*. This table presents the results for the regression model, shown in Equation (4), of option demand pressure on volatility risk premium (VRP).

$$VRP_t = \alpha_0 + \alpha_m MD_t + \phi_1 OIB_{1,t} + \phi_2 OIB_{2,t} + \sum_{j=1}^{12} \omega_j VRP_{t-j} + \varepsilon_t, \quad (4)$$

Two types of option order imbalance are used to measure the option net demand, one in number of trades (#OIB) and the other in dollars ($OIB). The results are reported in Panel A and Panel B, respectively. For each type of order imbalance measure, three order imbalance variables are calculated separately weighted by aggregate risk, volatility risk, and jump risk and are used to proxy, respectively, for option demand (DdAllRisk), volatility demand (DdVolRisk) and jump demand (DdJpRisk). They are individually included in the regression model to investigate the demand pressure effect on VRP. The dependent variable, VRP, is quantified as the model-free implied volatility less expected realized volatility. $OIB_1$ and $OIB_2$ denote the daily option order imbalances in the near and second months, respectively. MD is a Monday dummy and the $VRP_{t-j}$'s are lagged volatility risk premiums. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. For brevity, this table does not report $\hat{\alpha}_0$ and $\hat{w}_j$. ***, **, and * indicate that *t*-values are significant at the 0.01, 0.05, and 0.1 level, respectively.

Compared with the demand pressure effects in three demand variables, DdAllRisk and

DdJpRisk explain VRP better than DdVolRisk. A possible cause for the weak volatility demand pressure effect is that market makers ask for smaller compensation to take the relatively small volatility risk associated with small price moves. In addition, the significant and positive coefficients for dummy variable $\alpha_m$ in both Panels A and B confirm the Monday effect (i.e., VRP is greater on Monday). The Monday effect may result from the accumulation of information over the weekend nontrading period. The high uncertainty during weekend may increase demand for using options to adjust the portfolios against volatility risk or jumps and subsequently causes higher VRP on Monday.

Table 5 provides the results of demand pressure effect by controlling on interaction between recent market-maker hedged profits and demand pressure (IntDdP&L), daily realized volatility (RV), and daily index return (IR). As shown in Panels A and B, $\phi_1$ and $\phi_2$ are almost significant positive for the three demand variables. This evidence makes it clear that demand pressure has a positive impact on the level of VRP regardless of the sources of unhedgeable risk. In addition, all the $\beta_1$ coefficients are found to be significant negative in Panel A and Panel B. The negative coefficients on the interaction between market-maker hedged profits and option net demand indicate an increase (decrease) in the demand pressure effect on VRP following recent market-maker losses (profits). Facing the trading loss, market makers with risk aversion ask a higher risk premium for accepting additional risk, consistent with Gârleanu, Pedersen, and Poteshman (2009) who find strong linkage between demand pressure effect and risk aversion. The result also provides evidence in supportive to that market makers play a crucial role in determining VRP.

The negative coefficients for $\beta_3$ in Panels A and B suggest that a negative return may lead to higher VRP because investors are willing to pay more to hedge the potential decline than to hedge a possible increase.

Table 5 The effect of option demand pressure on VRP with control variables

| | DdAllRisk | | DdVolRisk | | DdJpRisk | |
|---|---|---|---|---|---|---|
| | Coeff. | t | Coeff. | t | Coeff. | t |
| Panel A: Demand measured by number of trades (#OIB) | | | | | | |
| $\phi_1$ | 0.0859 | 1.88* | 0.0710 | 1.32 | 0.0831 | 1.81* |
| $\phi_2$ | 0.0677 | 2.98*** | 0.0391 | 2.38** | 0.0698 | 2.87*** |
| $\beta_1$ | –0.0005 | –4.85*** | –0.0004 | –4.56*** | –0.0004 | –5.40*** |
| $\beta_2$ | –0.0109 | –0.97 | –0.0099 | –0.90 | –0.0116 | –1.04 |
| $\beta_3$ | –0.3752 | –3.19*** | –0.3929 | –3.34*** | –0.3710 | –3.19*** |
| $Adj.R^2$ | 0.8841 | – | 0.8828 | – | 0.8845 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |
| Panel B: Demand measured by traded dollars ($OIB) | | | | | | |
| $\phi_1$ | 0.0886 | 2.41** | 0.0860 | 2.17** | 0.0836 | 2.23** |
| $\phi_2$ | 0.0627 | 2.86*** | 0.0282 | 1.99** | 0.0668 | 2.82*** |
| $\beta_1$ | –0.0004 | –3.86*** | –0.0004 | –5.03*** | –0.0004 | –5.27*** |
| $\beta_2$ | –0.0118 | –1.06 | –0.0131 | –1.19 | –0.0132 | –1.19 |
| $\beta_3$ | –0.3896 | –3.34*** | –0.4208 | –3.60*** | –0.3888 | –3.37*** |
| $Adj.R^2$ | 0.8844 | – | 0.8840 | – | 0.8851 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |

*Notes*. This table presents the results for the regression model, shown in Equation (5), of option demand pressure on volatility risk premium (VRP) by controlling on the interaction between market-maker hedged profits and option net demand (IntDdP&L), daily realized volatility (RV), daily index return (IR), and lagged VRPs:

$$VRP_t = \alpha_0 + \alpha_m MD_t + \phi_1 OIB_{1,t} + \phi_2 OIB_{2,t} + \beta_1 IntDdP\&L_t + \beta_2 RV_t + \beta_3 IR_t + \sum_{j=1}^{12} \omega_j VRP_{t-j} + \varepsilon_t . \quad (5)$$

Two types of option order imbalance are used to measure the option net demand, one in number of trades (#OIB) and the other in dollars ($OIB). The results are reported in Panel A and Panel B, respectively. For each type of order imbalance measure, three order imbalance variables are calculated separately weighted by aggregate risk, volatility risk, and jump risk and are used to proxy, respectively, for option demand (DdAllRisk), volatility demand (DdVolRisk) and jump demand (DdJpRisk). They are individually included in the regression model to investigate the demand pressure effect on VRP. The VRP is quantified as the model-free implied volatility less expected realized volatility. $OIB_1$ and $OIB_2$ denote the daily option order imbalances in the near and second months, respectively. IntDdP&L is the interaction between market-maker hedged profits and option net demand. MD is a Monday dummy. The $VRP_{t-j}$'s are lagged volatility risk premiums. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. For brevity, this table does not report $\hat{\alpha}_0$, $\hat{\alpha}_m$, and $\hat{w}_j$. ***, **, and * indicate that *t*-values are significant at the 0.01, 0.05, and 0.1 level, respectively.

## 4.2. Option Demand Pressure on VRP with Time-Varying Risk Aversion

Table 6 reports the results of the demand pressure effect on VRP with jumps. All $\psi_1$ coefficients in Panels A and B are significantly positive and larger than those for $\phi_1$ for all three demand variables (DdAllRisk, DdVolRisk, and DdJpRisk). This indicates a greater impact of demand pressure on VRP at the time of the occurrence of market jumps. Specifically, the demand pressure effect with jumps is more than a fourth larger as that without jumps. For example, for all demand (DdAllRisk) measured by #OIB ($OIB), the estimates for demand effect $\psi_1$ and $\phi_1$ are 0.2818 and 0.0339 (0.2574 and 0.0493), respectively.

Table 6 The effect of option demand pressure on VRP with market jumps

| | DdAllRisk | | DdVolRisk | | DdJpRisk | |
|---|---|---|---|---|---|---|
| | Coeff. | t | Coeff. | t | Coeff. | t |
| Panel A: Demand measured by number of trades (#OIB) | | | | | | |
| $\phi_1$ | 0.0339 | 1.57 | 0.0094 | 0.43 | 0.0301 | 1.40 |
| $\phi_2$ | 0.0467 | 2.86*** | 0.0251 | 1.79* | 0.0456 | 2.50** |
| $\psi_1$ | 0.2818 | 2.87*** | 0.3122 | 2.77*** | 0.2424 | 2.84*** |
| $\psi_2$ | 0.0766 | 0.94 | 0.0459 | 0.97 | 0.1228 | 1.61 |
| $\beta_1$ | –0.0005 | –4.73*** | –0.0004 | –4.45*** | –0.0004 | –5.56 |
| $\beta_2$ | –0.0079 | –0.71 | –0.0088 | –0.79 | –0.0085 | –0.77 |
| $\beta_3$ | –0.3852 | –3.27*** | –0.4008 | –3.40*** | –0.3822 | –3.29 |
| $Adj.R^2$ | 0.8897 | – | 0.8886 | – | 0.8904 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |
| Panel B: Demand measured by traded dollars ($OIB) | | | | | | |
| $\phi_1$ | 0.0493 | 2.38** | 0.0516 | 2.46** | 0.0452 | 2.18** |
| $\phi_2$ | 0.0432 | 2.60*** | 0.0176 | 1.34 | 0.0423 | 2.30** |
| $\psi_1$ | 0.2574 | 2.31** | 0.2289 | 1.72* | 0.2118 | 1.97** |
| $\psi_2$ | 0.0794 | 0.93 | 0.0302 | 0.61 | 0.1504 | 1.79* |
| $\beta_1$ | –0.0004 | –3.74*** | –0.0004 | –4.65*** | –0.0004 | –5.46 |
| $\beta_2$ | –0.0091 | –0.83 | –0.0112 | –1.05 | –0.0101 | –0.94 |
| $\beta_3$ | –0.3926 | –3.33*** | –0.4208 | –3.51*** | –0.3927 | –3.38 |
| $Adj.R^2$ | 0.8900 | – | 0.8887 | – | 0.8911 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |

*Notes*. This table presents the results for the regression model, shown in Equation (6), of option demand pressure on volatility risk premium (VRP) with market jumps:

$$VRP_t = \alpha_0 + \alpha_m MD_t + \alpha_d D_t + \phi_1 OIB_{1,t} + \phi_2 OIB_{2,t} + \psi_1 D_t * OIB_{1,t} + \psi_2 D_t * OIB_{2,t} + \beta_1 IntDdP \& L_t + \beta_2 RV_t + \beta_3 IR_t + \sum_{j=1}^{12} \omega_j VRP_{t-j} + \varepsilon_t. \qquad (6)$$

The price jumps are identified by a nonparametric test proposed by Lee and Mykland (2008). Two types of option order imbalance are used to measure the option net demand, one in number of trades (#OIB) and the other in dollars ($OIB). The results are reported in Panel A and Panel B, respectively. For each type of order imbalance measure, three order imbalance variables are calculated separately weighted by aggregate risk, volatility risk, and jump risk and are used to proxy, respectively, for option demand (DdAllRisk), volatility demand (DdVolRisk) and jump demand (DdJpRisk).They are individually included in the regression model to investigate the demand pressure effect on VRP. The dependent variable, VRP, is quantified as the model-free implied volatility less expected realized volatility. $D_t$, a jump dummy variable, is equal to 1 if a price jump occurs during the daily trading time period on day *t*, and zero otherwise. $OIB_1$ and $OIB_2$ denote the daily option order imbalances in the near and second months, repsectively. IntDdP&L is the interaction between market-maker hedged profits and option net demand. RV is the daily realized volatility and IR is the daily index return. MD is a Monday dummy. The $VRP_{t-j}$'s are lagged volatility risk premiums. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. For brevity, this table does not report $\hat{\alpha}_0$, $\hat{\alpha}_m$, $\hat{\alpha}_d$, and $\hat{w}_j$. ***, **, and * indicate that *t*-values are significant at the 0.01, 0.05, and 0.1 level, respectively.

In particular, as the arrival of market jumps, there is a great increase in the effect of volatility demand pressure, arising from small price changes, suggests that jump activity motivates market makers to be more risk averse, thereby asking for more compensation for accepting unhedgeable risk. This result also supports the finding of Todorov (2010) that market jumps drives time-varying risk aversion.

### 4.3. Robustness Tests on Option Demand Pressure Effect on VRP

Two robustness checks are conducted to further verify the finding of a positive effect of demand pressure on VRP. First, a liquidity indicator of options is included into the regression model to control the probable influence on the VRP. Second, an alternative measure of realized volatility is used to re-examine whether the result of demand pressure effect on the VRP is robust. They are specified as follows.

First, option liquidity is likely to affect the effect of demand pressure on VRP. Brenner, Eldor, and Hauser (2001) and Chou, Chung, Hsiao, and Wang (2011) find that option liquidity impacts its implied volatility (price) associated with the estimation of the VRP, the implied volatility less expected realized volatility. Therefore, a liquidity indicator, the daily aggregate option liquidity (QSPR), is incorporated into the regression model as a control variable for potential bias due to liquidity in the option market.[15]

The QSPR averages daily percentage quoted spread of options in the near and second

[15] For conciseness, only the effect of option demand pressure on VRP is examined by controlling on the interaction between market-maker hedged profits and option net demand, daily realized volatility, daily index return, lag VRPs, and option liquidity.

months. For daily option percentage quoted spread in each contract month, the average of percentage quoted spread of call and put options is first calculated in every five-minute interval and then averaged across intervals in a day, in which the percentage quoted spread in calls (and puts) is equally weighted across all individual call (put) options with different exercise prices. As for the percentage quoted spread of individual option, it is calculated as the difference between ask and bid prices dividing the mid-quote.

The results are reported in Table 7. The coefficient of $\beta_4$ picks up the effect of option liquidity on VRP. Table 7 continues to show that a significant and positive effect of demand pressure on VRP persists after controlling for liquidity in options, consistent with the results in Table 5. In addition, the insignificant coefficients for liquidity indicator ($\beta_4$) indicate that option demand pressure in contrast to its liquidity explains the time-varying VRP well.

Table 7 The effect of option demand pressure on VRP by controlling on option liquidity

| | DdAllRisk | | DdVolRisk | | DdJpRisk | |
|---|---|---|---|---|---|---|
| | Coeff. | t | Coeff. | t | Coeff. | t |
| Panel A: Demand measured by number of trades (#OIB) | | | | | | |
| $\phi_1$ | 0.0851 | 1.84* | 0.0747 | 1.39 | 0.0821 | 1.77* |
| $\phi_2$ | 0.0687 | 3.01*** | 0.0396 | 2.39** | 0.0708 | 2.90*** |
| $\beta_1$ | -0.0005 | -4.88*** | -0.0004 | -4.58*** | -0.0004 | -5.41*** |
| $\beta_2$ | -0.0117 | -1.04 | -0.0108 | -0.98 | -0.0123 | -1.11 |
| $\beta_3$ | -0.3800 | -3.19*** | -0.3988 | -3.35*** | -0.3760 | -3.18*** |
| $\beta_4$ | -0.0455 | -0.88 | -0.0599 | -1.16 | -0.0454 | -0.88 |
| $Adj.R^2$ | 0.8842 | - | 0.8831 | - | 0.8846 | - |
| Panel B: Demand measured by traded dollars ($OIB) | | | | | | |
| $\phi_1$ | 0.0890 | 2.42** | 0.0943 | 2.37** | 0.0838 | 2.24** |
| $\phi_2$ | 0.0630 | 2.86*** | 0.0272 | 1.91* | 0.0674 | 2.84*** |
| $\beta_1$ | -0.0004 | -3.90*** | -0.0004 | -5.07*** | -0.0004 | -5.30*** |
| $\beta_2$ | -0.0126 | -1.13 | -0.0145 | -1.31 | -0.0140 | -1.26 |
| $\beta_3$ | -0.3945 | -3.34*** | -0.4302 | -3.62*** | -0.3939 | -3.37*** |
| $\beta_4$ | -0.0489 | -0.96 | -0.0798 | -1.52 | -0.0501 | -0.99 |
| $Adj.R^2$ | 0.8846 | - | 0.8844 | - | 0.8852 | - |

Note. This table presents the results of option demand pressure on volatility risk premium (VRP) by controlling on the interaction between market-maker hedged profits and option net demand (IntDdP&L), daily realized volatility

(RV), daily index return (IR), option liquidity (QRSP), and lag VRPs. The coefficient of $\beta_4$ picks up the effect of option liquidity on the VRP. Two types of option order imbalance are used to measure the option net demand, one in number of trades (#OIB) and the other in dollars ($OIB). The results are reported in Panel A and Panel B, respectively. For each type of order imbalance measure, three order imbalance variables are calculated separately weighted by aggregate risk, volatility risk, and jump risk and are used to proxy, respectively, for option demand (DdAllRisk), volatility demand (DdVolRisk) and jump demand (DdJpRisk). They are individually included in the regression model to investigate the demand pressure effect on VRP. QSPR is the daily ×liquidity in the option market. The VRP is quantified as the implied volatility less expected realized volatility. $OIB_1$ and $OIB_2$ denote the daily option order imbalances in the near and second months. RV is daily realized volatility, and IR is the daily index return. MD is a Monday dummy. The $VRP_{t-j}$'s are lagged volatility risk premiums. Moreover, Newey-West standard errors are used to calculate the *t*-statistics of the estimated parameters. For brevity, this table does not report the $\hat{\alpha}_0$, $\hat{\alpha}_m$ and $\hat{w}_j$'s. The Adj. $R^2$ denotes the adjusted $R^2$ for the regression. ***, **, and * indicate that *t*-values are significant at the 0.01, 0.05, and 0.1 level, respectively.

Second, an alternative measure of realized volatility is used to examine whether our results of the demand effect are robust under different measures. Many empirical studies find positive autocorrelation between high-frequency index returns. As reported in Andersen et al. (2001), the serial autocorrelation in high-frequency returns may bias the estimation of realized volatility, measured by summing up the squared intraday returns. This bias likely leads to an inaccurate estimate of VRP and can subsequently result in an improper conclusion from our analysis.

Andersen et al. (2001) suggest that the intraday returns should be cleaned up using an MA(1) filter before computing realized volatility. The de-meaned MA(1)-filtered returns can reduce serial correlation and are better suited for the calculation of realized volatility. Thus, this study follows their suggestion by applying the MA(1) filter to the 5-minute returns. Using the filtered series, the related variables are recalculated such as the expected realized volatility, VRP, and the detection of jumps and re-examine the effect of demand pressure on the VRP.

Table 8 The demand effect of option based on the MA(1)-filtered returns

| | DdAllRisk | | DdVolRisk | | DdJpRisk | |
|---|---|---|---|---|---|---|
| | Coeff. | t | Coeff. | t | Coeff. | t |
| Panel A: Demand measured by number of trades (#OIB) | | | | | | |
| $\phi_1$ | 0.0241 | 1.12 | –0.0001 | 0.00 | 0.0232 | 1.10 |
| $\phi_2$ | 0.0563 | 2.98*** | 0.0316 | 1.78* | 0.0549 | 2.59*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| $\psi_1$ | 0.3590 | 3.10*** | 0.4160 | 2.78*** | 0.3346 | 3.33*** |
| $\psi_2$ | 0.1344 | 1.56 | 0.0485 | 0.92 | 0.1504 | 1.79* |
| $\beta_1$ | –0.0005 | –4.82*** | –0.0004 | –4.40*** | –0.0004 | –5.56*** |
| $\beta_2$ | –0.0063 | –0.58 | –0.0077 | –0.71 | –0.0071 | –0.68 |
| $\beta_3$ | –0.3968 | –3.44*** | –0.4086 | –3.53*** | –0.3853 | –3.36*** |
| *Adj.R*$^2$ | 0.9021 | – | 0.9005 | – | 0.9029 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |
| Panel B: Demand measured by traded dollars ($OIB) | | | | | | |
| $\phi_1$ | 0.0414 | 2.12** | 0.0443 | 2.21** | 0.0402 | 2.06** |
| $\phi_2$ | 0.0533 | 2.78*** | 0.0233 | 1.44 | 0.0513 | 2.46** |
| $\psi_1$ | 0.2936 | 2.12** | 0.3103 | 1.69* | 0.2804 | 2.17** |
| $\psi_2$ | 0.1465 | 1.53 | 0.0270 | 0.50 | 0.1808 | 1.89* |
| $\beta_1$ | –0.0004 | –3.54*** | –0.0004 | –4.65*** | –0.0004 | –5.29*** |
| $\beta_2$ | –0.0071 | –0.67 | –0.0101 | –0.97 | –0.0088 | –0.84 |
| $\beta_3$ | –0.4091 | –3.58*** | –0.4284 | –3.65*** | –0.3992 | –3.52*** |
| *Adj. R*$^2$ | 0.9015 | – | 0.8997 | – | 0.9028 | – |
| *obs.* | 927 | – | 927 | – | 927 | – |

*Notes*. This table presents the results for the regression model, shown in Equation (6), of option demand pressure on the volatility risk premium (VRP) based on MA(1)-filtered returns:

$$VRP_t = \alpha_0 + \alpha_m MD_t + \alpha_d D_t + + \phi_1 OIB_{1,t} + \phi_2 OIB_{2,t} + \psi_1 D_t * OIB_{1,t} + \psi_2 D_t * OIB_{2,t} + \beta_1 IntDdP\,\&\,L_t + \beta_2 RV_t + \beta_3 IR_t + \sum_{j=1}^{12} \omega_j VRP_{t-j} + \varepsilon_t. \quad (6)$$

An MA(1) filter is used to remove the serial autocorrelation in high-frequency 5-minute returns. Subsequently, the filtered returns are used to recalculate related variables in the regression model. Two types of option order imbalance are used to measure the option net demand, one in number of trades (#OIB) and the other in dollars ($OIB). The results are reported in Panel A and Panel B, respectively. For each type of order imbalance measure, three order imbalance variables are calculated separately weighted by aggregate risk, volatility risk, and jump risk and are used to proxy, respectively, for option demand (DdAllRisk), volatility demand (DdVolRisk) and jump demand (DdJpRisk). They are individually included in the regression model to investigate the demand pressure effect on VRP. VRP is quantified as the implied volatility less expected realized volatility. $OIB_1$ and $OIB_2$ denote the daily option order imbalances in the near and second months, respectively. $D_t$, a jump dummy variable, is equal to 1 if a price jump occurs during the daily trading time period on day *t*, and zero otherwise. The price jumps are identified by a nonparametric test proposed by Lee and Mykland (2008). IntDdP&L is the interaction between market-maker hedged profits and option net demand. RV is daily realized volatility, and IR is the daily index return. MD is a Monday dummy. $VRP_{t-j}$ are lagged volatility risk premiums. Newey–West standard errors are used to calculate the *t*-statistics of the estimated parameters. For brevity, this table does not report $\hat{\alpha}_0, \hat{\alpha}_m, \hat{\alpha}_d$, and $\hat{w}_j$. ***, **, and * indicate that *t*-values are significant at the 0.01, 0.05, and 0.1 level, respectively.

The results of a positive demand pressure effect on VRP are similar to those in Tables 4, 5, and 6. For brevity, only the result of demand pressure on VRP with jumps is illustrated in Table 8. Panels A and B continue to show highly significant *t*-values of $\psi_1$ for all three demand variables, indicating that jumps generate a larger impact of demand pressure on

VRP. A positive and larger coefficients $\psi_1$ relative to $\phi_1$ for volatility demand at time of jump occurrence suggests that time-varying risk aversion is driven by market jumps. In sum, it is thus concluded that higher (lower) VRP is more likely to be the result of the positive (negative) demand pressure effect rather than the serial autocorrelation in high-frequency returns and liquidity effect.

## 5. CONCLUSIONS

This study examines the effect of option demand pressure on volatility risk premium (VRP) and investigates whether the demand pressure effect becomes stronger as market jumps occur. The order imbalance in options is used instead of option net demand to analyze the demand pressure effect on VRP. To the best of our knowledge, this study is the first to investigate the effect of option demand pressure on VRP and the linkage between demand effect and time-varying risk aversion.

The option net demand is gauged using two order imbalance measures: one in number of trades and the other in traded dollar amount. For every order imbalance measure, three order imbalance variables are calculated separately weighted by the aggregate risk, unexpected volatility, and sudden jumps in underlying price. They are proxies for all demand, volatility demand, and jump demand, respectively. The three demand variables are used to test the effect of demand pressure in the presence of the sources of unhedgeable risk.

Our empirical results show that demand pressure for an index option helps to explain time-varying VRP. A positive (negative) demand pressure raises (decreases) VRP. Specifically, market jumps generate a greater effect of demand pressure on VRP even for the volatility demand resulting from the small market price moves. This result provides evidence, as documented in Todorov (2010), that large, or extreme, market moves can drive time-varying risk aversion.

## CHAPTER 3 THE FEEDBACK EFFECT OF TRADING VOLATILITY RISK PREMIUM: EVIDENCE FROM THE TAIWAN INDEX OPTION MARKET

### 1. INTRODUCTION

Variations in market return volatility or jumps introduce a source of risk known as volatility risk. A large body of literature has found evidence that volatility risk is priced in options and compensated by a volatility risk premium (VRP), for example, Bakshi and Kapadia (2003), Buraschi and Jackwerth (2001), Carr and Wu (2009), Chernov and Ghysels (2000), Coval and Shumway (2001), and Ting (2007). Empirical evidence also indicates that higher volatility often leads to increased VRP (Bollerslev & Todorov, 2011; Todorov, 2010). Despite the overwhelming evidence for the presence and the cause of VRP, much less is known about the market reaction following a large VRP. The current study fills this gap by investigating the dynamic processes between VRP and volatility while focusing on the afterward effect of a large VRP. This study argues that a large VRP is followed by a feedback effect that increases market volatility. Specifically, a large VRP attracts volatility trading and is accompanied by hedging transactions, which could subsequently raise market volatility, resulting in a feedback effect that further enlarges market volatility. The mechanism is explained as follows.

A large volatility risk premium provides opportunities to engage in volatility trading. The VRP, estimated by the difference in option implied volatility and the actual volatility, is often substantial in the real market and could imply significant profits for option writers. Eraker (2008) finds that the implied volatility of the S&P 500 index option, measured by the VIX index, averages about 19%, while the unconditional annualized return volatility is only about 16%. The 3% volatility spread between implied and realized volatilities translates into an 18% premium for some options, indicating a nontrivial reward for sellers of index options.

Attracted by this premium, hedge funds, investment banks, and market makers actively search for options mispriced in volatility terms. Bakshi and Kapadia (2003) and Carr and Madan (1998) demonstrated that the time-varying VRP can be captured by using the delta-hedge approach. The delta-hedge approach employs the underlying spot assets of the options to neutralize price risk in the portfolio. The approach sells (buy) options with overvalued (undervalued) volatility and, at the same time, hedge away price risk through buying or selling the underlying shares.[16] Adjusting the delta-neutral portfolio dynamically, volatility traders target a profit roughly the size of the spread between implied volatility and future realized volatility.

The delta-hedging strategies employed by volatility traders may subsequently raise market volatility, leading to the feedback effect discovered in this study. According to the market crash model developed by Gennotte and Leland (1990), even relatively little hedging can cause price discontinuities, particularly in an illiquid market. The price discontinuities (or crashes) occur because investors mistake hedging activity for informed-based trades and thus revise their expectations for future prices. This incorrect perception reduces the willingness of liquidity provision necessary to absorb the impacts of dynamic-hedging transactions. As a result, a relatively small amount of hedging could drive significant market price change, leading to greater volatility. Frey and Stremme (1997) demonstrate that the demand generated by dynamic delta-hedge raises the volatility of the underlying assets. Similarly, Sircar and Papanicolaou (1998) and Schoenbucher and Wilmott (2000) find an increase in market volatility following the implementation of the delta-hedging strategy. The above studies imply that the hedging strategy employed by the

[16] According to the findings of Chaput and Ederington (2005), delta neutral is the primary concern of volatility traders when speculating on volatility changes. A delta-neutral position can be maintained by dynamically trading the underlying assets or, if available, futures contracts.

VRP-stimulated volatility trading could result in substantial increase in volatility.[17]

This study investigates the presence of the feedback effect from VRP to market volatility. The bidirectional causality between VRP and realized volatility is examined in 5-minute frequency using OLS regression, linear Granger causality, and nonlinear Granger causality tests. A finding that the VRP Granger causes volatility provides evidence in support of the presence of the feedback effect. To the best of our knowledge, this study is the first of its kind to explore the bidirectional relationship between VRP and market volatility. Our results provide useful information on the dynamic influence between volatility and volatility trading. Findings in this study also shed light on whether knowledge of past VRP improves the forecasts of current and future realized volatility, and vice versa.

The TXO index options offered by the Taiwan Futures Exchange are analyzed. The TXO options are written on the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and are one of the most liquid index options in the world.[18] At least two properties of the TXO make it the ideal venue for the study of the VRP feedback effect. First, the TXO option market is operated under an electronic call market with designated market makers, who trade for their own accounts and fulfill the exchange obligation of liquidity provision at the same time. To meet the obligation of liquidity provision, market makers hold positions of calls and puts of the same underlying but different strike prices while neutralizing the net exposure on the price risk by dynamically trading index futures or spot portfolios that replicate the index return.[19] Their trading portfolios thus resemble the

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[17] For index options, delta hedging is often implemented using index futures, which is much cheaper than hedging by trading the underlying portfolio. Dynamic hedge using index futures is also liable to have a destabilising effect on the market too. The concept is well discussed in the seminal works of Mark Rubinstein and Hayne Leland for portfolio insurance and the subsequent debates on the causes of the market crash of October 1987.

[18] The TXO is ranked the fifth most frequently traded index option on a global scale in 2010. The constituent stocks of the underlying spot index are also actively traded. The market capitalization and trading volume of Taiwan stock market rank respectively twenty-first and fourteenth in 2010, despite the relatively small scale of the local economy.

[19] In addition to market makers, individual, domestic institutions, and foreign institutions investors all actively engage in volatility trading using the TXO contracts. According to the summary statistics of Chang, Hsieh, and

popular volatility trading with the option/asset combination strategy. Since the market makers account for the lion's share of the TXO volume in recent years, we anticipate that the VRP feedback effect would be pronounced in this market.[20]

Since the underlying index of TXO options is not traded directly, delta hedging in Taiwan is often implemented using the index futures contract, an instrument with low transaction costs and high pricing efficiency.[21] The index futures traded on the Taiwan market share the same underlying index and maturity cycle as the TXO options. According to the seminal works of Mark Rubinstein and Hayne Leland in portfolio insurance and the discussions on the causes of the market crash of October 1987, the hedging-stimulated volatility on index futures prices could quickly transmit to the spot index.

Second, unlike the U.S. market, where instruments for directly trading volatility are available, in Taiwan market there is no derivative based on volatility index, nor vehicle specific for trading volatility spread. In U.S. market, for example, a variance swap allows investors to bet directly on the difference between realized stock price variation and the variation implicit in options prices (the VIX index).[22] With the presence of such instruments, volatility trading is straightforward and requires no dynamic hedging using the underlying spot assets. On the other hand, in Taiwan, where derivatives to trade volatility efficiently is still absent, strategies intended to profit from the changes in VRP are more likely to induce subsequent higher volatility because their hedging transactions involve spot assets. It is therefore expected that the VRP feedback effect will be more pronounced in

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Wang (2010), the most widely used volatility trading strategy in the Taiwan option market is the combination of options and futures trades with an almost neutral delta. Conventional straddle and strangle are rarely used.

[20] In 2010, approximately 53% of trading volume of the TXO options is contributed by market markers. Domestic individuals, domestic institutional investors, and foreign institutional investors respectively account for 39.6%, 1.5%, and 5.9 %.

[21] The liquidity, transaction costs, pricing efficiency, and price discovery has been explored by Roope and Zurbruegg (2002), Hsieh (2004), Huang (2004), and Chou and Wang (2006). Evidence in general confirms that the market of index futures is good in quality from all perspectives.

[22] A typical variance swap pays the difference between "realized variance", defined to be the average squared daily return, and the squared VIX index. The profits and losses from a variance swap depend only on the volatility spread but not the level changes of the underlying asset.

Taiwan than in the U.S. market. Our study in the Taiwan market sheds light on many other markets that are at a similar stage of development.[23]

This study uses both the linear and nonlinear causality tests to analyze the relationship between VRP and market volatility. The nonlinear causal test adopts a nonparametric method based on the modified version of the Baek and Brock (1992) nonlinear Granger causality test.

The significant two-way impact from lagged realized volatility to VRP and from lagged VRP to realized volatility is documented. The bidirectional causality found by the OLS regressions and the linear and nonlinear Granger causality tests, confirms the findings in literature (Bakshi and Kapadia, 2003; Bollerslev and Todorov, 2011; Eraker et al., 2003; Todorov, 2010) that uncertainty in volatility raises the VRP, and supports the contention that the feedback effect of VRP positively Granger causes the subsequent volatility. This finding suggests that VRP plays an important role in explaining future realized volatility: a large volatility premium could lead to greater realized volatility.

This study further decomposes the market volatility into three components: continuous volatility, negative jump volatility, and positive jump volatility, and examines the causality between VRP and each volatility component. The combined results of the linear and nonlinear causal tests show that the VRP feedback effect is the most pronounced for continuous volatility, moderate for negative jump volatility, and least pronounced for positive jump volatility. This pattern suggests that the dynamic delta-hedging is largely followed by small volatility change but less by large volatility shifts. Since the continuous volatility is the variation attributable to the small price movements (i.e., smooth price process) whereas jump volatility is the variation due to sudden and large-scale price movement,[24] the finding

[23] For instance, Korea and India both have very active index options, the KOPI 200 and NIFTY 50 index option, respectively, but the derivatives to trade volatility index have yet to be launched.

[24] According to Barndorff-Nielsen and Shephard (2004), Bollerslev and Todorov (2011), and Eraker, Johannes, and Polson (2003), the continuous volatility is estimated by suming small price changes

implies that the VRP stimulated trading/hedging, though tending to increase price fluctuation, does not frequently lead to sudden price jumps. In addition, the stronger feedback effect for negative jump volatility than for positive jump volatility indicates that the VRP induced jump, once it occurs, tends to be associated with a decline rather than an increase in price.

The feedback effect that the VRP nonlinearly Granger causes the three volatility components is robust even after controlling for the higher volatility attributed to unexpected information shocks. Results remain unchanged as adjusting for potential bias caused by the scale difference between overnight interval and the 5-minute intervals during regular trading session.

The remainder of this paper is organized as follows. Section 2 contains descriptions of methodologies used in this study. Section 3 provides a brief description of the data. Section 4 reports the empirical results. Section 5 performs robustness analyses for control of information flow and different treatments of overnight interval. Section 6 concludes the paper.

## 2. METHODOLOGY

### 2.1. Estimating Volatility Risk Premium

VRP represents the risk premium associated with the fluctuations in return volatility or jumps and is often measured by the difference between statistical and risk-neutral expectations of the forward variation in the asset return (Bollerslev and Todorov, 2011; Todorov, 2010). To measure the VPR faced by liquidity suppliers, this study follows

decomposed from the squared return increments, while the jump volatility is measured as the summation of large price discontinuities.

Todorov (2010) and define daily standardized VRP over the next τ trading days as the risk-neutral volatility less expected realized volatility, quantified as

$$VRP_t = 1/\sqrt{\tau}.E_t^Q(\sigma_{(t,t+\tau]} \mid \Omega_t) - 1/\sqrt{\tau}.E_t^P(\sigma_{(t,t+\tau]} \mid \Omega_t), \tag{7}$$

where $E^Q(.)$ and $E^P(.)$ indicate the expectations under risk-neutral and statistical measures, respectively, and $\Omega_t$ indicates information filtration for market participants.[25]

Todorov (2010) noted that the first term in Equation (7) can be viewed as the daily standardized volatility swap rate. Bakshi and Madan (2000), Britten-Jones and Neuberger (2000), and Carr and Wu (2009) show that the swap rate on the S&P 500 index can be inferred from a portfolio of short-maturity out-of-the-money options over a continuum of strike prices, which is adopted by the construction of the CBOE new VIX index since 2003. Therefore, the first term in Equation (7) is measured by the risk-neutral volatility computed from the VIX index, denoted by IV.

Since the VIX index is calculated using a calendar-counting convention involving 365 days in one year, and reflects volatility in a 30-day period, this study adopts Equation (8) to convert the VIX into a risk-neutral volatility that reflects one-day volatility under a business-day counting convention with 22 business days in each month. Following Todorov (2010), the VIX is converted into the daily risk-neutral volatility (IV) with horizon of 22 business days using following equations.

$$IV_t = \sqrt{30/365 * 1/22 * VIX_t^2} \tag{8}$$

[25] Note that our VRP measure in Equation (1) is different from the definition in Todorov (2010). Todorov (2010) calculates the VRP paid by hedgers, which is negative on average, whereas we measure the VRP earned by option liquidity suppliers, which is positive on average.

For the statistical measures of forward variation, the second term in Equation (7), the forecast of realized volatility is used as a proxy and denote as $RV_E$. Instead of forecasting the expected realized volatility directly from the past realized volatility, this study forecasts using a trivariate vector autoregressive (VAR) model consisting of continuous volatility (CV), positive jump volatility (pJV), and negative jump volatility (nJV), all decomposed from the realized volatility. Andersen, Bollerslev, and Diebold (2007) find that the forecasting to the future realized volatility improves significantly when using continuous volatility (CV) and jump volatility (JV) decomposed from realized volatility as separate regressors. They show that volatility components provide better forecasting than realized volatility itself because of the distinct features associated with the CV series and JV series: CV is strongly serially correlated while JV is less persistent and far less predictable than CV. The different features for the two components indicate separate roles in the forecast of realized volatility.

Barndorff-Nielsen and Shephard (2001), Bollerslev, Kretschmer, Pigorsch, and Tauchen (2009), and Todorov and Tauchen (2006, 2011) show that the future volatility increases more following negative price jumps. The jump volatility is decomposed into negative and positive jump volatility to capture the potential asymmetric impact of jumps on volatility.

The detailed process of decomposition is provided in Appendix A. In brief, the daily RV is first calculated using 5-minute intraday return series and then decomposed every one-day RV into three volatility components. This produces three daily series, one for each of the volatility components CV, nJV, and pJV.

Then the trivariate VAR model including $CV^2$, $nJV^2$, and $pJV^2$, as specified in equation (9), is used to forecast the one-period-ahead variance components. The realized volatility is the square root of the forecasts' sum for the three variance components forecasted by the

VAR model. The VAR model uses the three-dimensional vector, estimated previously, as the input.[26]

$$Z_t = M_0 + M_1 Z_{t-1} + M_5 \sum_{j=1}^{5} Z_{t-j} / 5 + M_{22} \sum_{j=1}^{22} Z_{t-j} / 22 + \varepsilon_t$$
$$Z_t = (CV_t^2,\ nJV_t^2,\ pJV_t^2)', \qquad (9)$$

where $Z_{t-1}$, $\sum_{i=1}^{5} Z_{t-i}$, and $\sum_{j=1}^{22} Z_{t-j}$ indicate the vector of the lag daily, weekly, and monthly variance components of realized variance, respectively. $M_0$ is a vector of the intercept term. $M_1$, $M_5$, and $M_{22}$ are matrices for the regression coefficients, in which the first column, second column, and third column in each matrix correspond to the parameters of the three variance components, respectively. The model uses the past 822 days for the estimation of parameters $M_0$, $M_1$, $M_5$, and $M_{22}$. The one-period-ahead variance component vector is obtained using the estimated parameters and the past 22 days' Zs.

For data of daily frequency, the process rolls forward daily, using the same window length (822 days) for each forecast. Since we intend to produce five-minute frequency forecasts, we roll the data forward every five minutes. That is, this study drops the earliest 5-minute return observation in the previous dataset and adds the next actual return, treating every 55 consecutive observations (which may span across two calendar days) as data of one 'trading day'. The updated dataset is used to re-calculate the 822 decomposed *Zs*, which will be the input of VAR model for parameter (*M*s) estimation and forecasting, following exactly the same procedures as above. This will produce a forecast of $Z_t$ every five minutes, where $Z_t$ is the forecasted realized volatility components in the next 'trading day'.

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[26] A similar reduced-form predictive procedure for realized volatility measure has been verified to work well empirically by Andersen et al. (2003). Our approach closely follows the procedures of Bollerslev and Todorov (2011) and Busch, Christensen, and Nielsen (2011).

2.2. Linear Granger Causality

A traditional linear Granger causality model is applied to estimate the dynamic relationship between VRP and the realized volatility. A finding that VRP Granger causes the realized volatility would support the VRP feedback effect.

Consider two time series, $X_t$ and $Y_t$. Linear Granger causality investigates whether lagged $Y_t$ has significant linear predictive power for current $X_t$, which is conditioned on past values of $X_t$. If so, then $Y_t$ linearly Granger causes $X_t$. Two-way causality exists if Granger causality runs in both directions.

The test for Granger causality between X and Y involves estimating a linear multivariate regression as

$$Z_t = A_0 + A_1 Z_{t-1} + \ldots + A_m Z_{t-m} + \varepsilon_t, \tag{10}$$

where $Z_t = (X_t, Y_t)'$ denotes the two-dimensional vector, $\varepsilon_t = (\varepsilon_{xt}, \varepsilon_{yt})'$ are zero-mean error terms. $A_0$, $A_1$,…, and $A_m$ indicate the regression coefficients. Two test statistics are used to detect the linear Granger causality. First, the Granger causality test statistic is computed based on the Lagrange Multiplier (LM) test, where the score covariance is estimated under assumption of heteroskedasticity and correlation of the residuals.[27] The asymptotic chi-square ($\chi 2$) statistic is used to test the null hypothesis that all the lag coefficients of X (Y) are jointly zero. A rejection of the null hypothesis indicates that X (Y) Granger causes Y (X). Next, we test for cumulative linear Granger noncausality from X (Y) to Y (X) by testing the null hypothesis that the sum of all the lagged coefficients of X (Y), denoted as b, is zero using a t-statistic. The t-statistics for the sum are calculated using the Newey-West (1987)

[27] The matlab code used here is kindly provided by Dr. Kevin Sheppard, http://www.kevinsheppard.com/wiki/MFE_ Toolbox.

autocorrelation and heteroskedasticity consistent covariance matrix. The optimal lag lengths (m) are determined using the Akaike information criterion (AIC).

## 2.3. Nonlinear Granger Causality

Baek and Brock (1992) developed a nonparametric test for potential nonlinear causality among time series. The test uncovers any remaining nonlinear causal relationship after the liner causal effect has been accounted for. To detect the nonlinear Granger causality from VRP to realized volatility, this study adopts the modified version of the Baek and Brock (1992)'s nonlinear Granger causality test, proposed by Hiemstra and Jones (1994). This modified test is based on the nonparametric estimators of temporal relations within and across time series. It relaxes the assumption of independent and identical distribution in each time series in Baek and Brock (1992), allowing each series to have weak temporal dependence. To determine whether nonlinear causality exist between given time series, we implement the modified Baek and Brock test to the residuals from Granger causality equation (10). Appendix B provides a detailed description of the modified Baek and Brock test used to detect the nonlinear causal relationship.

Assuming that $X_t$ and $Y_t$ are strictly stationary and weakly dependent and satisfy the mixing conditions as specified in Denker and Keller (1983). If $Y_t$ does not strictly Granger cause $X_t$, then the test statistic for nonlinear Granger causality, G, is asymptotically normally distributed. A rejection of the null hypothesis of Granger noncausality indicates that there exists nonlinear causality between the two time series. The statistic G is given as

$$G = \left(\frac{G1(m+Lx,Ly,d)}{G2(Lx,Ly,d)} - \frac{G3(m+Lx,d)}{G4(Lx,d)}\right) \overset{a}{\sim} N\left(0, \frac{1}{\sqrt{n}}\sigma^2(m,Lx,Ly,d)\right), \tag{11}$$

where G1, G2, G3, and G4 are joint probabilities; m is the lead length; Lx and Ly are, respectively, the lag lengths of X and Y; d is the distance measure; $n = T + 1 – m – max(Lx, Ly)$; and $\sigma^2(m,Lx,Ly,d)$ is the asymptotic variance of the modified Baek and Brock test statistic.[28]

## 3. DATA

The study collects two sets of data: the minute-by-minute Taiwan stock index data obtained from the Taiwan Economic Journal (TEJ) database for January 1, 2002 through December 31, 2009; and the minute-by-minute Taiwan VIX index data provided by the Taiwan Futures Exchange (TAIFEX) for December 18, 2006 through December 31, 2009.[29] The TAIFEX constructs its VIX index based on the European-style Taiwan index option (TXO) using the same approach as the CBOE new VIX index. This study retrieved, from TEJ database, the three month time deposit of the postal saving system for the risk-free interest rate.

For every 5 minutes, the daily risk-neutral volatility (IV) from the VIX index is computed using Equation (8) and the expected realized volatility ($RV_E$) is estimated using the VAR model in Equation (9). The 5-minute frequency VRP is obtained using equation (7) by subtracting $RV_E$ from IV.

Table 8 presents the results of parameter estimation for the realized volatility forecast based on the vector autoregressive model in Equation (9). The 5-minute rolling window procedure generates 41,195 estimations for each parameter during the sample period. Table 2 reports the average. The mean coefficients for $CV^2$, the first elements in the $M_1$, $M_5$, and $M_{22}$ matrices, are significantly positive, indicating a strong own persistence in the continuous variance over time. There are dynamically asymmetric dependencies between

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[28] Based on the Monte Carlo simulations, Hiemstra and Jones (1993) find that the modified test is not only robust to nuisance-parameter problems but also has good finite sample size and power properties.

[29] The TAIFEX began releasing data on the VIX on December 18, 2006.

$CV^2$, $nJV^2$, and $pJV^2$. For instance, $CV^2$ is lagged to $nJV^2$ as shown by the significant estimates for the second elements in the $M_1$ and M5 matrices; and $nJV^2$ is lagged to $CV^2$ as shown by the significant estimates for the first elements in the $M_5$ matrices in coefficients for $nJV^2$. Therefore, we include all three volatility components in forecasting the realized volatility.

Table 9 Parameter Estimates for the VAR Model in Equation (9)

| | $CV^2$ | | $nJV^2$ | | $pJV^2$ | |
|---|---|---|---|---|---|---|
| | Coeff. | t | Coeff. | t | Coeff. | t |
| $M_0$ | 0.0017 | 2.38** | –0.0006 | –0.52 | 0.0004 | 0.41 |
| | 26.6413 | 6.29*** | –10.7504 | –0.85 | 10.6337 | 0.90 |
| $M_1$ | 2.1806 | 1.71* | 7.6145 | 2.04** | –2.8320 | –0.88 |
| | –3.1440 | –1.39 | –3.8041 | –0.61 | –2.2845 | –0.55 |
| | 24.7616 | 3.08*** | 47.4784 | 2.12** | 14.7803 | 1.14 |
| $M_5$ | 14.3758 | 2.70*** | –17.4456 | –1.63 | 12.4233 | 2.41** |
| | –6.9938 | –0.99 | –19.1471 | –1.53 | –8.4190 | –0.75 |
| | 38.0826 | 4.01*** | –11.8802 | –0.61 | 4.8106 | 0.43 |
| $M_{22}$ | –0.2093 | –0.12 | 34.3943 | 1.96** | 18.5513 | 0.25 |
| | –19.5826 | –1.47 | 52.0699 | 1.61 | –7.5304 | –0.36 |

*Notes.* This table presents the estimating results of parameters for realized volatility forecast every 5 minutes based on the vector autoregressive model in Equation (9):

$$Z_t = M_0 + M_1 Z_{t-1} + M_5 \sum_{i=1}^{5} Z_{t-i} / 5 + M_{22} \sum_{j=1}^{22} Z_{t-j} / 22 + \varepsilon_t, \quad Z_t = [CV_t^2 \; nJV_t^2 \; pJV_t^2]. \tag{9}$$

The realized variation measures underlying the estimates are based on 5-minute return data from January 1, 2002 to December 31, 2009 inclusively. For each of the estimated parameters, it averages all parameter estimations with 41,195 observations during the sample period. The realized variance is decomposed into three variance components, including continuous variance ($CV^2$), negative jump variance ($nJV^2$), and positive jump variance ($pJV^2$). Based on the three variance components of realized variance, the expected realized volatility every 5 minutes is estimated using a vector autoregressive model for a three-dimensional vector. Coeff. and t are the estimated parameters of regression and *t*-value of parameter test, respectively. In Equation (9), $M_0$ is a vector of the intercept term. $M_1$, $M_5$, and $M_{22}$ are matrices for the regression coefficients, in which the first column, second column, and third column in each matrix correspond to the parameters of the three variance components ($CV^2$, $nJV^2$, $pJV^2$), respectively. All coefficients are multiplied by 100. ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

Figure 2 exhibits the plot of the 5-minute frequency time-series for the daily risk-neutral volatility (IV) and the expected realized volatility ($RV_E$). A visual inspection shows that both the IV and $RV_E$ closely track each other. The relationship holds even during the period of financial crisis in 2008 when the market experienced large fluctuation in volatility. Over the sample period, the daily risk-neutral volatility is slightly above the expected realized volatility by 15 basis points, indicating a positive VRP. This positive VRP is consistent with most other studies (Bakshi and Kapadia, 2003; Bollerslev and Todorov, 2011; Todorov, 2010).

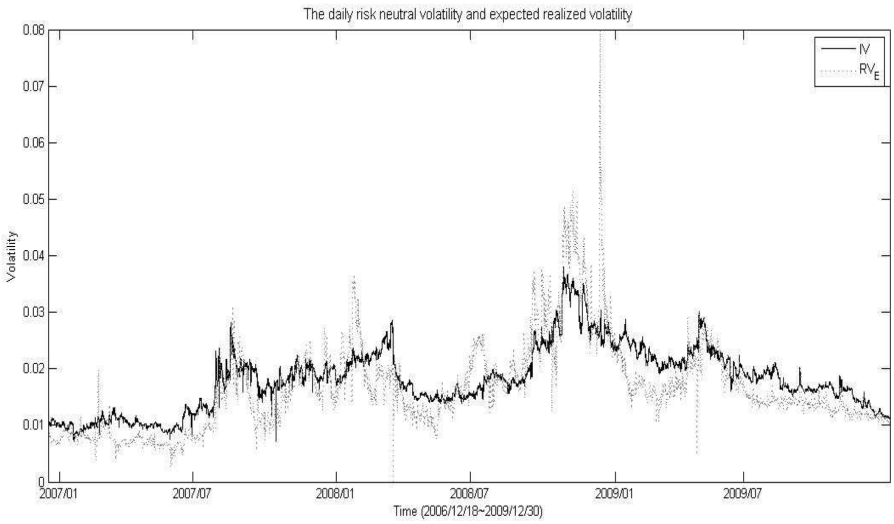


Figure 2. Time Series Plots of the Daily Risk-Neutral Volatility and Expected Realized Volatility. This figure depicts the time-series relation between daily risk-neutral volatility (IV) and expected realized volatility ($RV_E$) at five minute intervals. The time period is from December 18, 2006 to December 31, 2009, inclusive. The IV is computed from the VIX index using Equation (8); the $RV_E$ is estimated by using the vector autoregressive model in Equation (9).

Figure 2 also shows that the size of VRP changes over time and has a mean reversion tendency. It is consistent with the findings in Todorov (2010) that VRP increases significantly after large market moves and reverts to its long-term mean. Facing a mean-reversion trading opportunity, volatility traders engage trade based on the swing in the VRP rather than the size of the VRP. The deviation from the median VRP thus can better reflect the trading opportunities of volatility traders.[30] We therefore use the absolute deviations from the median, denoted by |dVRP|, as a proxy of volatility trading profit. Figure 3 shows that the |dVRP| fluctuates over time and is more volatile during 2008. Any

[30] We thank the referee for this insightful suggestion.

noticeable variation indicates a profitable opportunity for volatility traders.

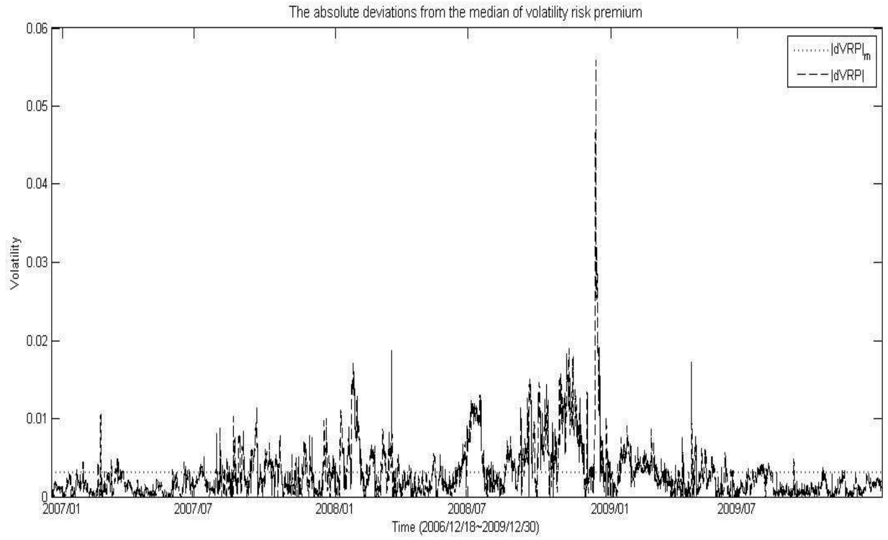


Figure 3. Time Series Plots of Absolute Deviations from Median Volatility Risk Premium. This figure depicts the 5-minute time-series of the absolute deviations from the median of volatility risk premium (|dVRP|). $|dVRP|_m$ is the average of the |dVRP| during the sample period. VRP is defined as the daily risk-neutral volatility less expected realized volatility, where the risk-neutral volatility is computed from the VIX index and the expected realized volatility is estimated by using the vector autoregressive model in Equation (9).

Table 10 provides summary statistics of the 5-minute time series for |dVRP|, VRP, IV, $RV_E$, RV, and the three components of realized volatility (CV, nJV, and pJV).[31] Note that both |dVRP| and VRP are positive in mean, indicating that volatility sellers, on average, may acquire profits about 4.8% annualized volatility spread. The augmented Dickey–Fuller (ADF) unit root tests significant reject the hypothesis of one unit root for every individual series, indicating that these variables are stationary.

[31] For RV, this study first obtains 5-minute index return series while treating the entire overnight period (clock time 13:30 to 9:00 next day) as one interval. The realized volatility over a day is defined as the variation of returns in any window that contains 55 consecutive intervals (including 54 5-minute returns and one overnight return). This study then estimates return variation within the window for a daily volatility estimate, using the Equation (A1) in Appendix A. By rolling the window forward at 5-minute intervals, the RV estimation is obtained every 5 minutes. For example, at t=1, realized volatility $RV_1$ is calculated using 5-minute returns from 9:00 to 9:00 next calendar day. At t=2, we roll the window 5 minutes forward, calculating the realized volatility $RV_2$ using 5-minute returns from 9:05 current day to 9:05 next calendar day, and so forth. This will produce a time series of 'daily' RV every 5 minutes, where a 'day' is defined as any consecutive 55 intervals that does not necessarily begin at 9:00 am. This process is similar to the approaches used in Andersen et al. (2003), Clements, Galvao, and Kim (2008), and Wright and Zhou (2009) to measure the monthly, quarterly, or yearly realized volatility with rolling window approach for every day. The data constructed above are used to calculate the three volatility components: CV, pJV, and nJV, adopting the methodology in Appendix A.

Table 10 Summary Statistics

| | \|dVRP\| | VRP | IV | $RV_E$ | RV | Volatility components | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | CV | nJV | pJV |
| Mean | 0.0030 | 0.0015 | 0.0181 | 0.0166 | 0.0153 | 0.0121 | 0.0029 | 0.0034 |
| Med | 0.0020 | 0.0023 | 0.0179 | 0.0153 | 0.0129 | 0.0112 | 0.0000 | 0.0000 |
| Min | 0.0000 | –0.0536 | 0.0072 | 0.0002 | 0.0030 | 0.0022 | 0.0000 | 0.0000 |
| Max | 0.0559 | 0.0210 | 0.0379 | 0.0808 | 0.0796 | 0.0796 | 0.0691 | 0.0599 |
| Std | 0.0035 | 0.0046 | 0.0056 | 0.0081 | 0.0098 | 0.0060 | 0.0085 | 0.0074 |
| Skew | 3.98 | –2.33 | 0.46 | 1.58 | 2.35 | 2.26 | 4.01 | 3.46 |
| Kurt | 33.91 | 16.84 | 3.19 | 7.33 | 10.78 | 17.65 | 21.96 | 19.05 |
| ADF | –283.84 | –206.85 | –20.56 | –61.94 | –350.29 | –140.47 | –722.13 | –784.69 |

*Notes*. This table presents summary statistics for absolute deviations from the median of volatility risk premium (|dVRP|), volatility risk premium (VRP), risk-neutral volatility (IV), expected realized volatility ($RV_E$), realized volatility (RV), and three volatility components of realized volatility. The volatility components decomposed from the realized volatility are continuous volatility (CV), negative jump volatility (nJV), and positive jump volatility (pJV). The data cover the period from December 18, 2006 to December 31, 2009. All series are computed in 5-minute frequency. The VRP is defined as IV less $RV_E$, where the IV is directly computed from VIX index and the $RV_E$ is estimated by a vector autoregressive model. ADF is the augmented Dickey–Fuller unit root test.

# 4. EMPIRICAL RESULTS

## 4.1. OLS Regressions

Figure 4 presents the intraday |dVRP| pattern by days of the week. The graph shows a strong opening spike on Monday and weak opening spike on Wednesday and Friday, indicating that the opening is often associated with heighted uncertainty in market volatility. The |dVRP| spike at opening may be caused by the accumulation of information shocks during overnight or weekend periods. In responding to the accumulated information during the non-trading period, option traders rush to adjust their portfolio at market opening. The strong trading demand at market open likely results in jumps in market price and subsequently increases the need of using options to adjust portfolios against jump risk and volatility risk. Facing higher unhedgeable risk, market makers require a higher premium for providing liquidity, which leads to greater VRP at the opening (Bollen and Whaley 2004; Gârleanu, Pedersen, and Poteshman 2009). The |dVRP| decays quickly afterward and levels off for the rest of the day. This matches the pattern of volatility risk premium under information shock documented in Todorov (2010): it increases after a large jump in price, then slowly reverts to its long-run mean.[32]

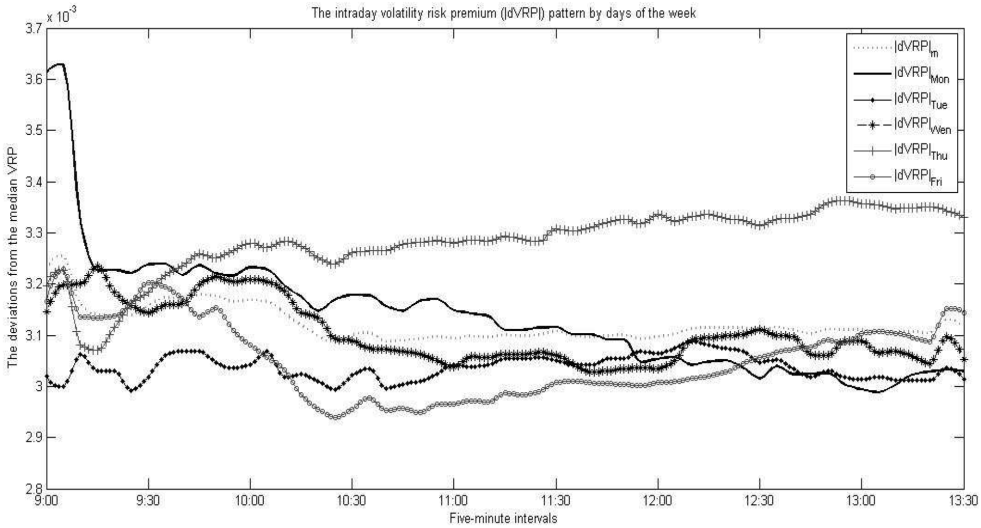


Figure 4. Intraday Pattern of |dVRP| by Day of the Week. This figure depicts the intraday pattern of the absolute deviations from median volatility risk premium (|dVRP|) from 9:00 AM to 1:30 PM (Taipei time) across weekdays. The volatility risk premium (VRP) is defined as the daily risk-neutral volatility less expected realized volatility. For each weekday, the |dVRP| is first computed every 5 minutes and then averaged them at each interval time. $|dVRP|_m$ denotes the average of the interval VRP across weekday.

Previous literature shows that raw series data with common regularities and time trends may lead to spurious conclusions in regression analyses. To mitigate the potential spuriousness problem, each individual raw time-series is adjusted for deterministic variables using regression equation (12) before proceeding with the causality tests. The approach is similar to that used in Roll, Schwartz, and Subrahmanyam (2007) for adjusting the series of the stock-futures basis. The innovations (regression residuals) from Equation (12) are used

[32] Note that while calculating the 5-minute return series, our process treats the entire overnight period as one 5-minute interval. This likely raises the concern of spurious result because of the scale difference in return, volatility, and VRP between overnight interval and the rest of the 5-minute intervals. In section 5, we perform robustness checks by adding a binary variable for overnight interval, and by removing the overnight period from the time series. Results are not materially changed with different treatments of overnight interval.

for subsequent causality analysis.

$$x_t = \alpha_0 + \sum_{i=1}^{4}\beta_i * Weekday_i + \sum_{j=1}^{11}\phi_j * Month_j + \sum_{k=1}^{4}\gamma_k * TimMat_k + \eta * Holiday_{-1} + \omega_1 * T + \omega_2 * T^2 + \delta * R_f + \varepsilon_t \quad (12)$$

In equation (12), the $x_t$ denotes the raw time series (|dVRP|, RV, CV, nJV, or pJV) to be adjusted. Following deterministic variables are chosen to adjust the raw series: (i) $Weekday_i$: four day-of-the-week dummies for Monday through Thursday; (ii) $Month_j$: eleven calendar month dummies for January through November; (iii) $TimMat_k$ : four dummies for the four days prior to option expiration to control for maturity-related effects, with $k$=1 representing the last trading day; (iv) $Holiday_{-1}$ : a dummy for the trading day prior to major holidays including New Year (January 1), Double Tenth National Day (October 10), and Chinese Lunar New Year; (v) a linear time trend, $T$, and a quadratic time trend, $T^2$, to remove any long-term trend; and (vi) $R_f$ : the risk-free rate.

Table 11 reports the coefficients of the adjustment regressions using Equation (12) for |dVRP|, RV, CV, nJV, and pJV. The regression R-squares range from 0.04 to 0.42, suggesting that the chosen variables explain a non-trivial portion of the realized volatility and volatility components. More importantly, many regressors are statistically significant across multiple regressions, indicating that |dVRP|, RV, CV, nJV, and pJV do share common components. The residuals of Equation (12), the series with common regularity removed, are used for subsequent OLS regression, linear Granger causality, and nonlinear Granger causality analyses. Residuals of the five regressions are stationary time series according to the results of the Dickey–Fuller test (not tabulated).

Table 11 Adjustment of Time Series Data

| | \|dVRP\| | | RV | | CV | | nJV | | pJV | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variables | Coeff. | t | Coeff. | t | Coeff. | t | Coeff. | t | Coeff. | t |
| Intercept | 0.0082 | 0.68 | 0.4121 | 12.53*** | 0.7726 | 42.21*** | –0.4824 | –15.15*** | –0.0227 | –0.79 |
| Monday | 0.0077 | 1.41 | 0.1508 | 10.26*** | –0.0034 | –0.42 | –0.0478 | –3.36*** | 0.2434 | 18.92*** |
| Tuesday | 0.0115 | 2.13** | –0.0357 | –2.45** | –0.0304 | –3.75*** | –0.0026 | –0.19 | –0.0585 | –4.58*** |
| Wednesday | 0.0120 | 2.23** | –0.0829 | –5.69*** | –0.0151 | –1.86* | –0.2209 | –15.66*** | 0.1074 | 8.42*** |
| Thursday | 0.0479 | 9.38*** | 0.1106 | 8.01*** | 0.0243 | 3.16*** | –0.0431 | –3.22*** | 0.1349 | 11.15*** |
| January | –0.0349 | –4.54*** | 0.3129 | 15.01*** | 0.0588 | 5.06*** | 0.2883 | 14.28*** | 0.2072 | 11.35*** |
| February | –0.1260 | –15.28*** | –0.3213 | –14.40*** | –0.4408 | –35.48*** | 0.0317 | 1.47 | 0.2235 | 11.44*** |
| March | –0.1475 | –19.93*** | –0.1370 | –6.84*** | –0.2772 | –24.85*** | 0.0141 | 0.73 | 0.2062 | 11.76*** |
| April | –0.3237 | –43.82*** | –0.3191 | –15.96*** | –0.3708 | –33.31*** | –0.1395 | –7.20*** | 0.2113 | 12.07*** |
| May | –0.2897 | –39.27*** | –0.3811 | –19.08*** | –0.4401 | –39.59*** | –0.0970 | –5.02*** | 0.2241 | 12.82*** |
| June | –0.2706 | –37.39*** | –0.3282 | –16.75*** | –0.3713 | –34.04*** | 0.0145 | 0.77 | 0.0164 | 0.95 |
| July | –0.1294 | –18.39*** | –0.2273 | –11.93*** | –0.3341 | –31.49*** | –0.0274 | –1.48 | 0.2243 | 13.45*** |
| August | –0.2332 | –32.84*** | –0.0720 | –3.75*** | –0.1949 | –18.21*** | 0.0283 | 1.52 | 0.1950 | 11.59*** |
| September | –0.1379 | –19.23*** | 0.1059 | 5.45*** | –0.1418 | –13.12*** | 0.1170 | 6.22*** | 0.2644 | 15.56*** |
| October | –0.0889 | –12.69*** | 0.2007 | 10.58*** | –0.1708 | –16.18*** | 0.4167 | 22.68*** | 0.1702 | 10.25*** |
| November | –0.0159 | –2.24** | 0.3279 | 17.07*** | –0.0091 | –0.85 | 0.3894 | 20.94*** | 0.1557 | 9.26*** |
| TimMat=1 | 0.0861 | 10.97*** | –0.0020 | –0.09 | 0.0632 | 5.35*** | –0.0040 | –0.19 | –0.1245 | –6.70*** |
| TimMat=2 | 0.0914 | 11.26*** | 0.2059 | 9.37*** | 0.0408 | 3.34*** | 0.0672 | 3.16*** | 0.2453 | 12.76*** |
| TimMat=3 | 0.1268 | 15.75*** | –0.2128 | –9.77*** | 0.0568 | 4.68*** | –0.0655 | –3.10*** | –0.2945 | –15.44*** |
| TimMat=4 | 0.1175 | 14.47*** | 0.0350 | 1.59 | 0.0066 | 0.54 | –0.1485 | –6.98*** | 0.1689 | 8.78*** |
| $Holiday_{-1}$ | –0.0556 | –3.94*** | 0.0248 | 0.65 | 0.1539 | 7.24*** | –0.1951 | –5.28*** | 0.0848 | 2.54*** |
| T | 0.0026 | 76.20*** | 0.0094 | 100.40*** | 0.0075 | 144.83*** | 0.0021 | 23.64*** | 0.0014 | 16.71*** |
| $T^2$ | –0.0000 | –57.96*** | –0.0000 | –75.36*** | 0.0000 | -111.64*** | –0.0000 | –14.25*** | –0.0000 | –13.18*** |
| $R_f$ | 0.0321 | 6.17*** | –0.1052 | –7.48*** | –0.2306 | –29.46*** | 0.2357 | 17.31*** | –0.0452 | –3.67*** |
| Adj. $R^2$ | 0.2553 | | 0.2942 | | 0.4165 | | 0.1104 | | 0.0412 | |

*Notes*. This table presents the adjustment of raw time-series data, including absolute deviations from the median of volatility risk premium (|dVRP|), realized volatility (RV), continuous volatility (CV), and negative and positive jump volatilities (nJV and pJV, respectively). All the variables are computed every 5 minutes. Dummy variables are included for days of the week and for months of the year. TimMat is the number of trading days until option contract expiration, with 1 representing the last trading day. $Holiday_{-1}$ is a dummy for the trading day prior to New Year (January 1), Double Tenth National Day (October 10), or Chinese Lunar New Year. $R_f$ , T and $T^2$ are risk-free interest rate and linear and quadratic time trends, respectively. Coeff. and t are the parameters of regression and *t*-value of parameter test, respectively. All coefficients are multiplied by 100. ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

The univariate OLS regressions are first performed to test whether shocks to |dVRP| have a feedback effect on realized volatility and its volatility components. This study regresses each of volatility components on lag one |dVRP|, where the |dVRP| is the innovation in Equation (12). Panel A of Table 12 shows that the coefficients of lag |dVRP| are all significantly positive in all regressions, suggesting that the lagged VRP can explain realized volatility and its components. This result provides preliminary evidence in support of our conjecture that VRP may affect realized volatility. Judged by the regression R-square, the feedback effect is mostly pronounced for the realized volatility and for the continuous volatility component but least significant for the jump volatility component. The result is consistent with the findings of Busch, Christensen, and Nielsen (2011) that the jump component is far less predictable than the continuous volatility.

Table 12 Ordinary Least Squares Regression Coefficients

| Indep. \ Dep. | \|dVRP\| | RV | CV | nJV | pJV | $R^2$ |
|---|---|---|---|---|---|---|
| Panel A: Each of the realized volatility and volatility components is regressed against the lagged \|dVRP\|. | | | | | | |
| Lag(\|dVRP\|) | — | 1.2350 (104.05$^{***}$) | — | — | — | 20.81% |
| Lag(\|dVRP\|) | — | — | 0.8950 (149.84$^{***}$) | — | — | 35.28% |
| Lag(\|dVRP\|) | — | — | — | 0.3930 (30.78$^{***}$) | — | 2.25% |
| Lag(\|dVRP\|) | — | — | — | — | 0.1726 (14.83$^{***}$) | 0.53% |
| Panel B: The \|dVRP\| is regressed against each of the lagged realized volatility and volatility components. | | | | | | |
| Lag(RV) | 0.1690 (104.40$^{***}$) | — | — | — | — | 20.92% |
| Lag(CV) | 0.3944 (149.98$^{***}$) | — | — | — | — | 35.32% |
| Lag(nJV) | 0.0589 (31.70$^{***}$) | — | — | — | — | 2.38% |
| Lag(pJV) | 0.0297 (14.30$^{***}$) | — | — | — | — | 0.49% |

*Notes*. This table presents regression results for the effect of lagged |dVRP| on each of RV, CV, nJV, and pJV in Panel A, and the effect of each lagged RV, CV, nJV, and pJV on |dVRP| in Panel B. The adjusted series are residuals resulting from the regression model in Equation (6). |dVRP|, RV, CV, nJV, and pJV denote the adjusted absolute deviations from the median of volatility risk premium, realized volatility, continuous volatility, negative jump volatility, and positive jump volatility, respectively. The *t*-values are given in parentheses. ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

In Panel B, the dependent and independent variables are reversed in the previous model by regressing |dVRP| on lagged RV, CV, nJV, and pJV. The reversed regressions examine whether changes in volatility induce VRP. In Panel B of Table 12, the coefficients of lag-one RV, CV, nJV, and pJV are found to be all positive and statistically significant. This is consistent with Bollerslev and Todorov (2011) and Todorov (2010) that both time-varying volatility and jump volatility are important determinants of VRP. The

R-squares in the regressions show that the VRP is explained most by CV (35.32%), followed by negative jump volatility (2.38%), and least by positive jump volatility (0.49%). The greater explanatory power of continuous volatility than jump volatility may result from the fact that stock index, as a weighted average of many individual stock prices, tends to move continuously but rarely jumps. The jump volatility therefore accounts for only a small portion in overall realized volatility. The changes in VRP thus are explained more by continuous volatility than jump volatility.

The negative jump volatility is more influential on future VRP, with $\hat{\beta}$=0.0589 and t=31.70, than positive jump volatility ( $\hat{\beta}$=0.0297, t=14.3), indicating that investors' fear for future uncertainty increases more following a large drop than a large increase in market price (Bollerslev and Todorov, 2011).

4.2. Linear Granger Test Results

The univariate OLS regressions in Table 12 indicate that VRP and RV are influenced by the lag-one terms of each other. Next, the linear Granger causality is used to test whether there is bidirectional causal relation between VRP and RV. The linear Granger causality test incorporates the own and other lag term beyond a one period lag. Thus, it is able to account for the autocorrelation in dependent variables. The dynamic relation between |dVRP| and RV is explored using the Granger causality test by specifying Z= [|dVRP|  RV] in Equation (10). The appropriate lag lengths in this model are set to be four, according to the Akaike information criterion (AIC). If VRP Granger causes RV, then the past values of VRP should contain information that helps predict RV. In other words, the Granger causality helps test whether the VRP feedback effect exists.

In Panel A of Table 13, the results of the linear Granger causality test are summarized by presenting the t-tests on the sum of the estimated coefficients, b, which represents the cumulative effect of lagged RVs on VRP, as well as the chi-square test for the jointly zero hypothesis of all the lag coefficients. For the |dVRP|, the null hypothesis of linear Granger non-causality from the realized volatility (RV) is strongly rejected by the significant summed coefficients of all lagged RVs (summed $\hat{\beta}$=0.0074, *t*-value = 13.47) and by the significant chi-square statistic ($\chi^2$=16.59, *p*-value <0.01). The finding that realized volatility positively Granger causes VRP suggests that the market prices of options reflect volatility risk. This is consistent with the findings of Bakshi and Kapadia (2003), Bollen and Whaley (2004), and Gârleanu et al. (2009) that the VRP compensates liquidity suppliers of options for bearing the volatility risk.

Table 13 Results of Linear Granger Causality Test

| x \ y | Statistics | \|dVRP\| | RV | CV | nJV | pJV |
|---|---|---|---|---|---|---|
| Panel A: Linear Causal Tests between \|dVRP\| and RV | | | | | | |
| \|dVRP\| | b | — | 1.0325<br>(3.04$^{***}$) | — | — | — |
| | $\chi^2$ | | 14.10<br>[0.0070] | | | |
| RV | b | 0.7352<br>(13.47$^{***}$) | — | — | — | — |
| | $\chi^2$ | 16.59<br>[0.0023] | | | | |
| Panel B: Linear Causal Tests between \|dVRP\| and nJV, pJV, and CV | | | | | | |
| \|dVRP\| | b | — | — | 0.3434<br>(2.57$^{***}$) | 0.0851<br>(0.19) | 0.4042<br>(1.07) |
| | $\chi^2$ | | | 22.27<br>[0.0023] | 11.17<br>[0.1316] | 7.46<br>[0.3828] |
| CV | b | 0.3630<br>(3.02$^{***}$) | — | — | — | — |
| | $\chi^2$ | 49.35<br>[0.0000] | | | | |
| nJV | b | 0.0650<br>(1.97$^{**}$) | — | — | — | — |
| | $\chi^2$ | 20.41<br>[0.0047] | | | | |
| pJV | b | 0.0066<br>(0.14) | — | — | — | — |
| | $\chi^2$ | 12.78<br>[0.1026] | | | | |

*Notes.* This table presents the sum b of all the lag coefficients for variable in first column and its *t*-values (in parentheses), and the chi-square statistics $\chi^2$ for linear Granger causality test and its *p*-value (in brackets). Both test statistics are used to detect the linear Granger causality. The sum b indicates the cumulative effect of lagged |dVRP| on realized volatility (RV) and its volatility components, and vice versa. The $\chi^2$ statistics test the null hypothesis that all the lag coefficients of column variable are jointly zero. A rejection of the null hypothesis indicates that column variable (x) Granger causes row variable (y). Panel A reports the results of linear causal tests between |dVRP| and RV, and Panel B presents the results of pairwise linear causal tests between |dVRP| and three volatility components of realized volatility. The *t*-statistic is calculated as t= $b/\sigma_b$, where $b = a_1 + a_2 + ... + a_n$ is the given sum of coefficients and n is number of lags on the independent variable. For instance, if n=3 then, $b=a_1+a_2+a_3$ and $\sigma_b = \sqrt{\sigma_{a_1}^2 + \sigma_{a_2}^2 + \sigma_{a_3}^2 + 2*(\sigma_{a_1a_2} + \sigma_{a_1a_3} + \sigma_{a_2a_3})}$. The *t*-statistics of b are calculated using the Newey-West (1987) autocorrelation and heteroskedasticity consistent covariance matrix. |dVRP| is absolute deviations from the median of volatility risk premium. nJV, pJV, and CV denote negative jump volatility, positive jump volatility, and continuous volatility, respectively. All coefficients are multiplied by 100. ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

More importantly, linear Granger causality also supports the existence of the feedback effect from VRP to RV. In Panel A of Table 13, the null hypothesis of linear Granger non-causality from |dVRP| to RV is rejected by the significant summed coefficients of all lagged |dVRP|s (summed $\hat{\beta}$=0.0103 and t-statistic 3.04) and the significant chi-square statistic ($\chi 2$=14.10, p-value <0.01). The finding supports the VRP feedback effect that higher VRP positively impacts future realized volatility. Frey and Stremme (1997), Gennotte and Leland (1990), Schoenbucher and Wilmott (2000), and Sircar and Papanicolaou (1998) suggest that dynamic hedging leads to greater market volatility. It is likely that the dynamic hedging induced by volatility trading that seeks to neutralize unanticipated price changes also affects the subsequent market volatility, resulting in the feedback effect found in Table 13.

To further examine the causal relation between |dVRP| and the three components of realized volatility (CV, nJV, and pJV), this study sets Z = [|dVRP| nJV pJV CV] in Equation (10) and performs the pairwise Granger-causality tests for |dVRP| versus each volatility component. The third column in Panel B shows the test whether individual volatility component Granger causes |dVRP|. The results show a significant causal relationship from CV to |dVRP| and from nJV to |dVRP| with t-values of 3.02 and 1.97, respectively.[33] This indicates that both continuous volatility and jump volatility due to large price declines

[33] Based on the Akaike information criterion (AIC), this study includes 8 lag variables while performing this model.

enlarge VRP (Bollerslev and Todorov 2011; Eraker et al. 2003; Todorov 2010), whereas volatility due to large price increases has less of an effect on the VRP. This finding is consistent with the OLS results in Table 11 that the CV and nJV play more important roles than pJV in explaining the VRP changes. The OLS and linear Granger causality together suggest an asymmetric effect of positive jump and negative jump on the VRP.

In the first row of Panel B, where the test is presented for the feedback effect, the linear Granger causality is only found from |dVRP| to CV but not from |dVRP| to nJV or from |dVRP| to pJV. One limit of the test in Table 13 is that the traditional Granger causality model aims to test for linear dependence. Thus, it has less power to detect nonlinear causal relations (Baek and Brock 1992; Hemstra and Jones 1994). If the impact from lagged |dVRP| to any component of jump volatility is nonlinear, the traditional approach may fail to uncover the feedback effect.

### 4.3. Nonlinear Granger Test Results

In this section, a more general form of the Granger causality test is provided. The modified Baek and Brock test, which allows nonlinear dependence in both |dVRP| and components of realized volatility, is adopted to examine the VRP feedback effect. The test statistic is specified in Equation (11). In this test, values for the lead length m, the lag lengths Lx and Ly, and the distance measure d need to be selected. Unlike linear causality testing, no approaches exist for choosing optimal values for lag lengths and distance measure. Following Hiemstra and Jones (1994), this study sets the lead length at m=1, Lx=Ly, and a common distance measure of d=1.5σ, where σ denotes the standard deviation of the time series. The results for lag lengths from 1 to 8 are presented for the robustness analysis.

Table 14 reports the results of the modified Baek and Brock test applied to the estimated residuals of linear Granger causality model for |dVRP| and RV. The nonlinear tests indicate stronger feedback effect than that shown previously by the linear test. The null hypothesis of no nonlinear Granger causality from RV to |dVRP| is strongly rejected at 1% significance level in every specification. The null hypothesis of no nonlinear Granger causality from |dVRP| to RV is also rejected. Results of nonlinear Granger tests again support that the causality between |dVRP| and RV is bidirectional. This bidirectional nonlinear relation holds for all the common lag lengths used in constructing the test. It suggests that the duration of the predictability of |dVRP| for RV is equivalent to that RV for |dVRP|. This nonlinear impact from lagged |dVRP| to current RV provides stronger evidence to the VRP feedback effect.

Table 14 Results of Nonlinear Granger Causality Test

| | Ho: RV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause RV | |
|---|---|---|---|---|
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0008 | 4.33*** | 0.0006 | 2.33** |
| 2 | 0.0022 | 7.15*** | 0.0029 | 7.00*** |
| 3 | 0.0023 | 7.07*** | 0.0025 | 6.33*** |
| 4 | 0.0023 | 6.86*** | 0.0022 | 5.47*** |
| 5 | 0.0027 | 7.29*** | 0.0018 | 4.46*** |
| 6 | 0.0026 | 6.95*** | 0.0017 | 3.96*** |
| 7 | 0.0027 | 6.75*** | 0.0014 | 3.34*** |
| 8 | 0.0027 | 6.52*** | 0.0012 | 2.76*** |

*Notes*. This table reports the results of the modified Baek and Brock nonlinear Granger causality tests applied to the vector autoregression residuals corresponding to absolute deviations from the median volatility risk premium (|dVRP|) and realized volatility (RV). Lx=Ly indicates the lag lengths of the residuals used in the test. In all cases, the tests are applied to unconditionally standardized series, the lead length, m, is set to 1, and the distance measure, d, is set to 1.5. Stat. and t, respectively, denote the test statistic in Equation (11) and its *t*-value. Under the null hypothesis of nonlinear Granger noncausality, the test statistic is asymptotically distributed $N(0,1)$. ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

Table 15 examines the pairwise nonlinear Granger causality between |dVRP| and each of the three volatility components of RV. The volatility components are found to be significantly Granger cause VRP, as shown by the significant t-values in the left part of the panel. This finding holds for every lag-length selection in every volatility component.

The feedback effects from VRP to volatility components are almost as pronounced as the impact from volatility components to VRP. In the last two columns of Panels A and B, the hypothesis of no nonlinear Granger causality from |dVRP| to CV and from |dVRP| to nJV is rejected in every case, clearly showing evidence for the VRP feedback effect. Only the nonlinear Granger causality from |dVRP| to pJV, reported in the last two columns of Panel C, is somehow weaker. The VRP Granger causes the positive volatility jump component for models with lags up to lag 4.

In summary, the modified Baek and Brock test reports significant VRP feedback effect for all volatility components. The VRP feedback effect is stronger for continuous volatility (with greater coefficient and higher significance) and lower on jump volatility. The feedback effect is asymmetrical such that negative jump volatility (nJV) responds more than positive jump volatility (pJV) to the changes in volatility risk premium.

Table15 Results of Pairwise Nonlinear Granger Causality Test

| Panel A: Nonlinear Causal Relation between \|dVRP\| and CV | | | | |
|---|---|---|---|---|
| | Ho: CV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause CV | |
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0043 | 9.94*** | 0.0044 | 9.78*** |
| 2 | 0.0083 | 14.11*** | 0.0074 | 13.02*** |
| 3 | 0.0082 | 13.66*** | 0.0072 | 12.71*** |
| 4 | 0.0082 | 13.18*** | 0.0067 | 11.86*** |
| 5 | 0.0076 | 12.45*** | 0.0066 | 11.33*** |
| 6 | 0.0078 | 12.24*** | 0.0062 | 10.80*** |
| 7 | 0.0078 | 11.96*** | 0.0061 | 10.36*** |
| 8 | 0.0080 | 11.75*** | 0.0061 | 10.03*** |
| Panel B: Nonlinear Causal Relation between \|dVRP\| and nJV | | | | |
| | Ho: nJV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause nJV | |
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0005 | 3.62*** | 0.0005 | 2.71*** |
| 2 | 0.0016 | 6.20*** | 0.0016 | 5.47*** |
| 3 | 0.0017 | 6.16*** | 0.0014 | 4.71*** |
| 4 | 0.0015 | 5.79*** | 0.0012 | 4.02*** |
| 5 | 0.0016 | 5.84*** | 0.0010 | 3.31*** |
| 6 | 0.0015 | 5.51*** | 0.0009 | 2.80*** |
| 7 | 0.0015 | 5.22*** | 0.0007 | 2.27** |
| 8 | 0.0015 | 5.15*** | 0.0006 | 1.78* |
| Panel C: Nonlinear Causal Relation between \|dVRP\| and pJV | | | | |
| | Ho: pJV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause pJV | |
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0008 | 4.32*** | 0.0004 | 1.92* |
| 2 | 0.0021 | 7.05*** | 0.0014 | 4.61*** |

| | | | | |
|---|---|---|---|---|
| 3 | 0.0022 | 6.84$^{***}$ | 0.0011 | 3.52$^{***}$ |
| 4 | 0.0023 | 6.87$^{***}$ | 0.0007 | 2.11$^{**}$ |
| 5 | 0.0027 | 7.35$^{***}$ | 0.0004 | 1.06 |
| 6 | 0.0027 | 7.09$^{***}$ | 0.0001 | 0.21 |
| 7 | 0.0028 | 6.99$^{***}$ | –0.0002 | –0.44 |
| 8 | 0.0028 | 6.77$^{***}$ | –0.0003 | –0.74 |

Note. This table reports the results of the pairwise nonlinear Granger causality tests between |dVRP| and CV, nJV, and pJV. They are reported in Panel A, Panel B, and Panel C, respectively. |dVRP| indicates absolute deviations from the median volatility risk premium; CV is continuous volatility; nJV is negative jump volatility; pJV is positive jump volatility. Lx=Ly indicates the lag lengths of the residuals used in the test. In all cases, the tests are applied to unconditionally standardized series, the lead length, m, is set to 1, and the distance measure, d, is set to 1.5. Stat. and t respectively denote the test statistic in Equation (11) and the *t*-value of test statistic. Under the null hypothesis of nonlinear Granger noncausality, the test statistic is asymptotically distributed N(0,1). ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

The explanations for the ranking of the VRP on the three volatility components are provided as follows. First, the higher VRP would lead to a measurable increase in jump volatility only if the dynamic-hedging transactions results in substantial price changes (a sudden shift in realized volatility is often associated with radical changes in price). This occurs in the scenario described in Gennotte and Leland (1990), that is, the dynamic-hedging transactions substantially alter the expectations and liquidity supply of other uninformed market participants. The consequence is that a relatively small amount of hedging would drive significant price and volatility change. This scenario, of course, is not commonly observed in the market, which is consistent with our results that the VRP feedback effect is less significant for jump volatility than continuous volatility.

Second, the results of asymmetric VRP feedback effect show that high VRP is more likely to be followed by a negative jump than a positive jump. This is consistent with prior evidence that investors are more sensitive to a large market decline than a large increase in return and are willing to pay more to hedge the potential decline than the possible increase. That is why the volatility risk premium widens more prior to a negative jump than a positive jump.[34]

[34] Pan (2002) and Bollerslev and Todorov (2011) provide evidence for the asymmetric responses to upward versus downward jumps. They find that such asymmetry in the fear of jump risk leads to a larger premium in the out-of-the- money puts than calls.

The asymmetric VRP feedback effect could be used to infer the strategies of volatility traders. The tendency of a negative jump after a large VRP implies that volatility traders tend to engage in hedge transactions that involve shorting spot assets or futures contracts, so that their hedging leads to negative jumps subsequently. Based on Chaput and Ederington (2005), popular volatility trading strategies that require delta hedge using short spot/futures positions include 1. long volatility by buying calls, 2. short volatility by selling puts, and 3. straddles. Chang, Hsieh, and Wang (2010) show that strategy 1. and 2. are the most frequently used volatility trading strategies in Taiwan. Since the sample in this study spans the period of global financial tsunami, a period characterized by high volatility and substantial market decline, there should be more opportunities for long volatility than for short volatility. It is therefore speculated that the long volatility by buying calls (strategy 1.) would be the most likely approach for volatility trading. The delta hedging of such strategy creates downward pressure on the underlying asset price and leads to subsequent widening in the VRP.

# 5. ROBUSTNESS ANALYSIS

## 5.1. Control of Information Flow

An alternative interpretation of the feedback effect is that the higher VRP implies that option traders perceive information shocks that soon shift the level of volatility. The increased volatility (and its components) following a large VRP might be merely the realization of the option traders' forecasts in volatility, rather than the feedback effect resulting from hedging the volatility trading.35 To examine whether the increased volatility followed by a large VRP is a direct result of information shock or the feedback effect due to

[35] Evidence of volatility changes due to information shocks is provided by Andersen (1996), who shows that return volatility dynamics is governed by information flows and Chen and Ghysels (2010), who find that both very good news and bad news increase volatility, with the latter having a more severe impact.

volatility trading, we assess the nonlinear bidirectional predictability between VRP and realized volatility (and its volatility components) while controlling for the impact of information flows.

A Granger causality test is performed by incorporating variables for returns due to positive and negative information to capture the dynamic impact of bad and good news on volatility components. Specifically, Z in equation (10) is re-specified as a six-dimensional vector, i.e., Z= [dVRP nJV pJV CV e+ e-], adding two variables respectively for the positive information impact, $e_t^+ = \sqrt{\max\{r_t - \bar{r}, 0\}}$ , and the negative information impact, $e_t^- = -1 * \sqrt{|\min\{r_t - \bar{r}, 0\}|}$, where rt is the index return at t and $\bar{r}$ is the average return in previous 30 days. For each series, we remove the effect of day-of-the-week, month-of-the-year, and time trends using regression equation (12) and use the innovations for the causality tests.

The linear Granger causality test is first performed using Equation (10) and then the residual is used for nonlinear Granger test applying Equation (11). Table 16 reports the test statistics and its t-values for pairwise nonlinear Granger causality between |dVRP| and each of nJV, pJV, and CV.

Table 16 Pairwise Nonlinear Causality Tests after Controlling of Information Flows

| Panel A: Nonlinear Causal Relation between \|dVRP\| and CV | | | | |
|---|---|---|---|---|
| | Ho: CV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause CV | |
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0044 | 10.18*** | 0.0045 | 9.91*** |
| 2 | 0.0084 | 14.19*** | 0.0075 | 13.18*** |
| 3 | 0.0083 | 13.74*** | 0.0073 | 12.84*** |
| 4 | 0.0083 | 13.27*** | 0.0067 | 11.96*** |
| 5 | 0.0077 | 12.55*** | 0.0066 | 11.36*** |
| 6 | 0.0078 | 12.33*** | 0.0062 | 10.82*** |
| 7 | 0.0079 | 12.04*** | 0.0061 | 10.36*** |
| 8 | 0.0080 | 11.87*** | 0.0060 | 9.98*** |
| Panel B: Nonlinear Causal Relation between \|dVRP\| and nJV | | | | |
| | Ho: nJV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause nJV | |
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0005 | 3.62*** | 0.0005 | 2.65*** |

| | | | | |
|---|---|---|---|---|
| 2 | 0.0016 | 6.29*** | 0.0016 | 5.51*** |
| 3 | 0.0017 | 6.22*** | 0.0014 | 4.69*** |
| 4 | 0.0016 | 5.84*** | 0.0012 | 3.99*** |
| 5 | 0.0016 | 5.90*** | 0.0010 | 3.27*** |
| 6 | 0.0016 | 5.54*** | 0.0009 | 2.76*** |
| 7 | 0.0015 | 5.26*** | 0.0007 | 2.23** |
| 8 | 0.0016 | 5.23*** | 0.0006 | 1.78* |

Panel C: Nonlinear Causal Relation between |dVRP| and pJV

| | Ho: pJV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause pJV | |
|---|---|---|---|---|
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0009 | 4.39*** | 0.0004 | 1.88* |
| 2 | 0.0022 | 7.12*** | 0.0014 | 4.57*** |
| 3 | 0.0022 | 6.90*** | 0.0011 | 3.49*** |
| 4 | 0.0023 | 6.90*** | 0.0007 | 2.10** |
| 5 | 0.0027 | 7.45*** | 0.0004 | 1.04 |
| 6 | 0.0027 | 7.19*** | 0.0001 | 0.18 |
| 7 | 0.0028 | 7.07*** | –0.0002 | –0.48 |
| 8 | 0.0029 | 6.87*** | –0.0003 | –0.76 |

*Notes*. This table reports the results of the pairwise nonlinear Granger causality tests between |dVRP| and CV, nJV, and pJV, reported in Panels A, B, and C, respectively, after controlling for impacts of information flows. The impact of information is controlled by adding variables representing positive and negative return innovations into the vector of Z in Equation (4). |dVRP| indicates absolute deviations from the median volatility risk premium; CV is continuous volatility; nJV is negative jump volatility; and pJV is positive jump volatility. Lx=Ly indicates the lag lengths of the residuals used in the test. In all cases, the tests are applied to unconditionally standardized series, the lead length, m, is set to 1, and the distance measure, d, is set to 1.5. Stat. and t, respectively, denote the test statistic in Equation (5) and the *t*-value of test statistic. Under the null hypothesis of nonlinear Granger noncausality, the test statistic is asymptotically distributed N(0,1). ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

In Table 16, the modified Baek and Brock test continues to show a bidirectional nonlinear Granger causality between |dVRP| and CV, nJV, and pJV. Focusing on the causality from VRP to the volatility components reported in the last two columns of each panel, the results of the significance of the modified Baek and Brock tests are comparable to the results in Table 14, with CV and nJV being significant for 8 lags and pJV being significant up to 4 lags. Results suggest that the nonlinear Granger causality from |dVRP| to CV, nJV, and pJV persists after controlling for the information shocks.[36] It is therefore concluded that the causality from VRP to realized volatility found in Table 14, 15, and 16 is more likely to be the result of VRP feedback effect rather than information shocks.

[36] The linear Granger causality between |dVRP| and RV, CV, nJV, and pJV are similar with and without controlling for information shocks.

5.2. Treatments of Overnight Interval

In section 4, the daily VRP series is computed in 5-minute frequency while treating the entire overnight period (13:30 to 9:00 next day) as one interval. This treatment of overnight returns leads to periodical spikes in the time series due to the larger price changes in overnight interval. Because of the scale difference between overnight interval and the 5-minute intervals in regular trading hours, the realized volatility and VRP measured in the overnight period may not be directly comparable to those in regular trading hours. In this section, two approaches are adopted to check the robustness of the VRP feedback effect under different treatments of the overnight interval.

The first approach re-performs the univariate time-series OLS regressions in Table 12, adding a dummy variable to distinguish the overnight period from the intraday 5-minute periods. Specifically, this study regresses realized volatility and each volatility component on lag one |dVRP|, whilst allowing the lag |dVRP| to be interacted with the overnight dummy variable. The coefficient of the interactive term, denoted by $\delta$, picks up the difference in the effect of VRP on realized volatility (and its volatility components) during overnight period and intraday 5-minute interval. Results are reported in Table 17.

Table 17 OLS Coefficients Distinguishing Overnight Observations

| Indep. \ Dep. | Parm. | \|dVRP\| | RV | CV | nJV | pJV | $R^2$ |
|---|---|---|---|---|---|---|---|
| Panel A: The Effect of lagged \|dVRP\| on each of RV, CV, nJV, and PJV | | | | | | | |
| Lag(\|dVRP\|) | $\beta$ | — | 1.2343 (102.96***) | — | — | — | 20.81% |
| | $\delta$ | | 0.0169 (1.41) | | | | |
| Lag(\|dVRP\|) | $\beta$ | — | — | 0.8931 (148.59***) | — | — | 35.29% |
| | $\delta$ | | | 0.0970 (2.35**) | | | |
| Lag(\|dVRP\|) | $\beta$ | — | — | — | 0.3926 (30.57***) | — | 2.25% |
| | $\delta$ | | | | 0.0737 (0.83) | | |
| Lag(\|dVRP\|) | $\beta$ | — | — | — | — | 0.1704 (14.48***) | 0.53% |
| | $\delta$ | | | | | 0.1045 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | | (1.02) | |
| Panel B: The Effect of each of the lagged RV, CV, nJV, and pJV on \|dVRP\| | | | | | | | |
| Lag(RV) | $\beta$ | 0.1686 (103.18***) | — | — | — | — | 20.93% |
| | $\delta$ | 0.0196 (1.66*) | | | | | |
| Lag(CV) | $\beta$ | 0.3936 (148.33***) | — | — | — | — | 35.33% |
| | $\delta$ | 0.0405 (2.06**) | | | | | |
| Lag(nJV) | $\beta$ | 0.0582 (31.56***) | — | — | — | — | 2.39% |
| | $\delta$ | 0.0162 (1.23) | | | | | |
| Lag(pJV) | $\beta$ | 0.0292 (13.94***) | — | — | — | — | 0.50% |
| | $\delta$ | 0.0203 (1.42) | | | | | |

*Notes*. This table presents regression results for the effect of lagged |dVRP| on each of RV, CV, nJV, and pJV in Panel A, and the effect of each lagged RV, CV, nJV, and pJV on |dVRP| in Panel B. For every univariate regression, this study includes a binary variable for overnight interval and allows it to interact with the independent variable. The coefficient of the interactive term is denoted as $\delta$. The adjusted series are residuals resulting from the regression model in Equation (6). |dVRP|, RV, CV, nJV, and pJV denote the adjusted absolute deviations from the median of volatility risk premium, realized volatility, continuous volatility, negative jump volatility, and positive jump volatility, respectively. The *t*-values are given in parentheses. ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

As reported in Panel A of Table 17, the coefficient of the interactive term is positive in every regression, indicating that the feedback effect is somehow stronger for overnight interval. However, the only significant $\delta$ is found for regression of CV. In Panel B, where |dVRP| is regressed on lagged realized volatility and its components, the $\delta$ coefficients for RV and CV are significantly positive. It shows that the realized volatility and continuous volatility induce higher VRP in the overnight period than in the intra-day 5-minute interval. These findings of large effect from RV and CV to VRP and from VRP to CV in the overnight period suggest that the overnight observations are different from the others.

Nevertheless, we note that the $\beta$ coefficients and their significance in both panels of Table 17 are very similar to the corresponding figures in Table 12, where overnight and intraday intervals are not distinguished. Result suggests that, despite the difference in effect during overnight period, the feedback effect documented previously are robust to different treatments of overnight interval.

In the second approach, all the linear and nonlinear Granger causality tests are redone in Table 13 through Table 15, with the overnight periods removed from the time series of |dVRP|, RV, CV, nJV, and pJV. To save space, this study only reports, in Table 18, the results of pairwise nonlinear Granger test for the causality between VRP and volatility components. The G statistics show only minor difference in their value and significance from those in Table 16 (where overnight interval is included as another 5-minute return). The hypothesis of no nonlinear Granger causality from |dVRP| to CV and from |dVRP| to nJV is again strongly rejected in every case in Panel A and B, supporting the presence of the VRP feedback effect. Similar to Table 15, only the nonlinear Granger causality from |dVRP| to pJV, reported in Panel C, has weaker significance: the VRP Granger causes the positive volatility jump component for models with lags up to lag 5. The findings of the feedback effect from VRP to realized volatility remain unchanged with and without the overnight period.[37]

In summary, the robust tests suggest that, despite the different nature in the overnight interval, our findings in the feedback effect are robust to various treatments of the overnight period.

Table 18 Results of Pairwise Nonlinear Granger Causality Test without Overnight Observation

Panel A: Nonlinear Causal Relation between |dVRP| and CV

| | Ho: CV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause CV | |
|---|---|---|---|---|
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0044 | 10.08*** | 0.0050 | 11.03*** |
| 2 | 0.0076 | 13.36*** | 0.0066 | 12.34*** |
| 3 | 0.0079 | 13.26*** | 0.0060 | 11.53*** |
| 4 | 0.0078 | 12.84*** | 0.0060 | 11.15*** |
| 5 | 0.0077 | 12.43*** | 0.0058 | 10.54*** |
| 6 | 0.0079 | 12.16*** | 0.0057 | 10.26*** |
| 7 | 0.0081 | 12.09*** | 0.0057 | 9.90*** |
| 8 | 0.0080 | 11.76*** | 0.0057 | 9.53*** |

Panel B: Nonlinear Causal Relation between |dVRP| and nJV

| | Ho: nJV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause nJV | |
|---|---|---|---|---|
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0010 | 4.95*** | 0.0004 | 2.34** |
| 2 | 0.0015 | 5.88*** | 0.0016 | 5.63*** |

[37] In unreported results, we reproduce the analysis in Table 12 and Table 13 using time series excluding overnight interval. Results are unaltered in that all significant variables keep their significance whilst the insignificant ones remain insignificant.

| | | | | |
|---|---|---|---|---|
| 3 | 0.0014 | 5.67$^{***}$ | 0.0015 | 4.96$^{***}$ |
| 4 | 0.0014 | 5.61$^{***}$ | 0.0013 | 4.29$^{***}$ |
| 5 | 0.0014 | 5.41$^{***}$ | 0.0011 | 3.61$^{***}$ |
| 6 | 0.0014 | 5.11$^{***}$ | 0.0010 | 3.14$^{***}$ |
| 7 | 0.0013 | 4.91$^{***}$ | 0.0009 | 2.64$^{***}$ |
| 8 | 0.0014 | 4.74$^{***}$ | 0.0007 | 2.15$^{**}$ |

Panel C: Nonlinear Causal Relation between |dVRP| and pJV

| | Ho: pJV Does Not Cause \|dVRP\| | | Ho: \|dVRP\| Does Not Cause pJV | |
|---|---|---|---|---|
| Lx=Ly | Stat. | t | Stat. | t |
| 1 | 0.0014 | 5.96$^{***}$ | 0.0001 | 1.73$^{*}$ |
| 2 | 0.0019 | 6.52$^{***}$ | 0.0016 | 5.17$^{***}$ |
| 3 | 0.0020 | 6.43$^{***}$ | 0.0013 | 4.05$^{***}$ |
| 4 | 0.0023 | 6.78$^{***}$ | 0.0010 | 2.88$^{**}$ |
| 5 | 0.0022 | 6.44$^{***}$ | 0.0007 | 1.88$^{*}$ |
| 6 | 0.0023 | 6.24$^{***}$ | 0.0004 | 1.05 |
| 7 | 0.0023 | 5.99$^{***}$ | 0.0001 | 0.35 |
| 8 | 0.0022 | 5.67$^{***}$ | –0.0000 | –0.12 |

Note. This table reports the results of the pairwise nonlinear Granger causality tests between |dVRP| and the three volatility components (CV, nJV, and pJV). They are reported in Panel A, Panel B, and Panel C, respectively. The observations of the overnight interval are removed from each time series of |dVRP|, CV, nJV, and pJV. |dVRP| indicates absolute deviations from the median volatility risk premium; CV is continuous volatility; nJV is negative jump volatility; pJV is positive jump volatility. Lx=Ly indicates the lag lengths of the residuals used in the test. In all cases, the tests are applied to unconditionally standardized series, the lead length, m, is set to 1, and the distance measure, d, is set to 1.5. Stat. and t respectively denote the test statistic in Equation (5) and the *t*-value of test statistic. Under the null hypothesis of nonlinear Granger noncausality, the test statistic is asymptotically distributed N(0,1). ***, **, and * indicate that the *t*-values are significant at the 0.01, 0.05, and 0.10 level, respectively.

## 6. CONCLUSIONS

Over the past few years, volatility trading has become increasingly popular. Large volatility risk premium (VRP), measured by the spread between option implied volatility and realized volatility, may attract volatility trading from investors who seek to benefit from the volatility spread. Despite the abundant evidence that large volatility increases VRP, much is unknown about what happens afterward, in particular how a widened VRP may affect subsequent volatility. This study examines the feedback effect from VRP to realized volatility. We postulate that a widened VRP may be followed by higher volatility, because volatility traders who seek to profit from the widened VRP need to hedge their exposure to changes in price. It is their delta hedging transactions that further destabilize price and result in the feedback effect from VRP to volatility.

The causal relationship between VRP and the realized market volatility is investigated while setting the stage on the Taiwan markets, where the index option is actively traded and volatility trading is frequently engaged. Both linear and nonlinear Granger causality tests show bidirectional influence between VRP and realized volatility. This indicates that VRP tends to be triggered by high volatility and plays an important role in explaining future realized volatility. The finding of higher volatility following enlarged VRP provides evidence for the presence of a feedback effect.

As decomposing the realized volatility into three components: continuous volatility, negative jump volatility, and positive jump volatility, the nonlinear Granger causality model reports significant feedback effect for all three volatility components, with the effect most pronounced for continuous volatility, followed by negative jump volatility, and least for positive jump volatility. The asymmetric VRP feedback effect on negative and positive jump volatility indicates that options traders are more sensitive to a large market decline than a large increase in return, a finding consistent with the asymmetric volatility to return changes documented in the literature.

Our findings on the feedback effect are robust even after controlling for shock by instantaneous information and different treatments of overnight interval.

## CHAPTER 4 SUMMARY AND CONCLUSIONS

Volatility risk premium (VRP) is the premium that compensates risk stemming from the fluctuation in volatility or jumps. In financial markets, this risk premium is commonly viewed as the price that option market makers require to provide liquidity and investors pay to hedge their tail risk. Although the abundant evidence has linked the VRP to liquidity, intermediation, and hedging demand, much less is known about the impact of an imbalance between supply and demand for options on VRP. In addition, higher volatility often leads to increased VRP. Inversely, large VRP attracts volatility investors that seek to benefit from the temporary mispricing in volatility. This gives a rise to an interesting but less understood question is about what happens afterward, in particular how a widened VRP may affect subsequent volatility. This dissertation therefore sets out to focus on two important VRP issues in financial market, including the impact of option demand pressure on VRP and the effect of trading the VRP.

In the first issue regarding the impact of option demand pressure on VRP, the results show that the level of demand for an index option plays a key role in determining the time variation in VRP. A positive (negative) demand pressure of an index option raises (decreases) the VRP, similar to the finding of Gârleanu, Pedersen, and Poteshman (2009) that a proportion of an option's expensiveness reflects the effect of demand pressure. This indicates that the option prices include a component that compensates market-makers' risk since market makers can not perfectly hedge their net exposure on the option positions.

In particular, the demand pressure effect on VRP is related to the risk aversion of market-makers supported by a significant and negative linkage between the effect of demand pressure and recent market-maker losses. Facing their trading losses, market makers with risk aversion ask a higher risk premium for accepting additional risk. Thus, these premiums for unhedgeable risks are all contributing more, thereby leading an increase in VRP. In addition, at the arrival of market jumps the demand pressure leads to a greater impact on VRP for all three demand variables due to increased jump fear. The result provides evidence to support the finding of Todorov (2010) that time-varying risk aversion is driven by large, or extreme, market moves.

The second issue in this dissertation is to investigate the dynamic processes between VRP and volatility while focusing on the afterward effect of a large VRP. The bidirectional causality in the OLS regressions and the linear and nonlinear Granger causality tests are documented. This result confirms the findings in literature (Bakshi & Kapadia, 2003; Bollerslev & Todorov, 2011; Eraker et al., 2003; Todorov, 2010) that uncertainty in volatility raises the VRP, and supports the contention that the feedback effect of VRP positively Granger causes the subsequent volatility. This finding suggests that VRP plays an important role in explaining future realized volatility: a large volatility premium could lead to greater realized volatility.

The feedback effect that the VRP nonlinearly Granger causes the three volatility components, continuous volatility, negative jump volatility, and positive jump volatility, is significant even after controlling for the higher volatility attributed to the unexpected information shocks.

In conclusion, this dissertation provides some insights into the issues of the impact of option demand on VRP and the effect of trading the VRP. The research results would provide us with empirical evidences to comprehend the importance of option demand pressure in determining VRP and the dynamic influence between volatility and volatility trading.

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APPENDIX

Appendix A: Decomposition of Realized Variance

This appendix presents the processes by which we decompose the realized volatility into three volatility components: continuous volatility, positive jump volatility, and negative jump volatility. Assume that dp(t) follows the general stochastic volatility jump diffusion process $dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t)$, $t \geq 0$. p(t) denotes the logarithmic asset price at time t; μ(t) is the instantaneous drift process; σ(t) is instantaneous volatility; W(t) is a Brownian motion process; κ(t) is the random jump size; and q(t) is a jump process with intensity λ(t).

Following Andersen and Bollerslev (1998) and Andersen, Benzoni, and Lund (2002), the realized variance ($RV^2$) over the day t is defined as the sum of the squared intraday returns,

$$RV_t^2 = \sum_{j=1}^{m-1} r_{t,j}^2, \tag{A1}$$

where $r_{t,j} = p_{t,j} - p_{t,j-1}$ is the compounded intra-period return, and m is the number of the observed prices during the period t that is sampled during the intra-period (Δ).

As $m\uparrow\infty$, $RV_t^2$ converges in probability to two different components, that is, the integrated variance (the variation attributable to continuous process, simplified as $CV_t^2$) and the sum of squared jumps (the variation due to price jumps, simplified as $JV_t^2$). It is represented as

$$RV_t^2 \to \int_{t-1}^{t} \sigma^2(s)ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2, \tag{A2}$$

where $N_t$ and $\kappa_{t,j}$ are the number of jumps and the jth jump size during day t, respectively.

This study separates the $CV^2$ and $JV^2$ from $RV^2$ using the realized bipower variation

(BV) presented in Equation (A3), following Barndorff-Nielsen and Shephard (2004 and 2006). According to Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen, Shephard, and Winkel (2006), the asymptotic convergence of BV only captures the continuous price variations even in the presence of jumps. For m↑∞, BV converges in probability to integrated volatility in Equation (A2). We thus estimate the contribution of jump to the realized variance by differencing $RV^2$ with BV.

$$BV_t = \frac{\pi}{2}\frac{m}{m-2}\sum_{j=3}^{m}|r_{t,j}||r_{t,j-2}| \qquad \text{(A3)}$$

This study is required to detect the arrival jumps up to intraday level. The significant intraday price jumps are identified using the nonparametric test proposed by Lee and Mykland (2008). By their approach, for any given time $t_i$ the arrival time and direction of detected jump can be accurately recognized. Another critical merit is that the test statistic can identify the multiple jumps during one trading day. The jump detection statistic *L* is given as

$$L_{t_i} = r_{t_i} / \hat{\sigma}_{t_i}, \; where \;\; \hat{\sigma}_{t_i}^2 = (K-2)^{-1}\sum_{j=i-K+1}^{i-1}|r_{t_j}||r_{t_{j-1}}|, \qquad \text{(A4)}$$

where $r_{t_i}$ is a realized return at given time $t_i$; $\hat{\sigma}_{t_i}$, an estimated instantaneous volatility, is the local variation only from the continuous part of asset return process; and K is the window size to estimate instantaneous volatility.

In the absence of jumps, Lee and Mykland (2008) address a reasonable rejection region by deriving the limiting distribution of the maximum of the statistic. This process guides us to choose the relevant threshold for the test to distinguish the presence of jumps at any testing time. The statistic is given as $\zeta = (L_{t_i} - C_n)/S_n$, where

$$C_n = \sqrt{2\log n}/c - (\log\pi + \log(\log n))/(2c\sqrt{2\log n}),\ c = \sqrt{2/\pi}\text{, and } S_n = 1/(c\sqrt{2\log n}).$$

The cumulative distribution function of ζ is given as $P(\zeta \le x) = \exp(-e^{-x})$. Given any significance level, we can solve for x to determine the threshold for significant jumps. For example, the corresponding threshold, rejecting the null hypothesis of no jumps, is 4.60 (2.97) at 1% (5%) significance level.

Based on a significance level α, the size of the jump on day t is denoted as

$$JV_t^2 = I_{\{\zeta_t > \Phi_{1-\alpha}\}}(RV_t^2 - BV_t), \tag{A5}$$

where I(.) is the indicator function; $\Phi_{1\text{-}\alpha}$ is the critical value for the (1–α) level test; and ζ is the statistic of detected jumps.

Obviously, $JV^2$ is the excess realized variance over the continuous variance. It is zero in the absence of jumps and greater than zero otherwise. Further, jump variance is split into negative jump variance ($nJV^2$) and positive jump variance ($pJV^2$), depending on the cumulative returns that correspond to the price jumps within the one-day period. If the cumulative return is negative (positive), then it is identified as a negative (positive) jump variance. By contrast, the variation contributed by continuous price process is written as

$$CV_t^2 = RV_t^2 - JV_t^2 \tag{A6}$$

In our empirical work, this study estimates $JV^2$ using α=0.99 and computes $RV^2$ using the 5-minute returns. In addition, following Lee and Mykland (2008), the jump test statistic L is calculated using the past 270 5-minute intraday returns.

Appendix B: The Modified Baek and Brock Test

This appendix details the modified Baek and Brock (1992)'s nonlinear Granger causality test, proposed by Hiemstra and Jones (1994). Baek and Brock (1992) developed a nonparametric statistical method for detecting nonlinear causal relationships. The nonlinear causality between time series is detected by using the correlation integral approach. Consider two strictly stationary and weakly dependent time series $X_t$ and $Y_t$. Let $X_t^m$ denote the m-length lead vector of $X_t$, and $X_{t-Lx}^{Lx}$ and $Y_{t-Ly}^{Ly}$ are the Lx-length and Ly-length lag vectors of $X_t$ and $Y_t$, respectively. For given values of m, Lx, and Ly≥1 and for d >0, Y does not strictly nonlinearly Granger cause X if

$$\begin{aligned} &P(\| X_t^m - X_s^m \| < d \,\big|\, \| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \| < d, \| Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly} \| < d) \\ &= P(\| X_t^m - X_s^m \| < d \,\big|\, \| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \| < d), \end{aligned} \quad \text{(B1)}$$

where P(.) is probability; ||.|| is the maximum norm for vector $Z \equiv (Z_1, Z_2, ..., Z_k) \in \Re^k$, which is defined as max($Z_i$), i =1,2, …, k; and s,t=max(Lx,Ly)+1, …, T–m+1.

The left-hand side of Equation (B1) is the conditional probability for two arbitrary m-length lead vectors of $X_t$ within a distance d of each other, given that two corresponding Lx-length lag vectors of $X_t$ and two Ly-length lag vectors of $Y_t$ are within distance d of each other. The probability on the right-hand side of Equation (B1) is the conditional probability that two arbitrary m-length lead vectors of $X_t$ are within a distance d of each other, conditional only on that their corresponding Lx-length lag vectors are within distance d of each other.

The test based on Equation (B1) can be restated by expressing the conditional probability in terms of the corresponding ratios of joint probabilities:

$$\frac{G1(m+Lx,Ly,d)}{G2(Lx,Ly,d)}=\frac{G3(m+Lx,d)}{G4(Lx,d)} \tag{B2}$$

The joint probabilities are defined as

$$\begin{aligned}
&G1(m+Lx,Ly,d)=P(\| X_{t-Lx}^{m+Lx}-X_{s-Lx}^{m+Lx} \|< d, | Y_{t-Ly}^{Ly}-Y_{s-Ly}^{Ly} \|< d)\\
&G2(Lx,Ly,d)=P(\| X_{t-Lx}^{Lx}-X_{s-Lx}^{Lx} \|< d, | Y_{t-Ly}^{Ly}-Y_{s-Ly}^{Ly} \|< d)\\
&G3(m+Lx,d)=P(\| X_{t-Lx}^{m+Lx}-X_{s-Lx}^{m+Lx} \|< d)\\
&G4(Lx,d)=P(\| X_{t-Lx}^{Lx}-X_{s-Lx}^{Lx} \|< d)
\end{aligned} \tag{B3}$$

The correlation-integral estimators of the G*i* (*i* = 1, 2, 3, and 4) in Equation (B3) are used to test the condition in Equation (B2). The correlation integral, an estimator of spatial dependence across time, is defined as a proportion of the number of observations within the distance d of each other to the total number of observations. These correlation-integral estimators are calculated as

$$\begin{aligned}
&G1(m+Lx,Ly,d)\equiv 2/(n(n-1))\sum_{t<s}\sum I(X_{t-Lx}^{m+Lx},X_{s-Lx}^{m+Lx},d).I(Y_{t-Ly}^{Ly},Y_{s-Ly}^{Ly},d)\\
&G2(Lx,Ly,d)=2/(n(n-1))\sum_{t<s}\sum I(X_{t-Lx}^{Lx},X_{s-Lx}^{Lx},d).I(Y_{t-Ly}^{Ly},Y_{s-Ly}^{Ly},d)\\
&G3(m+Lx,d)=2/(n(n-1))\sum_{t<s}\sum I(X_{t-Lx}^{m+Lx},X_{s-Lx}^{m+Lx},d)\\
&G4(Lx,d)=2/(n(n-1))\sum_{t<s}\sum I(X_{t-Lx}^{Lx},X_{s-Lx}^{Lx},d)
\end{aligned} \tag{B4}$$

Assume that $X_t$ and $Y_t$ are strictly stationary, weakly dependent, and satisfy the mixing conditions as specified in Denker and Keller (1983). Under the null hypothesis that $Y_t$ does not strictly Granger cause $X_t$, the test statistic G is asymptotically normally distributed, according to Hiemstra and Jones (1994). That is,

$$G = \left(\frac{G1(m+Lx,Ly,d)}{G2(Lx,Ly,d)} - \frac{G3(m+Lx,d)}{G4(Lx,d)}\right) \overset{a}{\sim} N\left(0, \frac{1}{\sqrt{n}}\sigma^2(m,Lx,Ly,d)\right), \tag{B5}$$

where s,t=max(Lx,Ly)+1, …, T–m+1; n=T+1–m-max(Lx,Ly). I($Z_1$,$Z_2$,d) denotes a kernel that equals 1 when two variables, $Z_1$ and $Z_2$, are within the maximum norm distance d of each other, and zero otherwise.

In Equation (B5), the asymptotic variance, $\sigma^2$(m,Lx,Ly,d), is calculated using the estimator derived in Hiemstra and Jones (1994) that allows for errors to be weakly dependent. This variance estimator is formulated as

$$\hat{\sigma}^2(m,Lx,Ly,d) = \hat{z}(n)\hat{\Sigma}(n)\hat{z}(n)', \tag{B6}$$

where

$$\begin{aligned}\hat{z}(n) = [&1/G2(Lx,Ly,d,n), -G1(m+Lx,Ly,d,n)/G2^2(Lx,Ly,d,n), -1/G4(Lx,d,n),\\ &G3(m+Lx,d,n)/G4^2(Lx,d,n)]\end{aligned} \tag{B7}$$

$$\hat{\Sigma}_{i,j}(n) = 4.\sum_{k=1}^{K(n)} w_k(n)\left[\frac{1}{2(n-k+1)}\sum_t(\hat{A}_{i,t}(n).\hat{A}_{j,t-k+1}(n) + \hat{A}_{i,t-k+1}(n).\hat{A}_{j,t}(n))\right] \tag{B8}$$

$$w_k(n) = \begin{cases} 1, & if\ k=1 \\ 2(1-[(k-1)/K(n)]), & otherwise \end{cases} \tag{B9}$$

$$\begin{aligned}
\hat{A}_{1,t}(n) &= \frac{1}{n-1}\left(\sum_{s\neq t} I(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, d).I(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, d)\right) - G1(m+Lx,Ly,d,n)\\
\hat{A}_{2,t}(n) &= \frac{1}{n-1}\left(\sum_{s\neq t} I(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, d).I(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, d)\right) - G2(Lx,Ly,d,n)\\
\hat{A}_{3,t}(n) &= \frac{1}{n-1}\left(\sum_{s\neq t} I(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, d)\right) - G3(m+Lx,d,n)\\
\hat{A}_{4,t}(n) &= \frac{1}{n-1}\left(\sum_{s\neq t} I(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, d)\right) - G4(Lx,d,n),
\end{aligned} \tag{B10}$$

and where t =max(Lx, Ly) +k,…, T–m+1; n =T+1–m-max(Lx, Ly); K(n)= (int)$n^{1/4}$. G*i*(., n), *i* = 1, 2, 3, and 4, is the correlation integral in Equation (B4).