Improving the Predictability of Stock Market Returns with the Growth of Option Open Interest

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Abstract

The purpose of this paper is to show that the growth of option open interest has predictive power for stock market returns. Predictability is demonstrated through in-sample tests, as evidenced by significant *p*-values and the improvement of adjusted R^2 in monthly predictive regressions, and by out-of-sample metrics. In addition, stock return predictability confirms the economic significance of the growth of option open interest, as shown by improving Sharpe ratios of returns from a predictor variable-based decision rule that exploits the growth of option open interest. Our empirical evidence indicates that the growth of option open interest provides additional information for future stock market returns, relative to other popular predictor variables.

JEL Classification: C53, G12, G13

Keywords: Option Open Interest, Predictability, Stock market returns

1. Introduction

Stock return predictability is a central topic in the financial literature and has been thoroughly investigated over the past two decades. Numerous studies related to the predictability of stock returns have discovered many predictor variables including, among others, the dividend yield, the default spread, the variance risk premium, and the consumption-wealth ratio. In this article, we investigate the ability of the growth of open interest in the option market to predict stock market returns beyond the predictive power of other popular predictor variables.

The informational linkage between the stock and option markets has been discussed with the trading volume of option for several years.[1,2] Black (1975) suggests that informed traders will first trade in the option market to use the financial leverage of option for higher returns. Consistent with that notion, Easley, O'Hara, and Srinivas (1998) develop a theoretical model in which the trading volumes of option provided by informed traders contain information about future stock prices. In their model, informed traders choose to trade in the option market before trading in the stock market; option information therefore reveals information about future stock price movements. In addition, Pan and Poteshman (2006) present the predictability of put-call ratios based on option trading volume for future stock prices in the pooling equilibrium of Easley, O'Hara, and Srinivas (1998). On the other hand, Chan, Chung, and Fong (2002) provide empirical evidence of the price discovery roles of the stock and option markets based on quote revisions and net trading volumes in each market. Their results support the idea that although financial leverage in the option market is a benefit, informed traders have more trades in the stock market than in the option market, and option trades contain less information for the stock market than do stock trades because of the limitation of liquidity in the option market.

Information of open interest in the option market has received relatively less attention than

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[1] See, for example, Vijh (1990), Chang, Hsieh, and Lai (2009), and Roll, Schwartz, and Subrahmanyam (2010).

[2] Recent empirical studies focusing on the information provided by option implied volatility or option price for future stock price movements include Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), and Doran and Krieger (2010).

information of trading volume.[3] Bhuyan and Chaudhury (2005) examine information based on the distribution of option open interest in individual stocks. They regard the distribution of option open interest across various strike prices as a proxy for the true or physical distribution of individual stock price at option maturity. Their results show that trading strategies based on option open interest yield higher returns than the S&P 500 index and the buy and hold strategy. Lakonishok, Lee, Pearson, and Poteshman (2007) investigate different classes of investors for individual equity option based on option open interest to describe option market activity across investors. They classify investors as firm proprietary traders, public customers of full-service brokers, public customers of discount brokers, and other public customers. They find that public customers of full-service brokers with nonmarket maker transactions have more written option open interest than bought option open interest for both calls and puts, especially for high put option open interest for value stocks. In addition, public customers of full-service brokers have more purchased call option open interest than purchased put option open interest and more written call option open interest than written put option open interest. For the above four groups of investors, the preponderance of call option open interest relative to put option open interest holds. Fodor, Krieger, and Doran (2011) use the change of open interest of call and put option as a predictor of future equity returns in individual stocks. Their empirical results show that an increase in call option open interest predicts increased equity returns. Although they suggest that an increase in put option open interest predicts decreased equity returns, the predictive power of put option open interest is much weaker after controlling for numerous factors. Unlike prior studies, we use option open interest as the demand of the hedger in the option market.[4] Large growth of option open interest is generally induced by large buy orders, while large growth of option trading volume can emerge in a variety of situations such as frequent

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[3] See, for example, Schachter (1988), Jayaraman, Frye, and Sabherwal (2001), and Chesney, Crameri, and Mancini (2011).

[4] Pan and Poteshman (2006) examine the information content of option trading on the S&P 100, S&P 500, and NASDAQ 100. Although they find significant informed trading at the individual stock level, they cannot provide evidence of informed trading in the index option market. This is consistent with the common belief that investors use index option mostly for hedging rather than for speculating and is the reason that we regard option open interest as the demand of the hedger in the S&P 500 index option market.

trading of specific options or the execution of large sell orders.

In an intriguing study on the relation between the demand of traders and the equilibrium in the option market, Garleanu, Pedersen, and Poteshman (2009) build a demand-pressure model in which the demand for option impacts the option price. They denote the agents who have a fundamental need for option exposure as end-users, such as public customers and firm proprietary traders, and find that net demand of end-users in the option market, as computed by long open interest minus short open interest, increases the expense of option. In contrast, we only focus on gross (as opposed to net) demand for option, regarded as gross hedging demand in the option market, and show that the growth of gross hedging demand in the option market includes information about future stock market returns.

To the best of our knowledge, our research is the first of its kind to examine the relation between the growth of gross hedging demand in the option market and future price movements of the aggregate market portfolio. Our model is motivated by the implications of the model of Hong and Yogo (2012). Hong and Yogo (2012) build a model of the futures market in which a growth rate of open interest in each futures market predicts each market returns. They show that the growth of open interest in commodity futures market predicts commodity returns, bond returns, and movements of the short rate. In addition, they find that the growth of open interest in currency, bond, and stock futures market predicts currency, bond, and stock returns, respectively, although the predictability is somewhat weaker than the growth of open interest in commodity futures market. In their model, the gross hedging demand for commodities by producers or consumers increases by more than the condition of the low expected state of the future economy if the state of the future economy is expected to be high because the producers of commodities that anticipate higher demand for products when the economy is in a high state may go short futures for products, and the consumers of commodities that anticipate higher demand for consumer goods when the economy is in a high state may go long futures for consumer goods. Along with their implications, an obvious question is: If hedgers exploit the option contract as well as the futures contract as a hedging instrument,[5] does the growth of option open interest exhibit predictive power for future stock returns?

Our model is as an extension of the model of Hong and Yogo (2012), but we focus on the stock option market instead of the stock futures market. In addition, hedgers in the option market determine not only their positions for option but also the strike prices of option based on their own information about the future economic state, whereas in Hong and Yogo (2012), hedgers only reflect their own information in positions of futures. Based on our model, we hypothesize that if the state of the future economy is expected to be high (low), the gross hedging demand caused by out-of-the money (*OTM*) call (put) option and in-the money (*ITM*) put (call) option increases. To verify our hypotheses, we empirically investigate the ability of the growth of each type of option open interest to predict aggregate excess market returns using the following criteria (i) significance of the coefficient estimate and improvement of adjusted R^2 in in-sample predictability analysis, (ii) significance of the test statistics in out-of-sample predictability analysis, and (iii) significance of the improvement in Sharpe ratios of returns from a predictor variable-based decision rule.

Using the S&P 500 index and option, the growth of *OTM* call option open interest and *ITM* put option open interest has positive significant predictive power for future excess market returns. The growth of *ITM* call option and *OTM* put option open interest predicts negative excess market returns, although its effect on the prediction of future excess market returns is not always significant. Based on our empirical results, we confirm the predictive power of the growth of option open interest for future aggregate stock market returns. Our empirical findings are robust to the addition of the information from option trading volume, the application of different filtering criteria, weighting methodology used to determine the growth of option open interest, and different criteria for the moneyness of option, controlling for other related variables such as the growth of the call-to-put option open interest ratio and call-to-put option volume, and the in-sample predictability analysis during the subsample period.

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[5] Frechette (2001) concludes that futures and option are highly substitutable, and that hedgers with high and moderate levels of risk aversion are nearly indifferent between the optimal futures-only strategy and the optimal option-only strategy.

The plan for the rest of the paper is as follows. Section 2 outlines a model in which the growth of open interest in the option market predicts aggregate stock market returns. Section 3 describes the data set and the empirical methodology for the growth of option open interest. Section 4 presents our main empirical findings. Section 5 represents the robustness tests for our empirical results. Section 6 concludes our study.

2. A model with open interest in option market

In this section, we develop a simple model of the option market in which the growth of option open interest can be a better predictor of future stock market return. Our model is a trade model of the option market in the spirit of Hong and Yogo (2012), wherein the under-reaction to news and the movements of asset prices by supply shocks are attributed to friction. There are notable differences. First, our model is based on an option market in which the option has two types of payoff (call and put) for the movements of underlying asset prices and different strike prices (moneyness), as opposed to the futures market in Hong and Yogo (2012). Thus, we exploit the properties of option to describe the relation between the decrease of the stock price and the growth of option open interest as well as the relation between the increase of the stock price and the growth of option open interest. Second, the hedgers' objective function is transformed by the asymmetric feature of the option payoff. Third, the hedgers utilize their own information on the state of the future economy to determine the strike price of option.

There are three periods indexed as t = 0, 1, and 2. The riskless interest rate is constant and normalized to zero. The maturity of option is period 2, and there is an option market in which the option is traded in periods 0 and 1. We assume that the stock price in period t (S_t) is exogenous and stochastic. In period 1, the economy is in one of two states: In the high state, stock price in period 2 is distributed as $N(S^H, \sigma^2)$, and the probability density function of S_2 in period 1 is $p_H(S_2)$. The probability of the high state is π. In the low state, the stock price in period 2 is distributed as $N(S^L, \sigma^2)$, and the probability density function of S_2 in period 1 is $p_L(S_2)$. The probability of the low state is 1-π. We assume that the stock price in the high economic activity of period 2 is higher than the stock price in period 1, and that the stock price in the low economic activity of period 2 is lower than the stock price in period 1, $S^H > S_1 > S^L$. In addition, for simplification, we make the assumption that the option has two strike prices (S^H and S^L).[6] According to their information and objective functions, traders in the option market are separated into three different types: hedgers, informed traders, and uninformed traders.

A. Hedgers

We assume that the hedgers know the state of the economy and the expectation for the stock price in period 2, but they are uncertain about the probability distribution of the stock price induced by variance (σ^2). The hedgers are infinitely risk averse and want to hedge the uncertainty of the movement of the stock price between periods 1 and 2. Thus, the hedgers will buy option in period 1. In each economic state, the hedgers choose $E_1(S_2|i)$ (*i*=*H*, *L*) as the strike price of option, because the hedgers use their own information for hedging. In the quantity of the stock that the hedgers need to hedge, Y_j^H denotes the quantity of stock which the hedgers guarantee to sell (*j*=*S*) or buy (*j*=*B*) in the high state. Y_j^L is the quantity of stock which the hedgers guarantee to sell (*j*=*S*) or buy (*j*=*B*) in the low state. If the hedgers guarantee to buy the stock, then $Y_B^H (Y_B^L) < 0$, and if the hedgers guarantee to sell the stock, then $Y_S^H (Y_S^L) > 0$.

When the hedgers want to buy stock in period 2, they choose the optimal position to minimize

[6] In our empirical study, we regard S^H as strike prices higher than the current stock price and S^L as strike prices lower than the current stock price. In Section 5.4, we adjust different criteria for the moneyness of option, and the results are similar to our main results.

the variance of their profit from hedging as shown below.

i) $Y_B^i < 0 (i = H, L)$

$$\min_{D_{C(K)}^H} Var_1(S_2 Y_B^i + (\max[(S_2 - K), 0] - P_{C(K),1}) D_{C(K)}^H) \tag{1}$$

$$\text{s.t} \quad S_2 \geq E_1(S_2 | i) = K,$$

where $D_{C(K)}^H$ is the position of the call option, and $P_{C(K),1}$ is the price of the call option with strike price K in period 1. The hedgers can perfectly hedge the uncertainty by choosing $D_{C(K)}^H = -Y_B^i$. This optimal position of the call option indicates that the hedgers who want to buy the stock have a long position for the call option with the same amount of stock. In addition, the hedgers would like to hedge the uncertainty about the upward pressure of the stock price above $E_1(S_2 | i)$ in period 2. If the stock price in period 2 is lower than $E_1(S_2 | i)$, then the hedgers can buy their stock at $E_1(S_2 | i)$, because the supply of the stock is larger than the demand for the stock at $E_1(S_2 | i)$. Thus, they do not need to consider this case.

On the other hand, when the hedgers want to sell stock in period 2, they choose the optimal position to minimize the variance of their profit from hedging as shown below.

ii) $Y_S^i > 0 (i = H, L)$

$$\min_{D_{P(K)}^H} Var_1(S_2 Y_S^i + (\max[(K - S_2), 0] - P_{P(K),1}) D_{P(K)}^H) \tag{2}$$

$$\text{s.t} \quad S_2 \leq E_1(S_2 | i) = K,$$

where $D_{P(K)}^H$ is the position of the put option, and $P_{P(K),1}$ is the price of the put option with strike price K in period 1. The hedgers can also perfectly hedge the uncertainty by choosing $D_{P(K)}^H = Y_S^i$. This optimal position of put option indicates that the hedgers who want to sell the stock have a long position for the put option with the same amount of stock. Moreover, the hedgers would like to hedge the uncertainty about the downward pressure of the stock price below $E_1(S_2 | i)$ in period 2. As with the call option, the hedgers do not need to consider the case in which the stock price in period 2 is higher than $E_1(S_2 | i)$ because of excess demand for the stock at $E_1(S_2 | i)$ in period 2.

B. Informed traders

In addition to the hedgers, there are two other groups of traders in the option market. The first group is the informed traders, who have mass $\lambda \in (0,1)$ among the traders in the option market. The informed traders know the state of the economy in period 1 and have information about the probability distribution of the stock price in period 2 at each point in time. Thus, they update their beliefs based on their information about S_2 and use new information to adjust their trading in the option market. The informed traders have the usual mean-variance objective function and choose the optimal position in periods 0 and 1 to maximize their objective function. The optimal call option position of the informed traders in period *t* (*t* = 0, 1) is as follows:

$$D^I_{C(K),t} = \frac{E_t(P_{C(K),t+1}) - P_{C(K),t}}{\gamma Var_t(P_{C(K),t+1} - P_{C(K),t})}, \tag{3}$$

where $P_{C(K),t}$ is the price of the call option with strike price K in period *t*, and γ is the risk aversion parameter. The optimal put option position of the informed traders is the same but with $P_{C(K),t}$ and $P_{C(K),t+1}$ replaced by $P_{P(K),t}$ and $P_{P(K),t+1}$, respectively.

C. Uninformed traders

The second remaining group consists of uninformed traders, who have mass $1-\lambda \in (0,1)$ among the traders in the option market. In contrast with the informed traders, the uninformed traders do not know the state of the economy in period 1, and their information about S_2 in period 1 is the same as that in period 0. The under-reaction to news about the state of the economy occurs because of the uninformed traders. The uninformed traders, like the informed traders, have the usual mean-variance objective function and choose the optimal position in periods 0 and 1 to maximize their objective function. The optimal call option position of the uninformed traders in period *t* (*t* = 0, 1) is as follows:

$$D^{U}_{C(K),t} = \frac{\overline{P_{C(K)}} - P_{C(K),t}}{\gamma Var_0(P_{C(K),2})}, \tag{4}$$

where $P_{C(K),t}$ is the price of the call option with strike price K in period *t*, $P^{H}_{C(K)} = \int (S_2 - K)^+ p_H(S_2) dS_2 = E_1(P_{C(K),2} | H)$, $P^{L}_{C(K)} = \int (S_2 - K)^+ p_L(S_2) dS_2 = E_1(P_{C(K),2} | L)$, and $\overline{P_{C(K)}} = \pi P^{H}_{C(K)} + (1-\pi) P^{L}_{C(K)} = E_0(P_{C(K),2})$. Along with the optimal position of the informed traders, the optimal put option position of the uninformed traders is the same but with $\overline{P_{C(K)}}$, $P_{C(K),t}$, and $P_{C(K),2}$ replaced by $\overline{P_{P(K)}}$, $P_{P(K),t}$, and $P_{P(K),2}$, respectively.

[Table 1 about here]

Based on the economic environment and three groups of traders, we can derive the relation between the growth of option open interest and future stock market returns. A detailed presentation of the model is described in the Appendix. In our empirical analysis, we regard the call option with the high strike price (S^H) and the call option with the low strike price (S^L) as *OTM* and *ITM*, respectively. The put option are also considered *OTM* for the low strike price (S^L) and *ITM* for the high strike price (S^H). Table 1 presents a summary of the position of option among the participants in the option market in the high state and the low state. Based on Table 1, we state our main result.

Proposition. *Regardless of the direction of hedging demand* (*i.e., whether* $Y^i_B < 0$ *or* $Y^i_S > 0$), *high growth of open interest of option with a high strike price* (*OTMC and ITMP*) *signals a high expected* *return* $E_1[R_2]$. *On the other hand, high growth of open interest of option with a low strike price* (*ITMC and OTMP*) *signals a low expected return* $E_1[R_2]$.

According to this proposition, in the subsequent sections we investigate in detail the predictability of future stock returns based on the growth of option open interest as provided by our model.

3. Data and Methodology

3.1 Data description

In this section, we describe the data used in this paper and introduce our predictor variables and established predictor variables. Our empirical analysis is based on the S&P 500 index as a proxy for the aggregate market portfolio. Because of the S&P 500 index option data availability from *OptionMetrics*, our sample period is from August 1996 through September 2010, for a total of 170 monthly observations.[7]

To evaluate rigorously the predictive power of the growth of option open interest for future stock returns, we consider a set of the traditional predictor variables. We obtain the monthly short rate (the three-month T-bill yield minus its trailing 12-month moving average),[8] default spread (the difference between Moody's BAA and AAA corporate bond yields), and term spread (the difference between the 10-year T-bond and the three-month T-bill yields)[9] from *the Federal Reserve Bank of St. Louis*. Monthly dividend yield[10] is constructed based on data from Robert Shiller's website. The lagged return is used as

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[7] The S&P 500 index option data is available from January 1996. Since we use the moving average of the monthly growth of option open interest, our sample period starts in August 1996.

[8] See, for example, Fama and Schwert (1977), Campbell (1987), Breen, Glosten, and Jagannathan (1989), and Ang and Bekaert (2007).

[9] Previous studies show the predictive power of the default spread and the term spread for future stock return. [See, e.g., Chen, Roll, and Ross (1986), Campbell (1987), Fama and French (1989), and Chen (1991)]

[10] See, for example, Campbell and Shiller (1988a, 1988b), Fama and French (1988), Hodrick (1992), Goetzmann and Jorion

the predictor variable to capture the momentum or mean reversion effects.[11]

In addition to the traditional predictor variables, we employ the recent predictor variables for comparison with the growth of option open interest. The variance risk premium (VRP)[12,13] is introduced by Bollerslev, Tauchen, and Zhou (2009). Bollerslev, Tauchen, and Zhou (2009) provide empirical evidence that stock market returns are predictable based on the VRP across various return horizons, especially at the quarterly horizon. The Chicago Fed National Activity Index (CFNAI) is taken from *the Federal Reserve Bank of Chicago*. We regard CFNAI as a measure of real economic activity, which is known to predict inflation, as in Stock and Watson (1999). The consumption-wealth ratio (CAY)[14], as defined in Lettau and Ludvigson (2001), is obtained from Martin Lettau's website. Lettau and Ludvigson (2001) show that CAY contains important predictive elements for stock market return over the short and intermediate horizons via the consumption-based framework. The BDI, defined as the change in the Baltic Dry Index over three months, is introduced by Bakshi, Panayotov, and Skoulakis (2011) and is obtained from daily data in *Bloomberg*. Bakshi, Panayotov, and Skoulakis (2011) show that the BDI has predictability for stock market returns, the returns of commodity indexes, and the growth in global economic activity due to global demand for raw materials.

[Table 2 about here]

(1995), Lamont (1998), Lewellen (2004), and Ang and Bekaert (2007).

[11] See, for example, Lo and Mackinlay (1990).

[12] The variance risk premium is constructed using method analogous to that in Bollerslev, Tauchen, and Zhou (2009). We should use the information to predict future stock return *ex ante* from the forecasting perspective. Therefore, we assume that the realized volatility is martingale and define the VRP at time t as the difference between *ex ante* risk-neutral expectation of the future return variance over $[t, t+1]$ and the *ex post* realized return variance over $[t-1, t]$. The S&P 500 index data (five-minute frequency) includes the period from 9:35 am to 4:00 pm (EST), and VIX is provided by the Chicago Board of Options Exchange (CBOE).

[13] See, for example, Zhou (2010) and Bollerslev, Marrone, Xu, and Zhou (2012).

[14] A monthly CAY series is defined as the most recent quarterly observation.

Table 2 reports basic summary statistics for the monthly excess return, the traditional predictor variables, and the recent predictor variables. The monthly mean excess return is 0.20%, and the monthly standard deviation of the excess return is 4.80%. All of the traditional predictor variables except the lagged return are persistent with high first-order autocorrelations. On the other hand, in the recent predictor variables, VRP, CFNAI, and BDI are quite a bit less persistent than the traditional predictor variables except for the lagged return, while CAY has high first-order autocorrelation along with most of the traditional predictor variables.

3.2 The growth of option open interest

To construct of the growth of option open interest, we use data on the S&P 500 index option open interest. The open interest of S&P 500 index option is secured from *OptionMetrics*. To strengthen the reliability of the empirical results, the following criteria are adopted for the index option data. First, any options with a zero bid price are removed from the sample. Options with prices below 0.05 are also eliminated. Second, options that violate the no-arbitrage condition are removed. Third, options with less than nine or more than 61 trading days remaining to maturity are eliminated from the sample. These options may have market microstructure concerns and the lack of liquidity. Finally, options whose trading volume or open interest is zero are eliminated to alleviate the error caused by the minimum tick size.

To construct the monthly growth of option open interest, we measure monthly option open interest as an equal-weighted average of the open interest of various options with different strike prices and maturities on the last trading day of each month. Then, we compute the growth of option open interest based on monthly option open interest as the ratio of option open interest on the last trading day of the present month relative to option open interest on the last trading day of the previous month. We smooth the monthly growth of option open interest by taking a six-month geometric average in the time series because the monthly growth of option open interest is noisy.[15] The moneyness of option is defined as follows: The call (put) is *OTM* if $K/S > 1$ ($K/S < 1$) and is *ITM* if $K/S < 1$ ($K/S > 1$), where S denotes the underlying stock price, and K is the strike price of the option. Based on these criteria, we classify the option according to the moneyness and the type of the exercise and examine the predictability of out-of-the money call option (*OTMC*), in-the money put option (*ITMP*), in-the money call option (*ITMC*), and out-of the money put option (*OTMP*) open interest for future stock return.[16]

[Table 3 about here]

Table 3 presents the summary statistics for option open interest and the growth of option open interest. According to the summary statistics for the number of option and option open interest in Panel A, investors tend to demand a long position of *OTM* option rather than a long position of *ITM* option, and there tends to be more variation in the demand for a long position with put option than with call option. In regards to the growth of option open interest, the growth of the demand for *ITM* option is higher and more volatile than that for *OTM* option. In addition, the growth of option open interest has lower first-order autocorrelations than the traditional predictor variables and the recent predictor variables except for the lagged return.[17] While almost all economic models imply very persistent expected stock market returns,

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[15] Similarly, Hong and Yogo (2012) smooth the monthly growth rate of futures open interest by taking a 12-month geometric average in the time series, because the monthly growth rate of futures open interest is noisy.

[16] For the open interest in each month, the moneyness of the option is based on the underlying stock price on the last trading day of each month. Then, we calculate the equal-weighted average of option open interest for each moneyness (*OTM* or *ITM*) and type of exercise (call or put). Based on the time-series of monthly option open interest, we calculate the monthly growth of option open interest and smooth it by taking a six-month geometric average in the time series.

[17] Ang and Bekaert (2007) show that when stock returns are predicted by persistent predictor variables and the prediction horizon is longer, there are considerable size distortions and over-rejections for the null hypothesis of the predictor variables, which means that the predictor variables do not have predictive power for stock returns. However, the growth of option open interest has small first-order autocorrelations, and our forecast horizon is only one-month. In addition, we use *p*-values following the procedures in Hodrick (1992), which are robust to the presence of persistent shocks, so there is no concern about distortions and over-rejections.

and existing predictor variables only capture the persistent component of expected stock market returns, the growth of option open interest can capture less persistent components of expected stock market returns. Thus, our results indicate the need to advance the existing structural models such as in the model we present in Section 2. Panel B of Table 3 reports the correlation between the growth of option open interest and other predictor variables. As we expected, future stock return is positively correlated with the growth of *OTMC* and *ITMP* open interest. The correlations of the growth of *ITMC* and *OTMP* open interest, respectively, with future stock return are negative, although the absolute values of their correlations are smaller than those of the growth of *OTMC* and *ITMP* open interest.

4. Predictability of the growth of option open interest for stock market return

Our empirical investigation focuses on whether the growth of option open interest contains useful information to predict future aggregate stock market returns. To achieve this, we examine predictive regression of the type

$$R^e_{t+1} = \alpha + \beta_b b_t + \varepsilon_{t+1}, \tag{5}$$

where R^e_{t+1} is the excess market return for month t+1, and $b_t = [b_{t1} \cdots b_{tn}]'$ is the vector of the traditional predictor variables, the recent predictor variables and the growth of option open interest in month t.

4.1 In-sample predictability analysis

A. The growth of OTMC open interest

[Table 4 about here]

In Table 4, we consider the hypothesis that the growth of *OTMC* open interest has predictive power for monthly subsequent stock market returns. We employ the Newey and West (1987) approach with 12 lags, and the Hodrick (1992) approach to evaluate the predictive power of the growth of option open interest for stock market returns in in-sample predictive regressions. In column (0), we can see the predictive power of the growth of *OTMC* open interest as a stand-alone predictor variable. The coefficient estimate on the growth of *OTMC* open interest is positive and highly significant, as we expected, and the adjusted R^2 in the regression is 2.54%. In column (1), we estimate a baseline model involving the traditional predictor variables, which are the short rate, the default spread, the term spread, the dividend yield, and the lagged return. Not surprisingly, most of the traditional predictor variables are insignificant, except the default spread and the dividend yield. The coefficient estimate on the default spread is negative and highly significant. While a negative coefficient estimate on the default spread is in contrast to a positive coefficient estimate in a few earlier studies (Fama and French (1989) and Chen (1991)), the coefficient estimate on the default spread is consistent with empirical evidence in recent sample periods (Li and Yu (2012)). As with the default spread, the dividend yield has significant impact on the stock market returns with a positive coefficient estimate, and the result for the dividend yield is consistent with the prior literature (Fama and French (1988) and Goetzmann and Jorion (1995)). Overall, the adjusted R^2 of the baseline model is 4.67%.

In column (2) of Table 4, we add the growth of *OTMC* open interest to the baseline model to compare its predictive power for future stock market returns with the traditional predictor variables. The growth of *OTMC* open interest is highly significant with a positive coefficient estimate, as we expected. The coefficient estimate on the growth of *OTMC* open interest is 0.128 with the Newey and West (NW) *t*-statistic of 3.053 (Hodrick *t*-statistic of 2.278). The above estimate is not only statistically significant but also economically important. A one standard deviation increase in *OTMC* open interest can lead to an annualized increment of 9.29% in excess returns. Combining the growth of *OTMC* open interest with the baseline model improves adjusted R^2 by 1.87%. Such a result indicates that the predictive power of the growth of *OTMC* open interest is not captured by the traditional predictor variables.

Column (3) of Table 4 represents the result for the baseline model with VRP. The coefficient estimate on VRP is positive with the NW *t*-statistic of 7.361 (Hodrick *t*-statistic of 2.888).[18] The result is consistent with the earlier result in Bollerslev, Tauchen, and Zhou (2009). The inclusion of VRP increases adjusted R^2 from 4.67% to 12.91%. In column (4), we compare the predictive power of the growth of *OTMC* open interest with that of VRP. The coefficient estimate on the growth of *OTMC* open interest maintains its own magnitude, sign, and significance, as in column (2). Similarly, VRP also sustains its impact on future stock market returns. The increment of adjusted R^2 based on the inclusion of the growth of *OTMC* open interest between columns (3) and (4) is 1.46%, and the coefficient estimates on the growth of *OTMC* open interest and VRP are still significant. This result confirms that the growth of *OTMC* open interest and VRP contain different information about future stock market returns, and the significance of the predictive power of the growth of *OTMC* open interest is comparable to that of VRP.

In column (5), we include CFNAI in the baseline model. The coefficient estimate on CFNAI is positive but insignificant. However, the coefficient estimate on the default spread is insignificant, unlike those in previous regressions. From this result, we can conjecture that the default spread has predictive power for future stock market returns in terms of predicted inflation, and that its predictive power dissipates with CFNAI. This is consistent with the fact that CFNAI has robust predictive power for inflation in Stock and Watson (1999). The adjusted R^2 of the baseline model with CFNAI is 7.94%. Still, the growth of *OTMC* open interest causes the stock price to increase significantly after controlling for the effect of predicted inflation in column (6). The addition of the growth of *OTMC* open interest does not

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[18] For the VRP, the difference between the NW *t*-statistic and the Hodrick *t*-statistic is very large in columns (3) and (4) of Table 4. However, the difference is generally small for non-overlapping regression in prior studies. With VRP and constant in the predictive regression, the coefficient estimate on VRP has the NW *t*-statistic of 4.172 and the Hodrick *t*-statistic of 2.222. Since difference between the two *t*-statistics in univariate regression of VRP is probable, we could conjecture that a larger difference between the two *t*-statistics is due to the larger NW *t*-statistic caused by the correlation between VRP and the traditional predictor variables.

change the coefficient estimate of CFNAI. The increased adjusted R^2 is 9.63%, and the increment of adjusted R^2 based on the growth of *OTMC* open interest with CFNAI is 1.69%, which is larger than that with VRP.

In column (7), we introduce CAY to the baseline model. The coefficient estimate on CAY is positive and more significant than that of CFNAI. The sign of the coefficient estimate on CAY is consistent with the empirical evidence provided by Lettau and Ludvigson (2001). However, the improvement of adjusted R^2 based on CAY, as compared with the adjusted R^2 in column (1), is 2.11%, which is smaller than the improvement based on CFNAI in column (5). Column (8) represents the result for the baseline model with CAY and the growth of *OTMC* open interest. Similar to the previous results with VRP and CFNAI, the coefficient estimate on CAY has little change when compared to that in column (7). In addition, the coefficient estimate on the growth of *OTMC* open interest is still positive and significant with CAY.

In column (9), we add BDI to the baseline model. The coefficient estimate on BDI is positive and significant, and the improvement of adjusted R^2 based on BDI is 6.23%. Column (10) reports the result for the baseline model with BDI and the growth of *OTMC* open interest. The coefficient estimate on the growth of *OTMC* open interest is highly significant and positive.

Moving to the Wald statistic for joint significance of the coefficient estimates, row 12 shows that all *p*-values are less than 0.05, implying that the null hypothesis — that the coefficient estimates for the predictor variables except intercept do not predict excess stock market returns — is rejected. This evidence is robust to the Wald statistic based on both the Hodrick (1992) standard error and the Newey and West (1987) standard error. Therefore, the growth of *OTMC* open interest has a significant effect on future stock market returns.

B. The growth of ITMP open interest

To evaluate the predictive power of the growth of *ITMP* open interest, we replace the growth of *OTMC* open interest with the growth of *ITMP* open interest in columns (0), (2), (4), (6), (8), and (10) of Table 4.

[Table 5 about here]

Table 5 reports the predictive power of the growth of *ITMP* open interest for monthly subsequent stock market returns. On the whole, the coefficient estimates on the growth of *ITMP* open interest are positive and less significant than those of *OTMC* open interest. The magnitude of the coefficient estimates on the growth of *ITMP* open interest is one third as large as that of the coefficient estimates on the growth of *OTMC* open interest, and the improvements of adjusted R^2 based on the growth of *ITMP* open interest are smaller than those based on the growth of *OTMC* open interest in all predictive regressions of Table 5. For example, while the coefficient estimate on the growth of *ITMP* open interest is 0.045 with an increased adjusted R^2 of 1.52% in column (10) of Table 5, the coefficient estimate on the growth of *OTMC* open interest is 0.150 with an increased adjusted R^2 of 2.83% in column (10) of Table 4. The sign, the magnitude, and the significance of the traditional predictor variables and the recent predictor variables of Table 5 are similar to those in Table 4.

C. The growth of ITMC open interest and the growth of OTMP open interest

In addition, we check whether the growth of *ITMC* and *OTMP* open interest has predictive power for monthly subsequent stock market returns. Consistent with our hypothesis, the coefficient estimates on the growth of *ITMC* and *OTMP* open interest are always negative, although the coefficient estimates on the growth of *ITMC* and *OTMP* open interest are insignificant. In general, the magnitude of the coefficient estimates on the growth of *OTMP* open interest is about three times larger than that on the growth of *ITMC* open interest. These results are available upon request.

D. Summary of In-sample predictability

In our model, we would expect the coefficient estimates on the growth of *OTMC* and *ITMP* open interest to be positive and significant. While the empirical results in Table 4 indicate that the growth of *OTMC* open interest has predictive power for future stock market returns in all regressions, the growth of *ITMP* open interest has predictive power in all cases except that of the stand-alone predictor. In addition, the results show that growth of *OTMC* and *ITMP* open interest has significant positive impact on future stock market returns using the traditional predictor variables and the recent predictor variables. The *t*-statistic of the coefficient estimate of the growth of *OTMC* open interest with BDI is largest in all regressions in Table 4, and that of *ITMP* open interest with CAY is largest in all regressions in Table 5. In addition, the *t*-statistic of the coefficient estimate of the growth of *OTMC* with VRP is smallest in all regressions in Table 5, and that of *ITMP* open interest in column (0) is smallest in all regressions in Table 5. In the standardized regressions, a one standard deviation increase in *OTMC* open interest leads to annualized increases of 10.16%, 9.29%, 8.35%, 8.93%, 8.86%, and 10.89% in excess returns for columns (0), (2), (4), (6), (8), and (10) in Table 4, respectively. In the case of the growth of *ITMP* open interest, a one standard deviation increase leads to annualized increments of 5.44%, 7.33%, 6.70%, 6.49%, 8.16%, and 9.42% in excess returns for columns (0), (2), (4), (6), (8), and (10) in Table 5, respectively.

From the perspective of the improvement in adjusted R^2 based on the inclusion of the growth of *OTMC* open interest, the largest improvement is 2.83% and the smallest improvement is 1.46%. For the growth of *ITMP* open interest, the largest improvement in adjusted R^2 is 1.52% with the traditional predictor variables and BDI, and the smallest improvement is 0.43% with the traditional predictor variables and CFNAI. The growth of *OTMC* open interest has stronger predictive power for future stock market returns than does the growth of *ITMP* open interest, and the enhancement of predictive power has quite different patterns for the growth of both types of option open interest. The key point is that the growth of *OTMC* and *ITMP* open interest has strong predictive power for future stock market returns beyond that of VRP, CFNAI, CAY, and BDI and efficiently complements the recent predictor variables, which do not lose their predictive power for future stock market returns with inclusion of the growth of *OTMC* and *ITMP* open interest in all regressions in Tables 4 and 5.

Meanwhile, we also propose that the growth of *ITMC* and *OTMP* open interest has significant predictive power for future stock market returns based on our model. Although the evidence to support our hypothesis is somewhat weaker, the direction of hedging demand from the growth of *ITMC* and *OTMP* open interest would be consistent with the interpretation of our hypothesis. For the growth of *ITMC* open interest, we view the insignificance as a result of lack of liquidity.[19] Due to the illiquidity of option, we could conjecture that the hedgers are suspicious about the role of *ITMC* as the hedging instrument against the downward movement of the stock price and do not prefer *ITMC*. In the case of the growth of *OTMP* open interest, a compelling explanation for the insignificance is the desire to maintain large *OTMP* open interest, because of high demand by the traders, including uninformed traders in the option market with concern about the decline in the stock market.[20] In Table 3, the growth of *OTMP* open interest is less volatile and has higher autocorrelation than that of other option types. From this evidence, we could conjecture that the effect of hedging demand is diluted by steadily high demand for *OTMP*.

4.2. Out-of-sample predictability analysis

In the analysis above, we evaluate the ability of the growth of option open interest to predict aggregate stock market returns from in-sample predictive regressions over the full sample period. In this

[19] In unreported results for option trading volume, *ITMC* trading volume has the lowest mean and median in equally-weighted average, value-weighted average, and aggregate summation of the option trading volume for four option types.

[20] Garleanu, Pedersen, and Poteshman (2009) show that net demand for the S&P 500 index option by end-users is concentrated at moneyness where puts are *OTM*. This evidence supports our conjecture for the insignificance of the growth of *OTMP* open interest.

section, we report the results for the predictive power of the growth of option open interest in the out-of-sample predictability analysis. Based on the results in Section 4.1, we assess the predictive power of the growth of *OTMC* open interest, which has more significant predictive power for stock market returns than the growth of other types of option open interest.[21] The procedure for forecasts of stock market returns at time t+1 involves recursive parameter estimation based on data from time 1 through time t. The initial parameter estimation uses data available from August 1996 through November 2004, a total of 100 observations. The estimated parameter is used to forecast stock market returns in December 2004. The next parameter estimation is based on the period from August 1996 through December 2004, and the forecast of stock market returns in January 2005 is recomputed, and so on, until the final forecast for September 2010 is computed. From this procedure, we compute 70 forecasts of stock market returns. In order to choose significant predictor variables among all predictor variables, above all we test the predictive power of the traditional predictor variables. Among the traditional predictor variables, only the short rate reveals significant predictive power for stock market returns in univariate regressions of the out-of-sample predictability analysis. For the recent predictor variables, we exclude CFNAI and CAY. CFNAI for the current month is released at the following month, and therefore we could not use CFNAI to compute the forecast of stock market returns practically. The frequency of CAY is quarterly, and thus CAY is inappropriate for the out-of-sample predictability analysis of monthly stock market returns. In common with the short rate, VRP and BDI have significant predictive power for future stock market returns in univariate regressions of the out-of-sample predictability analysis.

For the evaluation of predictive power, we employ four test statistics. The out-of-sample R^2 (OOS R^2) statistic is suggested by Welch and Goyal (2008) and Campbell and Thompson (2008); it measures the reduction in the mean squared forecast error of the model compared to the mean squared forecast error of the benchmark model. Let the forecasted excess return for month τ+1 be

[21] In the in-sample regression with four types of growth of option open interest, the coefficient estimate on the growth of *OTMC* open interest is positive and only significant at the 5% level.

$\widehat{R^e_{\tau+1}} = \hat{\alpha} + \hat{\beta}_b b_\tau$, from the coefficient estimates in the predictive regression $R^e_{t+1} = \alpha + \beta_b b_t + \varepsilon_{t+1}$ (the unrestricted model) using data up to month τ, and let $\overline{R^e_{\tau+1}}$ be the historical average excess return (the benchmark model) up to month τ. The OOS R^2 statistic is $1 - \frac{\sum_{\tau=0}^{T-1}(R^e_{\tau+1} - \widehat{R^e_{\tau+1}})^2}{\sum_{\tau=0}^{T-1}(R^e_{\tau+1} - \overline{R^e_{\tau+1}})^2}$. A positive OOS R^2 statistic means that the unrestricted model with additional predictor variables reduces forecast errors more than does the benchmark model.

The *ENC-NEW* statistic is the encompassing test statistic of Clark and McCracken (2001) for the null hypothesis that the benchmark model encompasses the unrestricted model with additional predictor variables. The *ENC-NEW* statistic is $T \times \frac{\sum_{\tau=0}^{T-1}\left[(R^e_{\tau+1} - \overline{R^e_{\tau+1}})^2 - (R^e_{\tau+1} - \overline{R^e_{\tau+1}})(R^e_{\tau+1} - \widehat{R^e_{\tau+1}})\right]}{\sum_{\tau=0}^{T-1}(R^e_{\tau+1} - \widehat{R^e_{\tau+1}})^2}$, where T is the number of out-of-sample forecasts.

The *MSE-F* statistic is the equal forecast accuracy test statistic of McCracken (2007) for the null hypothesis that the benchmark model has equal or less mean squared error than the unrestricted model with additional predictor variables. Then the *MSE-F* statistic is

$$T \times \frac{\sum_{\tau=0}^{T-1}(R^e_{\tau+1} - \overline{R^e_{\tau+1}})^2 - \sum_{\tau=0}^{T-1}(R^e_{\tau+1} - \widehat{R^e_{\tau+1}})^2}{\sum_{\tau=0}^{T-1}(R^e_{\tau+1} - \widehat{R^e_{\tau+1}})^2}, \tag{6}$$

where T is the number of out-of-sample forecasts.

The mean square prediction error (*MSPE)-adjusted* statistic proposed by Clark and West (2007) is the t-statistic obtained from the regression of $f_{t+1} = (R^e_{t+1} - \overline{R^e_{t+1}})^2 - \left[(R^e_{t+1} - \widehat{R^e_{t+1}})^2 - (\overline{R^e_{t+1}} - \widehat{R^e_{t+1}})^2\right]$ on a constant, and the significance of the *MSPE-adjusted* statistic is based on the one-sided p-value. The null hypothesis of the *MSPE-adjusted* statistic is that the unrestricted model and the benchmark model have equal MSPE, while the alternative is that the unrestricted model has a smaller MSPE than the benchmark model. The null hypothesis is rejected if the test statistic is sufficiently positive.

[Table 6 about here]

The results for the out-of-sample predictability analysis are reported in Table 6. In row 1, the growth of *OTMC* open interest has 2.42% of the OOS R^2, and the *ENC-NEW*, *MSE-F*, and *MSPE-adjusted* statistics indicate statistically significant predictability in out-of-sample predictability analysis. While the short rate has a larger OOS R^2 than does the growth of *OTMC* open interest but a similar *MSE-F* statistic, the *ENC-NEW* statistic of the short rate is less significant than that of the growth of *OTMC* open interest. In addition, the *MSPE-adjusted* statistic of the short rate is insignificant. The model that uses the growth of *OTMC* open interest and the short rate as predictor variables is substantially improved over the constant expected returns benchmark model and has better performance than the models that use either the growth of *OTMC* open interest or the short rate as the only predictor variable. VRP has better prediction performance than does the growth of *OTMC* open interest or the short rate, except for the *MSPE-adjusted* statistic. In row 4, VRP has 3.11% of the OOS R^2, and the *ENC-NEW* and *MSE-F* statistic show that the improvement in predictive power is statistically significant. However, the *MSPE-adjusted* statistic is similar to that of the short rate and insignificant. The model with the growth of *OTMC* open interest and VRP has 7.36% of the OOS R^2, which is larger than the simple sum of the OOS R^2 of both variables (5.53%), and the improvement in predictive power is strongly statistically significant. In row 6, BDI is the best predictor variable in univariate regressions of the out-of-sample predictability analysis. BDI has 11.67% of the OOS R^2, and the improvement from BDI is statistically significant in the other three measures. The model that uses the growth of *OTMC* open interest and BDI as predictor variables has 17.25% of the OOS R^2, which is larger than the simple sum of the OOS R^2 of both variables (14.09%). For rows 9, 11, and 13, the growth of *OTMC* open interest helps to improve out-of-sample performance with a pair of other predictor variables. In row 15, the model that uses the above four predictor variables has the best performance for all test statistics in all rows. Overall, the out-of-sample statistics validate the predictability of the growth of *OTMC* open interest, and the predictive power of the growth of *OTMC* open interest in the out-of-sample predictability analysis is consistent with the predictive power of the growth of *OTMC* open interest in the in-sample predictability analysis.

4.3 Analysis of Sharpe ratios of returns from the predictor variable-based decision rule

To assess the economic significance of the growth of *OTMC* open interest for future stock market returns, we employ a decision rule in which we take a long position in the stock market at the end of month t if a positive return is predicted for month t+1. On the other hand, if the predicted return for month t+1 is negative, we do not have any position in the stock market.

To be consistent with the out-of-sample predictability analysis in Section 4.2, the predicted returns are obtained in predictive regressions with initial parameter estimation based on 100 observations. Then, we estimate the recursive parameter for the next predicted return based on the extended period. We compare the Sharpe ratios of the conditional strategy to those of the unconditional strategy to evaluate the economic significance of the predictive power of the growth of *OTMC* open interest for future stock market returns.

[Table 7 about here]

Table 7 presents the Sharpe ratios of the returns from the conditional strategy associated bootstrap p-values and the number of the month at the end of which the conditional strategy takes a long position in the stock market. A p-value is computed as the proportion of 25,000 bootstrap trials for the null hypothesis that the Sharpe ratio of the conditional strategy is not abnormally larger than that of the unconditional strategy.

The Sharpe ratio of the period from December 2004 to September 2010 is 0.64 and the number of the month (out of 70 months) in which the realized stock return is positive is 40. Comparing the result of Table 7 with the Sharpe ratio of the period, the growth of *OTMC* open interest improves the Sharpe ratio significantly. For the strategy of the univariate predictor variable, the Sharpe ratio of the growth of *OTMC* open interest is 1.8 times larger than that of the unconditional strategy and significant, while the Sharpe ratios of the short rate, VRP, and BDI are smaller than the Sharpe ratio of the growth of *OTMC* open interest and insignificant. A notable feature of the result in Table 7 is that VRP and BDI, which exhibit excellent performance in the in-sample predictability analysis and the out-of-sample predictability analysis, have the worst performance. For the strategy of multivariate predictor variables, the growth of *OTMC* open interest still improves the Sharpe ratio along with each of the short rate, VRP, and BDI. The combination of the growth of *OTMC* open interest, the short rate, and VRP has the largest Sharpe ratio, and it is the most significant combination in Table 7. In conclusion, the predictive power of the growth of *OTMC* open interest improves profitability measured by the trade-off in mean and variance.

5. Robustness tests

Overall, our empirical evidence shows that the growth of option open interest contains information for future aggregate stock market returns. In this section, we discuss other results from some robustness tests.

5.1 Analysis with the growth of option trading volume

Some of the literature shows empirical evidence that the trading volume as a proxy for the activity of the informed trader has predictive power for stock returns (Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006)). On the other hand, the predictive power of the growth of option open interest originates from hedging demand in our model. If the predictive power for stock returns of the activity of the informed trader and hedging demand is revealed upon the basis of similar information, the growth of option trading volume can affect the predictive power of the growth of option open interest. Therefore, we test whether the information on the growth of option open interest is different from that on the growth of option trading volume.

We only report the results for the growth of *OTMC* open interest, because the growth of *OTMC* open interest has the strongest predictive power among the four types of growth of option open interest. For the in-sample predictability analysis, first, we add the growth of *OTMC* open interest to a baseline model with VRP, CFNAI, CAY, and BDI for robustness tests of the predictive power.[22] Second, we include the growth of *ITMP* trading volume from the previous regression.[23] Because the growth of *ITMP* trading volume has the strongest predictive power among the four types of growth of option trading volume, we report the result for the growth of *ITMP* trading volume. In addition, we repeat the out-of-sample predictability analysis and the analysis with the Sharpe ratios of returns as in Sections 4.2 and 4.3.

[Table 8 about here]

The results for repeated analyses with the growth of *ITMP* trading volume are reported in Table 8. In column (9) of Panel A, the coefficient estimate on the dividend yield is only significant among the traditional predictor variables. While VRP and BDI retain their significant effect on future stock market returns, the coefficients on CFNAI and CAY are insignificant. In column (10), the coefficients on the growth of *OTMC* open interest, the dividend yield, VRP, and BDI are significant and positive. The inclusion of the growth of *OTMC* open interest improves adjusted R^2 by 2.00%, as compared with column

[22] We also examine the growth of *ITMP*, *ITMC*, and *OTMP* open interest and find that the results for the growth of all of them are similar to the results in Section 4.1.

[23] The growth of option trading volume is constructed using a method analogous to that used to construct the growth of option open interest. We also examine the growth of *OTMC*, *ITMC*, and *OTMP* trading volume and find that the results for the inclusion of the growth of all of them are analogous to the result for the inclusion of the growth of *ITMP* trading volume.

(9), which is larger than the improvements from column (1) to column (2) in Table 4. In column (11), while the coefficient estimate on the growth of *ITMP* trading volume is insignificant, the growth of *OTMC* open interest still helps to predict future stock returns. The addition of the growth of *ITMP* trading volume increases adjusted R^2 by 0.28%.[24]

In Panel B, the combination of the growth of *OTMC* open interest, the growth of *ITMP* trading volume, VRP, the short rate, and BDI improves out-of-sample performance significantly, as compared with the combination of the growth of *ITMP* trading volume, VRP, the short rate, and BDI. In Panel C, while the Sharpe ratio of return is insignificant without the growth of *OTMC* open interest in row 1, the Sharpe ratio of return from the conditional strategy, which includes the growth of *OTMC* open interest, is significant with *p*-value below 0.05. Therefore, we confirm that the growth of option open interest and the growth of option trading volume provide different information for future stock market returns.

5.2 Analysis with the different filtering criteria for the option

According to the filtering criteria in Section 3.2, we employ open interest of option with positive trading volume and positive open interest in the previous analyses. In the filtering criteria, we eliminate illiquid option that the hedgers do not want to buy. However, one can argue that there is a selection bias, because we build the growth of option open interest based only on active option. Therefore, we repeat our analyses, replacing our filtering criteria with new filtering criteria that remove the condition for positive trading volume in the established filtering criteria.

[Table 9 about here]

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[24] In unreported results for the regression of column (9) with the growth of *ITMP* trading volume, the improvement in adjusted R^2 based on the growth of *ITMP* trading volume is 1.10%, which is smaller than the improvement based on the growth of *OTMC* open interest.

Panel A of Table 9 reports the results for the in-sample predictability analysis of the growth of *OTMC* open interest and *ITMP* open interest. Similar to the results in Tables 4 and 5, the growth of *OTMC* open interest and *ITMP* open interest is almost significant with positive coefficient estimates. The magnitude and significance of coefficient estimates on the growth of *OTMC* and *ITMP* open interest in Table 9 is also similar to those in Tables 4 and 5. The result for the out-of-sample predictability analysis in Panel B and analysis of the Sharpe ratios of returns in Panel C is similar to the result in Tables 6 and 7, respectively.

In conclusion, the predictive power of the growth of *OTMC* open interest is robust to the different filtering criteria. The result with different filtering criteria is consistent with our hypothesis, and we confirm that the selection bias is insignificant.

5.3 Analysis with the growth of the option open interest based on value-weighted average

Based on the option open interest as an equal-weighted average of the open interest of various options with different strike prices and maturities on the last trading day of each month, we have examined the predictive power of the growth of option open interest for future stock market returns in previous sections. It is possible that options with large open interest have more information than those with small open interest. To consider this possibility, we calculate the option open interest as a value-weighted average of various option open interest. The results of repeated analyses based on the value-weighted average of option open interest are reported in Table 10.

[Table 10 about here]

In Panel A, the magnitude of the coefficient estimate on the growth of *OTMC* open interest is similar to that in Table 4, and the adjusted R^2 of the regression and the *t*-statistics of the coefficient estimate on the growth of *OTMC* open interest are higher than those in all columns of Table 4 except (0-C) and (6-C). In the case of the growth of *ITMP* open interest, the size of the coefficient estimate is also similar to that in Table 5, but the adjusted R^2 of the regression is larger than those in all columns of Table 5 except (0-P) and (4-P). In Panel B, the pattern of the improvement is similar to that in all rows of Table 6 except rows 1 and 2. In Panel C, the Sharpe ratio is also significant when only the conditional strategy exploits the growth of *OTMC* open interest, VRP, and the short rate. In summary, although the results of the value-weighted average of option open interest are less significant than those of the equal-weighted average of option open interest, our empirical results are confirmed with a different weighting method.

5.4 Other robustness analyses

In Section 4, our examination is based on the moneyness of option defined as follows: The call (put) is *OTM* if $K/S > 1$ ($K/S < 1$) and is *ITM* if $K/S < 1$ ($K/S > 1$), where S denotes the underlying stock price, and K is the strike price of the option. One can easily argue that the hedgers want to minimize the conditional variance with a different threshold. Thus, we define the new moneyness criteria as follows: The call (put) is *OTM* if $K/S > 1.02$ ($K/S < 0.98$) and is *ITM* if $K/S < 0.98$ ($K/S > 1.02$). These results are omitted for brevity. Although the significance is weaker, the coefficient estimate on the growth of *OTMC* open interest is positive and significant at the 5% or 10% level except for the Hodrick *t*-statistics for the baseline model with VRP and the baseline model with CFNAI. Although the coefficient estimates on the growth of *ITMP*, *ITMC*, and *OTMP* are insignificant, the signs of the coefficient estimates on the growth of *ITMP*, *ITMC*, and *OTMP* are consistent with our proposition.

Our model in Section 2 is an extension of Hong and Yogo (2012) on the option market. Thus, it is important to control for the mechanism already identified in Hong and Yogo (2012).[25] In addition, we

[25] Similar to Hong and Yogo (2012), we run the regressions with the growth of option open interest and the growth of S&P 500

need to investigate some other related variables such as the growth of the call-to-put option open interest ratio and call-to-put option volume, as used in Fodor, Krieger, and Doran (2010). We construct the growth of the call-to-put option open interest ratio and the call-to-put option volume based on the equal-weighted average and the aggregate summation. For the equal-weighted average method, we calculate the ratio of the equal-weighted average of the call option open interest and the equal-weighted average of the put option open interest, and the growth of this ratio. For the aggregate summation method, we calculate the ratio of the summation of the call option open interest and the summation of the put option open interest, and the growth of this ratio. Similarly, the call-to-put option volume is constructed. These results are similar to the results in Section 4 and are omitted for brevity. After controlling for the growth of the call-to-put option open interest ratio and the call-to-put option volume, the coefficient estimate on the growth of *OTMC* open interest is still positive and highly significant. Other growth of option open interest also has similar results to those in Section 4.

One can argue that the predictability of the growth of option open interest is due to the U.S. stock market recovery starting in 2009. Thus, we repeat the in-sample predictability analysis using data only through December 2008. The result of the in-sample predictability analysis is similar to the results in Section 4 and is omitted for brevity. For instance, the coefficient estimate on the growth of *OTMC* open interest has a positive sign and is significant at the 1% (5%) level based on the NW (Hodrick) *t*-statistic, and the adjusted R^2 is 2.28% in univariate regression. In addition, the results are not sensitive to control for the traditional predictor variables and recent predictor variables.

In summary, although the results with different moneyness criteria are less significant than those in Section 4, our empirical results are confirmed with different moneyness criteria. In addition, controlling the growth of the call-to-put option open interest ratio and the call-to-put option volume does not affect our empirical results. The in-sample predictability analysis during the subsample period also supports our

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futures open interest (the long and short positions of commercial traders). As a result, the growth of S&P 500 futures open interest does not have an effect on the significance and the sign of the coefficient estimates on the growth of option open interest.

proposition empirically.

6. Conclusion

This paper makes a contribution by investigating the predictive power of the growth of option open interest for future stock market returns based on the trading behavior of hedgers, whereas most extant studies have examined the predictive power of informed trading by informed traders. Our main hypothesis is that under the conditions of under-reaction by uninformed traders to news and the movement of asset prices based on supply shocks, the demand of hedgers in the option market is informative for future price movements in the stock market. In our model, hedgers in the option market demand relatively more call and put option with high strike prices when the state of the future economy is expected to be high. Conversely, hedgers in the option market demand relatively more call and put option with low strike prices when the state of the future economy is expected to be low.

Our empirical analysis reveals that the growth of open interest in the option market as a proxy for the change in demand of the hedgers in the option market is a powerful predictor of aggregate stock market returns. Specifically, the empirical results in this article verify the predictive power of the growth of S&P 500 index option open interest for subsequent monthly S&P 500 index returns and are consistent with our hypothesis. This predictive power is robust to the presence of the traditional predictor variables, VRP, CFNAI, CAY, and BDI. The out-of-sample predictability analysis provides further evidence for predictability, and the analysis with the Sharpe ratios of returns reveals profitability and economic significance from enhancement of the Sharpe ratios based on the conditional strategy that exploits trading signals generated using the growth of *OTMC* open interest.

In addition, while the predictor variables in previous studies only capture the persistent component of expected stock market returns, the growth of *OTMC* open interest captures the less persistent component of expected stock market returns. Our empirical result with the growth of *OTMC* open interest suggests the necessity of developing new structural models. We also find evidence that the information induced by the open interest of option is different from the information provided by the trading volume of option. This evidence confirms that the economic source of the predictive power of the growth of option open interest is hedgers' demand in the option market with asymmetric information rather than the informed trading of informed traders in the option market.

There are two important implications of our empirical results. The first is the consideration of the demand for hedging in the option market. While many previous studies provide evidence that the information of informed trading has predictive power for future stock movements (Easley, O'Hara, and Srinivas (1998), Chan, Chung, and Fong (2002), Pan and Poteshman (2006), Chang, Hsieh, and Lai (2009), and Roll, Schwartz, and Subrahmanyam (2010)), this paper presents evidence that the growth of hedging demand revealed by the growth of option open interest subsumes useful information for future stock movements beyond the information given by the traditional predictor variables and the recent predictor variables. In addition, the information on hedging demand (the growth of option open interest) and the information on informed trading (the growth of option trading volume) provide different signals for future stock market movements. This suggests that many papers need to pay more attention to the behavior of hedgers in the option market to shed light on the information of option for the movement of future stock prices.

The second implication involves the information of the hedgers in the option market about the stock. Hong and Yogo (2012) investigate whether the movements of open interest in the futures market predict returns in commodity, currency, bond, and stock markets. Their empirical results show that the movement of futures open interest has relatively less informative and significant predictive power for stock returns than for commodity returns, currency returns, and bond returns. On the other hand, our results indicate the significant informational role of the option market for hedging against aggregate stock market movements, even though a direct comparison between our empirical results and the empirical results in Hong and Yogo (2012) is difficult because of the difference between the sample periods and the sample stocks for the stock market. Our analyses propose that the option market as well as the futures market is informative for hedging activity against changes in the stock market. However, prior studies have found empirical evidence that hedging performance of futures outperforms that of option.[26] When compared to prior empirical results for the hedging performance of option and futures, our result that the hedging demand in the option market contains information for future stock market returns is a bit puzzling.

In this paper, we examine the informational linkage between the growth of option open interest from hedgers and future aggregate stock market returns. Hedgers could also participate in other markets with different underlying assets, such as the currency market and the bond market, and checking for the predictive power of option open interest in different markets is very important to confirm the informativeness of hedging activity for the future economic state. In addition, another attractive issue is whether the profitability of the conditional strategy that exploits the growth of option open interest under different economic conditions or investor sentiment (Yu and Yuan (2011)) will change. Investigating the predictability in different markets and the effect of the economic condition or investor sentiment on the profitability of the conditional strategy is a potential area for future research.

[26] A currency futures contract is a better hedging instrument than are currency option (Chang and Shanker (1986), Hsin, Kuo, and Lee (1994), and Lien and Tse (2001)). Benet and Luft (1995) use tick data to compare the performance of frequent dynamic hedging strategies between the S&P 500 index futures and option and provide evidence that futures reveal distinct and superior hedging effectiveness relative to option once hedging costs and market friction are considered.

Appendix. The Model

We solve for the equilibrium option price in period 1. The market clearing condition in period 1 for call option is as follows:

$$\lambda D^{I}_{C(K),1} + (1-\lambda) D^{U}_{C(K),1} + D^{H}_{C(K)} = 0. \tag{A.1}$$

The market clearing condition in period 0 for the call option to solve the equilibrium option price in period 0 is as follows:

$$\lambda D^{I}_{C(K),0} + (1-\lambda) D^{U}_{C(K),0} = 0. \tag{A.2}$$

The market clearing conditions in periods 0 and 1 for the put option are similar to those for the call option in the respective periods. Further, we consider not only the type of option but also the moneyness of option.

A. Call option with $K = S^H$

In the high state, the hedgers who want to buy stocks choose the call option with strike price S^H. Under the market clearing condition in period 1, we can solve for the equilibrium price of the call option in period 1. From the substitution of the demand functions for the hedgers and the traders into the market clearing condition in period 1, the price of the call option with strike price S^H in the high state is

$$P^{H}_{C(S^H),1} = \omega_1^H P^{H}_{C(S^H)} + (1-\omega_1^H)\overline{P_{C(S^H)}} - \frac{\omega_1^H \gamma \sigma^2_{C(S^H)|H} Y_B^H}{\lambda}, \tag{A.3}$$

where $\sigma^2_{C(S^H)|H} = Var_1(P_{C(S^H),2} | H)$ and $\omega_1^H = \dfrac{\lambda Var_0(P_{C(S^H),2})}{\lambda Var_0(P_{C(S^H),2}) + (1-\lambda)\sigma^2_{C(S^H)|H}}$.

The price of the call option with strike price S^H in the low state is

$$P^{L}_{C(S^H),1} = \omega_2^H P^{L}_{C(S^H)} + (1-\omega_2^H)\overline{P_{C(S^H)}}, \tag{A.4}$$

where $\sigma^2_{C(S^H)|L} = Var_1(P_{C(S^H),2} | L)$ and $\omega_2^H = \dfrac{\lambda Var_0(P_{C(S^H),2})}{\lambda Var_0(P_{C(S^H),2}) + (1-\lambda)\sigma^2_{C(S^H)|L}}$.

Similarly, we can also derive the equilibrium price of the call option with strike price S^H in period 0 from the market clearing condition in period 0. The price of the call option in period 0 with strike price S^H is

$$P_{C(S^H),0} = \omega_3^H \left[\pi\omega_1^H \left(P^H_{C(S^H)} - \overline{P_{C(S^H)}} - \frac{\gamma\sigma^2_{C(S^H)|H} Y_B^H}{\lambda} \right) + (1-\pi)\omega_2^H \left(P^L_{C(S^H)} - \overline{P_{C(S^H)}} \right) \right] + \overline{P_{C(S^H)}}, \quad \text{(A.5)}$$

where $\omega_3^H = \dfrac{\lambda Var_0(P_{C(S^H),2})}{\lambda Var_0(P_{C(S^H),2}) + (1-\lambda) Var_0(P_{C(S^H),1})}$.

The open interest of the call option with strike price S^H in period 0 is

$$O_{C(S^H),0} = \lambda \left| D^I_{C(S^H),0} \right| = (1-\lambda) \left| D^U_{C(S^H),0} \right| = \frac{1-\lambda}{\gamma Var_0(P_{C(S^H),2})} \left| \overline{P_{C(S^H)}} - P_{C(S^H),0} \right|$$

$$= \frac{(1-\lambda)\omega_3^H}{\gamma Var_0(P_{C(S^H),2})} \left| \pi\omega_1^H \left(P^H_{C(S^H)} - \overline{P_{C(S^H)}} - \frac{\gamma\sigma^2_{C(S^H)|H} Y_B^H}{\lambda} \right) + (1-\pi)\omega_2^H \left(P^L_{C(S^H)} - \overline{P_{C(S^H)}} \right) \right|. \quad \text{(A.6)}$$

The open interest of the call option with strike price S^H in the high state is

$$O^H_{C(S^H),1} = \lambda D^I_{C(S^H),1} + D^H_{C(S^H)} = \frac{\lambda (P^H_{C(S^H)} - P^H_{C(S^H),1})}{\gamma\sigma^2_{C(S^H)|H}} - Y_B^H$$

$$= \frac{\lambda (1-\omega_1^H)(P^H_{C(S^H)} - \overline{P_{C(S^H)}})}{\gamma\sigma^2_{C(S^H)|H}} - (1-\omega_1^H) Y_B^H. \quad \text{(A.7)}$$

The open interest of the call option with strike price S^H in the low state is

$$O^L_{C(S^H),1} = (1-\lambda) D^U_{C(S^H),1} = \frac{(1-\lambda)\omega_2^H (\overline{P_{C(S^H)}} - P^L_{C(S^H)})}{\gamma Var_0(P_{C(S^H),2})} = \frac{\lambda (1-\omega_2^H)(\overline{P_{C(S^H)}} - P^L_{C(S^H)})}{\gamma\sigma^2_{C(S^H)|L}}. \quad \text{(A.8)}$$

Assume that π = 0.5 and $\sigma^2_{C(S^H)|H} > \sigma^2_{C(S^H)|L}$,[27] we know that $\overline{P_{C(S^H)}} - P^L_{C(S^H)} = P^H_{C(S^H)} - \overline{P_{C(S^H)}}$ and $\omega_1^H < \omega_2^H$. The open interest of the call option with strike price S^H in the high state is higher than that in the low state if the hedging demand is sufficiently high. More formally, $O^H_{C(S^H),1} > O^L_{C(S^H),1}$ if

$$0 < \frac{\lambda(1-\lambda)\left(1-\dfrac{\sigma^2_{C(S^H)|L}}{\sigma^2_{C(S^H)|H}}\right)(\overline{P_{C(S^H)}} - P^L_{C(S^H)})}{\gamma(\lambda Var_0(P_{C(S^H),2}) + (1-\lambda)\sigma^2_{C(S^H)|L})} < -Y_B^H. \tag{A.9}$$

B. Put option with $K = S^H$

In the high state, the hedgers who want to sell the stock choose the put option with strike price S^H. Similar to the price of the call option, the price of the put option with strike price S^H in the high state is

$$P^H_{P(S^H),1} = \omega_4^H P_{P(S^H)} + (1-\omega_4^H)\overline{P_{P(S^H)}} + \frac{\omega_4^H \gamma \sigma^2_{P(S^H)|H} Y_S^H}{\lambda}, \tag{A.10}$$

where $\sigma^2_{P(S^H)|H} = Var_1(P_{P(S^H),2}|H)$ and $\omega_4^H = \dfrac{\lambda Var_0(P_{P(S^H),2})}{\lambda Var_0(P_{P(S^H),2}) + (1-\lambda)\sigma^2_{P(S^H)|H}}$.

The price of the put option with strike price S^H in the low state is

$$P^L_{P(S^H),1} = \omega_5^H P^L_{P(S^H)} + (1-\omega_5^H)\overline{P_{P(S^H)}}, \tag{A.11}$$

where $\sigma^2_{P(S^H)|L} = Var_1(P_{P(S^H),2}|L)$ and $\omega_5^H = \dfrac{\lambda Var_0(P_{P(S^H),2})}{\lambda Var_0(P_{P(S^H),2}) + (1-\lambda)\sigma^2_{P(S^H)|L}}$.

[27] In Section 2, we assume that the conditional variance of the probability density of the stock price in the high state is equal to that in the low state. Thus, since the probability density of the call option price only depends on the expectation of future stock price, the conditional variance of the probability density of the call option price in the high state is always higher than that in the low state.

The price of the put option with strike price S^H in period 0 is

$$P_{P(S^H),0} = \omega_6^H \left[\pi\omega_4^H \left(P_{P(S^H)}^H - \overline{P_{P(S^H)}} + \frac{\gamma\sigma_{P(S^H)|H}^2 Y_S^H}{\lambda} \right) + (1-\pi)\omega_5^H \left(P_{P(S^H)}^L - \overline{P_{P(S^H)}} \right) \right] + \overline{P_{P(S^H)}}, \tag{A.12}$$

where $\omega_6^H = \dfrac{\lambda Var_0(P_{P(S^H),2})}{\lambda Var_0(P_{P(S^H),2}) + (1-\lambda)Var_0(P_{P(S^H),1})}$.

The open interest of the put option with strike price S^H in period 0 is

$$O_{P(S^H),0} = \lambda \left| D_{P(S^H),0}^I \right| = (1-\lambda)\left| D_{P(S^H),0}^U \right| = \frac{1-\lambda}{\gamma Var_0(P_{P(S^H),2})} \left| \overline{P_{P(S^H)}} - P_{P(S^H),0} \right|$$

$$= \frac{(1-\lambda)\omega_6^H}{\gamma Var_0(P_{P(S^H),2})} \left| \pi\omega_4^H \left(P_{P(S^H)}^H - \overline{P_{P(S^H)}} + \frac{\gamma\sigma_{P(S^H)|H}^2 Y_S^H}{\lambda} \right) + (1-\pi)\omega_5^H \left(P_{P(S^H)}^L - \overline{P_{P(S^H)}} \right) \right|. \tag{A.13}$$

The open interest of the put option with strike price S^H in the high state is

$$O_{P(S^H),1}^H = (1-\lambda)D_{P(S^H),1}^U + D_{P(S^H)}^H = \frac{(1-\lambda)(\overline{P_{P(S^H)}} - P_{P(S^H),1}^H)}{\gamma Var_0(P_{P(S^H),2})} + Y_S^H$$

$$= \frac{\lambda(1-\omega_4^H)(\overline{P_{P(S^H)}} - P_{P(S^H)}^H)}{\gamma\sigma_{P(S^H)|H}^2} + \omega_4^H Y_S^H = \frac{(1-\lambda)\omega_4^H(\overline{P_{P(S^H)}} - P_{P(S^H)}^H)}{\gamma Var_0(P_{P(S^H),2})} + \omega_4^H Y_S^H. \tag{A.14}$$

The open interest of the put option with strike price S^H in the low state is

$$O_{P(S^H),1}^L = \lambda D_{P(S^H),1}^I = \frac{\lambda(P_{P(S^H)}^L - P_{P(S^H),1}^L)}{\gamma\sigma_{P(S^H)|L}^2}$$

$$= \frac{\lambda(1-\omega_5^H)(P_{P(S^H)}^L - P_{P(S^H),1}^L)}{\gamma\sigma_{P(S^H)|L}^2} = \frac{(1-\lambda)\omega_5^H(P_{P(S^H)}^L - \overline{P_{P(S^H)}})}{\gamma Var_0(P_{P(S^H),2})}. \tag{A.15}$$

Assume that that π = 0.5 and $\sigma_{P(S^H)|H}^2 < \sigma_{P(S^H)|L}^2$, we know that $\overline{P_{P(S^H)}} - P_{P(S^H)}^H = P_{P(S^H)}^L - \overline{P_{P(S^H)}}$ and

$\omega_4^H > \omega_5^H$. Therefore, $O^H_{P(S^H),1} > O^L_{P(S^H),1}$.

C. Call option and Put option with $K = S^L$

Similar to the growth of the open interest of the call option and the put option with strike price S^H, we derive the properties for the growth of the open interest of the call option and the put option with strike price S^L. The open interest of the call option with strike price S^L in the low state is always larger than that in the high state under the assumptions, which are π = 0.5 and $\sigma^2_{C(S^L)|H} > \sigma^2_{C(S^L)|L}$. On the other hand, for the put option with strike price S^L, the open interest in the low state is larger than that in the high state under the conditions, which are π = 0.5 and $\sigma^2_{P(S^L)|H} < \sigma^2_{P(S^L)|L}$, and with sufficiently high hedging demand. More formally, the last condition is as follows:

$$0 < \frac{\lambda(1-\lambda)\left(1-\frac{\sigma^2_{P(S^L)|H}}{\sigma^2_{P(S^L)|L}}\right)(P^L_{P(S^L)} - \overline{P_{P(S^L)}})}{\gamma(\lambda Var_0(P_{P(S^L),2}) + (1-\lambda)\sigma^2_{P(S^L)|H})} < Y^L_S. \tag{A.16}$$

D. Expected return

Based on the put-call parity and the price of option with strike price S^H, the expected return on the stock between periods 1 and 2 in the high state is defined as:

$$\begin{aligned} E_1\left[R_2 \middle| H\right] &= E_1\left[S_2 \middle| H\right] - S_1 \\ &= E_1\left[P_{C(S^H),2} - P_{P(S^H),2} \middle| H\right] - \left(P_{C(S^H),1} - P_{P(S^H),1}\right) \\ &= P^H_{C(S^H)} - P^H_{P(S^H)} - P^H_{C(S^H),1} + P^H_{P(S^H),1} \end{aligned}$$

$$= \left(P^H_{C(S^H)} - P^H_{C(S^H),1}\right) - \left(P^H_{P(S^H)} - P^H_{P(S^H),1}\right). \tag{A.17}$$

Likewise, the expected return on the stock between periods 1 and 2 based on the use of option with strike price S^L in the high state can be defined as: $E_1\left[R_2 \middle| H\right] = \left(P^H_{C(S^L)} - P^H_{C(S^L),1}\right) - \left(P^H_{P(S^L)} - P^H_{P(S^L),1}\right)$.

Similarly, the expected return on the stock between periods 1 and 2 can be determined based on the price of option with strike price S^H and S^L in the low state. Under our assumptions, the necessary and sufficient conditions for a positive relation between expected return in the high state and the growth of open interest of the option with strike price S^H and a negative relation between expected return in the low state and the growth of open interest of the option with strike price S^L are:

$$\left[\begin{array}{l} 2(\lambda\sigma^2_{C(S^H)|H} + (2-\lambda)\sigma^2_{C(S^H)|L}) > \lambda(P^H_{C(S^H)} - P^L_{C(S^H)})^2 > 2\lambda(\sigma^2_{C(S^H)|H} + \sigma^2_{C(S^H)|L}) \\ \dfrac{0.5\lambda(1-\lambda)\left(1 - \dfrac{\sigma^2_{C(S^H)|L}}{\sigma^2_{C(S^H)|H}}\right)(P^H_{C(S^H)} - P^L_{C(S^H)})}{\gamma(\lambda Var_0(P_{C(S^H),2}) + (1-\lambda)\sigma^2_{C(S^H)|L})} < -Y^H_B < \dfrac{0.5\lambda(1-\omega^H_1)(P^H_{C(S^H)} - P^L_{C(S^H)})}{\omega^H_1 \gamma \sigma^2_{C(S^H)|H}} \end{array}\right. \tag{A.18}$$

and

$$\left[\begin{array}{l} 2((2-\lambda)\sigma^2_{P(S^L)|H} + \lambda\sigma^2_{P(S^L)|L}) > \lambda(P^L_{P(S^L)} - P^H_{P(S^L)})^2 > 2\lambda(\sigma^2_{P(S^L)|H} + \sigma^2_{P(S^L)|L}) \\ \dfrac{0.5\lambda(1-\lambda)\left(1 - \dfrac{\sigma^2_{P(S^L)|H}}{\sigma^2_{P(S^L)|L}}\right)(P^L_{P(S^L)} - P^H_{P(S^L)})}{\gamma(\lambda Var_0(P_{P(S^L),2}) + (1-\lambda)\sigma^2_{P(S^L)|H})} < Y^L_S < \dfrac{0.5\lambda(1-\omega^L_5)(P^L_{P(S^L)} - P^H_{P(S^L)})}{\omega^L_5 \gamma \sigma^2_{P(S^L)|L}} \end{array}\right. \tag{A.19}$$

where $\sigma^2_{P(S^L)|L} = Var_1(P_{P(S^L),2} \middle| L)$ and $\omega^L_5 = \dfrac{\lambda Var_0(P_{P(S^L),2})}{\lambda Var_0(P_{P(S^L),2}) + (1-\lambda)\sigma^2_{P(S^L)|L}}$.

The first conditions rule out extremely small or large differences between the exact prices of call option with strike price S^H in the high state and the low state and the exact prices of put option with strike price S^L in the high state and the low state, respectively. In addition, as the mass of the informed traders increases more and more, the variation of the difference between the exact prices of option in the high state and the low state declines, because the effect of the under-reaction of the uninformed traders on the equilibrium price of the option in period 1 is on the decrease. The second conditions essentially rule out the extreme case in which the hedging demand is large or small enough to disturb the under-reaction of the option price to news in period 1.

Reference

Ang, Andrew and Geert Bekaert, 2007. Stock Return Predictability: Is it There? Review of Financial Studies 20, 651-707.

Bakshi, Gurdip, George Panayotov, and Georgios Skoulakis, 2011. The Baltic Dry Index as a Predictor of Global Stock Returns, Commodity Returns, and Global Economic Activity. Working Paper, University of Maryland.

Benet, Bruce A. and Carl F. Luft, 1995. Hedging Performance of SPX Index Options and S&P 500 Futures. Journal of Futures Markets 15, 691-717.

Bhuyan, Rafiqul and Mo Chaudhury, 2005. Trading on the information content of open interest: Evidence from the US equity options market. Derivatives Use, Trading & Regulation 11, 16-36.

Black, Fisher, 1975. Fact and Fantasy in the Use of Options. Financial Analysts Journal 31, 36-72.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009. Expected Stock Returns and Variance Risk Premia. Review of Financial Studies 22, 4463-4492.

Bollerslev, Tim, James Marrone, Lai Xu, and Hao Zhou, 2012. Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence. Working Paper, Federal Reserve Board.

Breen, William, Lawrence R. Glosten, and Ravi Jagannathan, 1989. Economic Significance of Predictable Variations in Stock Index Returns. Journal of Finance 44, 1177-1189.

Campbell, John Y., 1987. Stock Returns and The Term Structures. Journal of Financial Economics 18, 373-399.

Campbell, John Y. and Robert J. Shiller, 1988a. Stock Prices, Earnings, and Expected Dividends. Journal of Finance 43, 661-676.

Campbell, John Y. and Robert J. Shiller, 1988b. The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. Review of Financial Studies 1, 195-228.

Campbell, John Y. and Samuel B. Thompson, 2008. Predicting Excess Stock Returns Out of Sample: Can

Anything Beat the Historical Average? Review of Financial Studies 21, 1509-1531.

Chan, Kalok, Y. Peter Chung, and Wai-Ming Fong, 2002. The Informational Role of Stock and Option Volume. Review of Financial Studies 15, 1049-1075.

Chang, Chuang-Chang, Pei-Fang Hsieh, and Hung-Neng Lai, 2009. Do informed option investors predict stock returns? Evidence from the Taiwan stock exchange. Journal of Banking & Finance 33, 757-764.

Chang, Jack S. K. and Latha Shanker, 1986. Hedging Effectiveness of Currency Options and Currency Futures. Journal of Futures Markets 6, 289-305.

Chen, Nai-Fu, 1991. Financial Investment Opportunities and the Macroeconomy. Journal of Finance 46, 529-554.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986. Economic Forces and the Stock Market. Journal of Business 59, 383-403.

Chesney, Marc, Remo Crameri, and Loriano Mancini, 2011. Detecting Informed Trading Activities in the Options Markets. Working Paper, National Centre of Competence in Research Financial Valuation and Risk Management.

Clark, Todd E. and Michael W. McCracken, 2001. Tests of equal forecast accuracy and encompassing for nested models. Journal of Econometrics 105, 85-110.

Clark, Todd E. and Kenneth D. West, 2007. Approximately normal tests for equal predictive accuracy in netsted models. Journal of Econometrics 138, 291-311.

Cremers, Martijn and David Weinbaum, 2010. Deviations from Put-Call Parity and Stock Return Predictability. Journal of Financial and Quantitative Analysis 45, 335-367.

Doran, James S. and Kevin Krieger, 2010. Implications for Asset Returns in the Implied Volatility Skew. Financial Analysts Journal 66, 65-76.

Easley, David, Maureen O'Hara, and P. S. Srinivas, 1998. Option Volume and Stock Prices: Evidence on Where Informed Traders Trade. Journal of Finance 53, 431-465.

Fama, Eugene F. and Kenneth R. French, 1988. Dividend Yields and Expected Stock Returns. Journal of

Financial Economics 22, 3-25.

Fama, Eugene F. and Kenneth R. French, 1989. Business Conditions and Expected Returns on Stocks and Bonds. Journal of Financial Economics 25, 23-49.

Fama, Eugene F. and G. William Schwert, 1977. Asset Returns and Inflation. Journal of Financial Economics 5, 115-146.

Frechette, Darren L., 2001. The Demand for Hedging with Futures and Options. Journal of Futures Markets 21, 693-712.

Fodor, Andy, Kevin Krieger, and James S. Doran, 2011. Do option open-interest changes foreshadow future equity returns? Financial Markets and Portfolio Management 25, 265-280.

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, 2009. Demand-Based Option Pricing. Review of Financial Studies 22, 4259-4299.

Goetzmann, William N. and Philippe Jorion, 1995. A Longer Look at Dividend Yields. Journal of Business 68, 483-508.

Hodrick, Robert J., 1992. Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement. Review of Financial Studies 5, 357-386.

Hong, Harrison and Motohiro Yogo, 2012. What Does Futures Market Interest Tell Us about the Macroeconomy and Asset Prices? Journal of Financial Economics 105, 473-490.

Hsin, Chin-Wen, Jerry Kuo, and Cheng-Few Lee, 1994. A New Measure to Compare the Hedging Effectiveness of Foreign Currency Futures versus Options. Journal of Futures Markets 14, 685-707.

Jayaraman, Narayanan, Melissa B. Frye, and Sanjiv Sabherwal, 2001. Informed Trading around Merger Announcements: An Empirical Test Using Transaction Volume and Open Interest in Options Market. Financial Review 37, 45-74.

Lakonishok, Josef, Inmoo Lee, Neil D. Pearson, and Allen M. Poteshman, 2007. Option Market Activity. Review of Financial Studies 20, 813-857.

Lamont, Owen, 1998. Earnings and Expected Returns. Journal of Finance 53, 1563-1587.

Lettau, Martin and Sydney Ludvigson, 2001. Consumption, Aggregate Wealth, and Expected Stock Returns. Journal of Finance 56, 815-849.

Lewellen, Jonathan, 2004. Predicting returns with financial ratios. Journal of Financial Economics 74, 209-235.

Li, Jun and Jianfeng Yu, 2012. Investor attention, psychological anchors, and stock return predictability. Journal of Financial Economics 104, 401-419.

Lien, Donald and Yiu Kuen Tse, 2001. Hedging downside risk: futures vs. options. International Review of Economics and Finance 10, 159-169.

Lo, Andrew W. and A. Craig Mackinlay, 1990. When Are Contrarian Profits Due to Stock Market Overreaction? Review of Financial Studies 3, 175-205.

McCracken, Michael W., 2007. Asymptotics for out of sample tests of Granger causality. Journal of Econometrics 140, 719-752.

Newey, Whitney K. and Kenneth D. West, 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703-708.

Ng, S., and P. Perron, 1995. Unit Root Tests in ARMA Models with Data-Dependent Methods for the Selection of the Truncation Lag. Journal of the American Statistical Association 90, 268-281.

Pan, Jun and Allen M. Poteshman, 2006. The Information in Option Volume for Future Stock Prices. Review of Financial Studies 19, 871-908.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam, 2010. O/S: The relative trading activity in options and stock. Journal of Financial Economics 96, 1-17.

Schachter, Barry, 1988. Open Interest in Stock Options Around Quarterly Earnings Announcements. Journal of Accounting Research 26, 353-372.

Stock, James H. and Mark W. Watson, 1999. Forecasting inflation. Journal of Monetary Economics 44, 293-335.

Vijh, Anand M., 1990. Liquidity of the CBOE Equity Options. Journal of Finance 45, 1157-1179.

Welch, Ivo and Amit Goyal, 2008. A Comprehensive Look at The Empirical Performance of Equity Premium Prediction. Review of Financial Studies 21, 1455-1508.

Xing, Yuhang, Xiaoyan Zhang, and Rui Zhao, 2010. What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns? Journal of Financial and Quantitative Analysis 45, 641-662.

Yu, Jianfeng and Yu Yuan, 2011. Investor sentiment and the mean-variance relation. Journal of Financial Economics 100, 367-381.

Zhou, Hao, 2010. Variance Risk Premia, Asset Predictability Puzzles, and Macroeconomic Uncertainty. Working Paper, Federal Reserve Board.

Table 1

Summary of Position of Option in High state and Low state

The table represents the summary of the position of the option in the high state and the low state. The types of the participants in the option market are the hedgers, the informed traders, and the uninformed traders. The kinds of the option is out-of-the money call option (*OTMC*), in-the money call option (*ITMC*), out-of-the money put option (*OTMP*), and in-the money put option (*ITMP*).

Call option	Position of option	
State of economy	Long	Short
High	Hedgers (*OTMC*), Informed traders (*OTMC*, *ITMC*)	Uninformed traders (*OTMC*, *ITMC*)
Low	Hedgers (*ITMC*), Uninformed traders (*OTMC*, *ITMC*)	Informed traders (*OTMC*, *ITMC*)

Put option	Position of option	
State of economy	Long	Short
High	Hedgers (*ITMP*), Uninformed traders (*ITMP*, *OTMP*)	Informed traders (*ITMP*, *OTMP*)
Low	Hedgers (*OTMP*), Informed traders (*ITMP*, *OTMP*)	Uninformed traders (*ITMP*, *OTMP*)

Table 2

Summary Statistics for Monthly Excess Return and Predictor Variables

The R_m - R_f denotes the return on the S&P 500 index in excess of the three-month T-bill yield. The short rate *RREL* denotes as the three-month T-bill yield minus its trailing twelve-month moving average. The default spread *DFSP* is the difference between Moody's BAA and AAA corporate bond yields. The term spread *TMSP* is the difference between the ten-year T-bond and the three-month T-bill yields. The dividend yield *DIV* and the lagged return LR_m are dividend yield and lagged one month return of S&P 500 index, respectively. *VRP* is the variance risk premium and is defined by the difference between the risk-neutral return variance and the realized return variance. *CFNAI* is the Chicago Fed National Activity Index as a weighted average of 85 monthly indicators of U.S. economic activity. *CAY* is the consumption-wealth ratio and is defined by the most recent available quarterly observations. *BDI* is the growth rate of the Baltic Dry Index over three months. The augmented Dickey-Fuller (ADF) test is a *t*-statistics on β in the regression of each variable x_t, $x_t = \alpha + \beta x_{t-1} + \delta_1 \Delta x_{t-1} + \cdots + \delta_{p-1} \Delta x_{t-p+1} + \varepsilon_t$. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. Lag orders are selected by Ng and Perron (1995) procedure. All variables except the excess return and *BDI* are annualized. The sample period is from August 1996 through September 2010.

	R_m - R_f	*RREL*	*DFSP*	*TMSP*	*DIV*	LR_m	*VRP*	*CFNAI*	*CAY*	*BDI*
					Summary statistics					
Mean (%)	0.20	-0.19	1.02	1.65	1.75	0.38	3.08	-23.81	-0.62	7.70
Std. dev. (%)	4.80	0.83	0.50	1.23	0.46	4.78	2.39	93.77	1.91	35.56
Skewness	-0.61	-0.69	2.77	0.08	1.55	-0.63	1.31	-1.81	0.23	0.87
Kurtosis	3.58	3.13	11.53	1.72	6.48	3.60	6.74	7.54	1.88	6.05
AR(1)	0.10	0.97	0.96	0.98	0.97	0.11	0.56	0.76	0.96	0.68
ADF test	-11.596^{***}	-2.859^{*}	-3.006^{**}	-2.991^{**}	-1.385	-11.543^{***}	-3.440^{**}	-3.185^{**}	-1.802	-3.771^{***}
					Correlation matrix					
R_m - R_f		0.13	-0.09	-0.02	0.08	0.10	0.23	0.20	0.12	0.27
RREL			-0.43	-0.35	-0.23	0.15	-0.29	0.57	0.20	0.07
DFSP				0.42	0.79	-0.16	0.30	-0.78	-0.18	0.14
TMSP					0.39	-0.06	0.16	-0.23	-0.04	0.08
DIV						-0.07	0.23	-0.60	-0.23	0.16
LR_m							-0.13	0.18	0.10	0.22
VRP								-0.26	0.27	0.15
CFNAI									0.10	0.02
CAY										-0.09

Table 3

Summary Statistics for Option Open Interest and Growth of Option Open Interest

The table reports the summary statistics for option open interest and the growth of option open interest. The sample period of option open interest is from January 1996 through August 2010, and the sample period of the growth of option open interest is from July 1996 through August 2010. In Panel A, Number of option is the summary statistics for option at the last trading day of each month. Option open interest is an equal-weighted average of various options with different strike prices and maturities at the last trading day of each month. The growth of option open interest is a six-month geometric average of the monthly growth of option open interest in the time series. The augmented Dickey-Fuller (ADF) test is a *t*-statistics on β in the regression of each variable x_t, $x_t = \alpha + \beta x_{t-1} + \delta_1 \Delta x_{t-1} + \cdots + \delta_{p-1} \Delta x_{t-p+1} + \varepsilon_t$. *, **, *** represent significance at the 10%, 5%, 1% levels, respectively. Lag orders are selected by Ng and Perron (1995) procedure. The classification of option is identical to Table 1. In Panel B, the correlations of the growth of option open interest with other predictor variables are represented.

Panel A

	OTMC	*ITMP*	*ITMC*	*OTMP*
Number of option				
Mean	30.67	14.19	15.73	48.13
Median	24	12	15	37
Std.dev.	17.43	7.89	7.21	27.45
Max	95	41	38	129
Min	9	2	1	15
Option open Interest				
Mean	13052.08	10459.21	11749.46	17806.36
Median	10622.91	7534.01	8261.38	14264.38
Std. dev.	7876.32	10797.49	9575.96	10876.42
Growth of Option open Interest				
Mean (%)	1.12	2.49	1.97	1.08
Median (%)	1.15	-0.02	0.85	1.04
Std. dev. (%)	6.05	17.45	15.78	4.98
Skewness	0.15	0.67	0.62	0.76

Kurtosis	2.81	4.11	5.19	5.10
AR(1)	0.16	0.07	-0.01	0.46
ADF test	-4.650***	-3.265**	-3.679***	-4.446***

Panel B

	R_m - R_f	*RREL*	*DFSP*	*TMSP*	*DIV*	LR_m	*VRP*	*CFNAI*	*CAY*	*BDI*
					Correlation matrix					
OTMC	0.18	0.11	-0.16	0.02	-0.06	-0.16	0.01	0.16	0.02	-0.15
ITMP	0.09	-0.01	-0.15	-0.06	-0.08	-0.42	0.03	0.11	-0.07	-0.23
ITMC	-0.03	-0.05	0.10	0.07	0.09	0.49	-0.14	-0.03	0.10	0.03
OTMP	-0.00	0.18	-0.25	0.09	-0.12	0.25	-0.13	0.25	0.20	-0.02

Table 4

Predictability of Growth of OTMC Open Interest for Excess Return

The table reports estimates from *OLS* regressions of excess return on the predictor variables with the growth of *OTMC* open interest. The *GOI* is the growth of *OTMC* open interest. All predictor variables are lagged one month, and all of the regressions are based on monthly observations. All variable definitions are identical to Table 2, except for *GOI*. Robust *t*-statistics following Hodrick (1992) are reported in square brackets, and Newey-West (1987) corrected *t*-statistics with 12 lags are reported in parentheses. The Wald statistic is the test statistic for the null hypothesis that the slope coefficient estimates except intercept are jointly equal to zero, and the Wald statistic based on Hodrick (1992) and Newey-West (1987) standard error is reported in square bracket and parenthesis, respectively. The sample period is from August 1996 through September 2010.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	4.4×10^{-4}	-0.032	-0.034	-0.043	-0.044	-0.053	-0.054	-0.037	-0.038	-0.028	-0.029
	[0.119]	[-1.767]*	[-1.832]*	[-2.251]**	[-2.292]**	[-2.465]**	[-2.493]**	[-2.008]**	[-2.058]**	[-1.522]	[-1.581]
	(0.099)	(-2.078)**	(-2.067)**	(-4.257)***	(-4.045)***	(-2.720)***	(-2.722)***	(-2.453)**	(-2.434)**	(-2.213)**	(-2.211)**
RREL		0.376	0.309	0.726	0.657	-0.315	-0.360	0.718	0.640	0.156	0.062
		[0.809]	[0.661]	[1.475]	[1.325]	[-0.551]	[-0.629]	[1.419]	[1.259]	[0.341]	[0.136]
		(0.841)	(0.744)	(2.504)**	(2.363)**	(-0.502)	(-0.617)	(1.953)*	(1.817)*	(0.328)	(0.150)
DFSP		-3.319	-2.798	-3.781	-3.301	-1.153	-0.713	-3.032	-2.546	-3.841	-3.265
		[-2.205]**	[-1.850]*	[-2.521]**	[-2.191]**	[-0.579]	[-0.359]	[-1.981]**	[-1.657]*	[-2.517]**	[-2.137]**
		(-3.909)***	(-2.925)***	(-4.960)***	(-3.883)***	(-0.668)	(-0.405)	(-2.957)***	(-2.379)**	(-4.489)***	(-3.418)***
TMSP		0.047	-0.025	0.052	-0.013	-0.219	-0.281	0.061	-0.008	-0.005	-0.094
		[0.153]	[-0.079]	[0.168]	[-0.041]	[-0.687]	[-0.877]	[0.199]	[-0.026]	[-0.017]	[-0.298]
		(0.181)	(-0.085)	(0.200)	(-0.044)	(-0.736)	(-0.911)	(0.238)	(-0.028)	(-0.020)	(-0.343)
DIV		3.882	3.617	3.680	3.448	4.219	3.957	4.177	3.913	3.803	3.487
		[2.903]***	[2.703]***	[2.761]***	[2.584]**	[3.186]***	[2.985]***	[3.101]***	[2.903]***	[2.847]***	[2.611]***
		(3.622)***	(3.224)***	(4.879)***	(4.286)***	(3.786)***	(3.411)***	(3.457)***	(3.312)***	(3.745)***	(3.225)***

LR_m		0.058 [0.616] (0.629)	0.092 [0.950] (0.951)	0.081 [0.848] (1.129)	0.111 [1.135] (1.487)	0.049 [0.526] (0.544)	0.082 [0.855] (0.880)	0.038 [0.402] (0.413)	0.072 [0.735] (0.749)	-0.006 [-0.067] (-0.093)	0.029 [0.299] (0.385)
GOI	0.140 [2.571]** (3.217)***		0.128 [2.278]** (3.053)***		0.115 [2.048]** (2.809)***		0.123 [2.170]** (2.987)***		0.122 [2.179]** (2.889)***		0.150 [2.639]*** (3.902)***
VRP				0.625 [2.888]*** (7.361)***	0.609 [2.810]*** (6.732)***						
CFNAI						0.018 [1.568] (1.516)	0.018 [1.523] (1.499)				
CAY								0.439 [2.147]** (2.866)***	0.422 [2.062]** (2.995)***		
BDI										0.036 [2.634]*** (3.469)***	0.039 [2.792]*** (3.589)***
Wald statistic	[6.612]** (10.351)***	[13.969]** (23.975)***	[18.533]*** (28.767)***	[20.669]*** (107.545)***	[24.363]*** (82.265)***	[15.811]** (38.943)***	[20.527]*** (54.724)***	[18.120]*** (23.194)***	[21.946]*** (30.706)***	[17.745]*** (40.386)***	[22.755]*** (46.330)***
Adj. R^2*(%)*	2.54	4.67	6.54	12.91	14.37	7.94	9.63	6.78	8.46	10.90	13.73

Table 5

Predictability of Growth of ITMP Open Interest for Excess Return

The table reports estimates from *OLS* regressions of excess return on the predictor variables with the growth of *ITMP* open interest. The *GOI* is the growth of *ITMP* open interest. All predictor variables are lagged one month, and all of the regressions are based on monthly observations. All variable definitions are identical to Table 2, except for *GOI*. Robust *t*-statistics following Hodrick (1992) are reported in square brackets, and Newey-West (1987) corrected *t*-statistics with 12 lags are reported in parentheses. The Wald statistic is the test statistic for the null hypothesis that the slope coefficient estimates except intercept are jointly equal to zero, and the Wald statistic based on Hodrick (1992) and Newey-West (1987) standard error is reported in square bracket and parenthesis, respectively. The sample period is from August 1996 through September 2010.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

	(0)	(2)	(4)	(6)	(8)	(10)
Constant	0.001	-0.034	-0.044	-0.054	-0.039	-0.029
	[0.375]	[-1.857]*	[-2.323]**	[-2.504]**	[-2.122]**	[-1.619]
	(0.302)	(-2.190)**	(-4.369)***	(-2.758)***	(-2.616)***	(-2.397)**
RREL		0.433	0.774	-0.242	0.803	0.215
		[0.923]	[1.560]	[-0.420]	[1.564]	[0.466]
		(0.939)	(2.642)***	(-0.377)	(2.206)**	(0.436)
DFSP		-2.825	-3.324	-0.778	-2.458	-3.235
		[-1.837]*	[-2.175]**	[-0.388]	[-1.564]	[-2.087]**
		(-3.192)***	(-4.310)***	(-0.462)	(-2.298)**	(-3.538)***
TMSP		0.058	0.062	-0.201	0.075	0.006
		[0.189]	[0.200]	[-0.632]	[0.242]	[0.018]
		(0.211)	(0.230)	(-0.650)	(0.284)	(0.020)
DIV		3.617	3.440	3.971	3.897	3.454
		[2.669]***	[2.546]**	[2.959]***	[2.863]***	[2.554]**
		(3.257)***	(4.356)***	(3.498)***	(3.174)***	(3.307)***

LR_m		0.116	0.133	0.101	0.102	0.064
		[1.095]	[1.252]	[0.971]	[0.965]	[0.609]
		(1.187)	(1.774)	(1.108)	(1.055)	(0.804)
GOI	0.026	0.035	0.032	0.031	0.039	0.045
	[1.407]	[1.706]*	[1.567]	[1.525]	[1.892]*	[2.177]**
	(1.509)	(2.238)**	(2.085)**	(2.000)**	(2.542)**	(2.514)**
VRP			0.618			
			[2.860]***			
			(7.361)***			
CFNAI				0.018		
				[1.517]		
				(1.463)		
CAY					0.467	
					[2.252]**	
					(3.101)***	
BDI						0.039
						[2.777]***
						(3.410)***
Wald	[1.979]	[16.191]**	[22.036]***	[17.972]**	[20.276]***	[20.820]***
statistic	(2.276)	(24.936)***	(98.479)***	(40.076)***	(28.682)***	(36.280)***
Adj. R^2(%)	0.87	5.33	13.42	8.37	7.79	12.42

Table 6

Out-of-Sample Predictive Power

The table reports results from one-month-ahead out-of-sample forecast comparisons of stock market returns. The *GOI* is the growth of *OTMC* open interest. The *VRP* is the variance risk premium and is defined by the difference between the risk-neutral return variance and the realized return variance. The *RREL* denotes as the three-month T-bill yield minus its trailing twelve-month moving average. The *BDI* is the growth rate of the Baltic Dry Index over three months. Each Row report forecast comparisons of unrestricted models, which include predictor variables for stock market returns, with the constant expected returns benchmark (*const*). The out-of-sample R^2 statistic (*OOS* R^2) is suggested by Welch and Goyal (2008) and Campbell and Thompson (2008). *ENC-NEW* statistic is the forecast encompassing test statistic of Clark and McCracken (2001). *MSE-F* statistic is the equal forecast accuracy test statistic of McCracken (2007). *MSPE-adjusted* statistic is the forecasting error test statistic of Clark and West (2007).

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Row	Comparison	*OOS* R^2	*ENC-NEW*	*MSE-F*	*MSPE-adjusted*
1	*GOI* vs. *const*	2.42%	1.783^{**}	1.736^{**}	1.552^{*}
2	*RREL* vs. *const*	2.59%	1.292^{*}	1.861^{**}	1.276
3	(*GOI*, *RREL*) vs. *const*	3.81%	2.815^{**}	2.771^{**}	1.703^{**}
4	*VRP* vs. *const*	3.11%	3.052^{***}	2.245^{**}	1.128
5	(*GOI*, *VRP*) vs. *const*	7.36%	4.760^{***}	5.564^{***}	2.020^{**}
6	*BDI* vs. *const*	11.67%	10.001^{***}	9.251^{***}	2.109^{**}
7	(*GOI*, *BDI*) vs. *const*	17.25%	14.781^{***}	14.589^{***}	2.630^{***}
8	(*VRP*, *RREL*) vs. *const*	10.98%	7.542^{***}	8.634^{***}	2.064^{**}
9	(*GOI*, *VRP*, *RREL*) vs. *const*	13.51%	8.805^{***}	10.934^{***}	2.668^{***}
10	(*VRP*, *BDI*) vs. *const*	10.19%	12.502^{***}	7.942^{***}	2.043^{**}
11	(*GOI*, *VRP*, *BDI*) vs. *const*	17.60%	17.140^{***}	14.953^{***}	2.585^{***}
12	(*RREL*, *BDI*) vs. *const*	13.91%	10.937^{***}	11.308^{***}	2.329^{**}
13	(*GOI*, *RREL*, *BDI*) vs. *const*	18.24%	15.315^{***}	15.619^{***}	2.748^{***}
14	(*VRP*, *RREL*, *BDI*) vs. *const*	16.66%	16.763^{***}	14.000^{***}	2.420^{***}
15	(*GOI*, *VRP*, *RREL*, *BDI*) vs. *const*	21.97%	20.766^{***}	19.712^{***}	2.841^{***}

Table 7

Sharpe ratios of returns from a predictor variable-based decision rule

The table reports Sharpe ratios of returns, obtained from the predictor variable-based decision rule. The *GOI* is the growth of *OTMC* open interest. The *VRP* is the variance risk premium and is defined by the difference between the risk-neutral return variance and the realized return variance. The *RREL* denotes as the three-month T-bill yield minus its trailing twelve-month moving average. The *BDI* is the growth rate of the Baltic Dry Index over three months. Conditional returns are based on a decision rule to take a long position in stock market at the end of month t if a positive return is predicted for month t+1, and to do nothing if a negative return is predicted for month t+1. The predicted returns are obtained in predictive regressions with initial parameter estimation based on 100 observations and sequentially recursive parameter estimation. $N[l]$ is a number of the month out of 70 months at the end of which the conditional strategy takes a long position in stock market. $B[p]$ is a bootstrap p-value computed as the proportion of 25,000 bootstrap trials for the null hypothesis that Sharpe ratio of a conditional strategy is not abnormally larger than that of the unconditional strategy.

Row	Predictors	$N[l]$	*Sharpe ratios*	$B[p]$
1	*GOI*	45	1.13	0.08
2	*RREL*	49	1.01	0.14
3	*GOI, RREL*	43	1.27	0.04
4	*VRP*	30	0.65	0.48
5	*GOI, VRP*	31	1.06	0.11
6	*BDI*	43	0.41	0.74
7	*GOI, BDI*	39	1.05	0.12
8	*VRP, RREL*	34	0.87	0.24
9	*GOI, VRP, RREL*	35	1.47	0.01
10	*VRP, BDI*	33	1.08	0.10
11	*GOI, VRP, BDI*	37	1.22	0.05
12	*RREL, BDI*	44	0.64	0.49
13	*GOI, RREL, BDI*	42	0.98	0.16
14	*VRP, RREL, BDI*	35	1.08	0.10
15	*GOI, VRP, RREL, BDI*	36	1.33	0.03

Table 8

Predictability of Growth of Option Open Interest and Option Trading Volume for Excess Return

The table reports estimates from *OLS* regressions of excess return on the predictor variables with the growth of *OTMC* open interest and *ITMP* trading volume. The *GOI* is the growth of *OTMC* open interest, and the *GTV* is the growth of *ITMP* trading volume. All predictor variables are lagged one month, and all of the regressions are based on monthly observations. All variable definitions are identical to Table 2, except for *GOI* and *GTV*. In Panel A, in-sample predictability analysis is reported. Robust *t*-statistics following Hodrick (1992) are reported in square brackets, and Newey-West (1987) corrected *t*-statistics with 12 lags are reported in parentheses. In Panel B, out-of-sample predictability analysis is reported. In Panel C, analysis for Sharpe ratios of returns is reported.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Panel A: In-sample predictability analysis			
	(9)	(10)	(11)
Constant	-0.055	-0.055	-0.056
	[-2.584]**	[-2.564]**	[-2.596]***
	(-3.958)***	(-4.045)***	(-4.028)***
RREL	0.120	0.048	-0.032
	[0.196]	[0.079]	[-0.052]
	(0.221)	(0.093)	(-0.060)
DFSP	-2.259	-1.846	-1.654
	[-1.123]	[-0.921]	[-0.817]
	(-1.412)	(-1.158)	(-1.002)
TMSP	-0.189	-0.255	-0.274
	[-0.601]	[-0.805]	[-0.864]
	(-0.841)	(-1.075)	(-1.129)
DIV	4.078	3.797	3.785
	[3.068]***	[2.857]***	[2.848]***
	(5.023)***	(4.711)***	(4.563)***
LR_m	0.008	0.037	0.047
	[0.080]	[0.378]	[0.474]

	(0.124)	(0.585)	(0.727)
GOI		0.129	0.109
		[2.256]**	[1.863]*
		(3.375)***	(2.732)***
GTV			0.022
			[1.482]
			(1.742)*
VRP	0.486	0.463	0.436
	[2.089]**	[1.989]**	[1.858]*
	(3.828)***	(3.568)***	(3.297)***
CFNAI	0.014	0.013	0.014
	[1.236]	[1.169]	[1.203]
	(1.259)	(1.222)	(1.247)
CAY	0.228	0.223	0.251
	[1.012]	[0.988]	[1.097]
	(1.929)*	(2.165)**	(2.491)**
BDI	0.028	0.031	0.031
	[2.096]**	[2.264]**	[2.246]**
	(3.716)***	(3.933)***	(3.773)***
Wald statistic	[24.424]***	[28.185]***	[29.856]***
	(207.366)***	(182.171)***	(224.505)***
Adj. R^2*(%)*	19.14	21.14	21.42

Panel B: Out-of-sample predictability analysis

Row	Comparison	*OOS* R^2	*ENC-NEW*	*MSE-F*	*MSPE-adjusted*
1	(*GTV, VRP, RREL, BDI*) vs. *const*	19.22%	19.369***	16.658***	2.701***
2	(*GOI, GTV, VRP, RREL, BDI*) vs. *const*	22.30%	22.102***	20.092***	2.971***

Panel C: Analysis for Sharpe ratios of returns

Row	Predictors	*N*[*l*]	*Sharpe ratios*	*B*[*p*]
1	*GTV, VRP, RREL, BDI*	37	0.88	0.24
2	*GOI, GTV, VRP, RREL, BDI*	34	1.25	0.04

Table 9

Predictability of Growth of Option Open Interest with Different Filtering Criteria for Excess Return

The table reports estimates from *OLS* regressions of excess return on the predictor variables with the growth of *OTMC* open interest and *ITMP* open interest based on different filtering criteria for the option except the condition of the trading volume. The *GOI* is the growth of option open interest. Columns (N-C) (N=0, 2, 4, 6, 8, 10) is for *OTMC* open interest, and columns (N-P) (N=0, 2, 4, 6, 8, 10) is for *ITMP* open interest. All predictor variables are lagged one month, and all of the regressions are based on monthly observations. All variable definitions are identical to Table 2, except for *GOI*. In Panel A, in-sample predictability analysis is reported. Robust *t*-statistics following Hodrick (1992) are reported in square brackets, and Newey-West (1987) corrected *t*-statistics with 12 lags are reported in parentheses. In Panel B, out-of-sample predictability analysis for the growth of *OTMC* open interest is reported. In Panel C, analysis for Sharpe ratios of returns by the conditional strategy from the growth of *OTMC* open interest is reported.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Panel A: In-sample predictability analysis

	(0-C)	(2-C)	(4-C)	(6-C)	(8-C)	(10-C)	(0-P)	(2-P)	(4-P)	(6-P)	(8-P)	(10-P)
Constant	4.7×10^{-4}	-0.033	-0.044	-0.054	-0.038	-0.029	0.001	-0.034	-0.044	-0.054	-0.039	-0.029
	[0.126]	[-1.825]*	[-2.289]**	[-2.510]**	[-2.053]**	[-1.575]	[0.379]	[-1.850]*	[-2.317]**	[-2.530]**	[-2.110]**	[-1.613]
	(0.1060)	(-2.025)**	(-3.955)***	(-2.706)***	(-2.402)**	(-2.141)**	(0.309)	(-2.182)**	(-4.337)***	(-2.776)***	(-2.590)***	(-2.385)**
RREL		0.313	0.661	-0.371	0.645	0.076		0.372	0.719	-0.312	0.730	0.136
		[0.669]	[1.332]	[-0.649]	[1.265]	[0.166]		[0.800]	[1.460]	[-0.547]	[1.441]	[0.297]
		(0.750)	(2.360)**	(-0.638)	(1.805)*	(0.183)		(0.843)	(2.505)**	(-0.500)	(2.046)**	(0.289)
DFSP		-2.781	-3.282	-0.639	-2.528	-3.263		-2.859	-3.360	-0.727	-2.508	-3.262
		[-1.842]*	[-2.183]**	[-0.323]	[-1.649]	[-2.137]**		[-1.878]*	[-2.220]**	[-0.366]	[-1.613]	[-2.123]**
		(-2.968)***	(-3.935)***	(-0.357)	(-2.409)**	(-3.445)***		(-3.154)***	(-4.262)***	(-0.420)	(-2.280)**	(-3.513)***
TMSP		-0.044	-0.032	-0.308	-0.027	-0.110		0.054	0.058	-0.210	0.069	$-2.0*10^{-4}$
		[-0.140]	[-0.100]	[-0.955]	[-0.086]	[-0.348]		[0.174]	[0.186]	[-0.660]	[0.224]	[$-1.0*10^{-3}$]
		(-0.153)	(-0.106)	(-1.002)	(-0.096)	(-0.410)		(0.196)	(0.214)	(-0.683)	(0.266)	($-1.0*10^{-3}$)
DIV		3.623	3.450	3.961	3.919	3.510		3.633	3.457	3.974	3.915	3.465
		[2.707]***	[2.586]**	[2.984]***	[2.906]***	[2.628]***		[2.692]***	[2.568]**	[2.969]***	[2.886]***	[2.574]**
		(3.219)***	(4.253)***	(3.430)***	(3.319)***	(3.233)***		(3.241)***	(4.372)***	(3.479)***	(3.136)***	(3.287)***

LR_m		0.086 [0.895] (0.881)	0.105 [1.091] (1.417)	0.077 [0.807] (0.809)	0.066 [0.680] (0.680)	0.022 [0.226] (0.288)		0.114 [1.099] (1.167)	0.131 [1.256] (1.775)*	0.103 [1.006] (1.099)	0.099 [0.957] (1.032)	0.064 [0.614] (0.796)
GOI	0.142 [2.453]** (3.598)***	0.126 [2.133]** (3.157)***	0.115 [1.937]* (2.898)***	0.125 [2.103]** (3.094)***	0.121 [2.041]** (2.973)***	0.141 [2.372]** (3.825)***	0.027 [1.382] (1.480)	0.033 [1.612] (1.968)*	0.030 [1.463] (1.872)*	0.032 [1.556] (1.910)*	0.037 [1.773]* (2.207)**	0.044 [2.136]** (2.516)**
VRP			0.611 [2.819]*** (6.731)***						0.619 [2.860]*** (7.419)***			
CFNAI				0.018 [1.555] (1.524)						0.018 [1.553] (1.498)		
CAY					0.423 [2.064]** (2.973)***						0.460 [2.232]** (3.064)***	
BDI						0.038 [2.742]*** (3.625)***						0.039 [2.790]*** (3.434)***
Wald statistic	[6.018]** (12.948)***	[18.008]*** (25.367)***	[23.971]*** (81.933)***	[20.512]*** (45.530)***	[21.813]*** (31.265)***	[22.158]*** (46.309)***	[1.911] (2.192)	[15.933]** (26.601)***	[21.801]*** (102.327)***	[18.230]** (41.094)***	[20.073]*** (28.946)***	[20.861]*** (38.196)***
Adj. R^2(%)	2.63	6.49	14.37	9.74	8.43	13.36	0.34	5.18	13.27	8.40	7.56	12.28

Panel B: Out-of-sample predictability analysis

Row	Comparison	*OOS R^2*	*ENC-NEW*	*MSE-F*	*MSPE-adjusted*
1	*GOI* vs. *const*	3.63%	2.149**	2.640**	1.763**
2	(*GOI*, *RREL*) vs. *const*	4.91%	3.226**	3.615**	1.846**

3	(*GOI, VRP*) vs. *const*	8.22%	5.283***	6.268***	2.075**
4	(*GOI, BDI*) vs. *const*	17.68%	14.791***	15.037***	2.683***
5	(*GOI, VRP, RREL*) vs. *const*	14.17%	9.436***	11.561***	2.689***
6	(*GOI, VRP, BDI*) vs. *const*	17.69%	17.305***	15.041***	2.612***
7	(*GOI, RREL, BDI*) vs. *const*	18.67%	15.380***	16.067***	2.805***
8	(*GOI, VRP, RREL, BDI*) vs. *const*	22.07%	21.070***	19.825***	2.869***

Panel C: Analysis for Sharpe ratios of returns

Row	Predictors	$N[l]$	*Sharpe ratios*	$B[p]$
1	*GOI*	46	1.13	0.08
2	*GOI, RREL*	42	1.27	0.04
3	*GOI, VRP*	29	1.18	0.06
4	*GOI, BDI*	39	1.04	0.12
5	*GOI, VRP, RREL*	34	1.23	0.05
6	*GOI, VRP, BDI*	35	1.34	0.02
7	*GOI, RREL, BDI*	42	0.83	0.27
8	*GOI, VRP, RREL, BDI*	37	1.27	0.04

Table 10

Predictability of Growth of Option Open Interest based on Value-Weighted Average for Excess Return

The table reports estimates from *OLS* regressions of excess return on the predictor variables with the growth of *OTMC* open interest and *ITMP* open interest based on the value-weighted average of option open interest. The *GOI* is the growth of option open interest. Columns (N-C) (N=0, 2, 4, 6, 8, 10) is for *OTMC* open interest and columns (N-P) (N=0, 2, 4, 6, 8, 10) is for *ITMP* open interest. All predictor variables are lagged one month, and all of the regressions are based on monthly observations. All variable definitions are identical to Table 2, except for *GOI*. In Panel A, in-sample predictability analysis is reported. Robust *t*-statistics following Hodrick (1992) are reported in square brackets, and Newey-West (1987) corrected *t*-statistics with 12 lags are reported in parentheses. In Panel B, out-of-sample predictability analysis for the growth of *OTMC* open interest is reported. In Panel C, analysis for Sharpe ratios of returns by the conditional strategy from the growth of *OTMC* open interest is reported.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Panel A: In-sample predictability analysis												
	(0-C)	(2-C)	(4-C)	(6-C)	(8-C)	(10-C)	(0-P)	(2-P)	(4-P)	(6-P)	(8-P)	(10-P)
Constant	-3.1×10^{-4}	-0.034	-0.044	-0.053	-0.038	-0.029	0.001	-0.033	-0.043	-0.053	-0.038	-0.029
	[-0.084]	[-1.846]*	[-2.284]**	[-2.480]**	[-2.062]**	[-1.597]	[0.312]	[-1.824]*	[-2.280]**	[-2.477]**	[-2.074]**	[-1.574]
	(-0.070)	(-2.069)**	(-3.973)***	(-2.605)***	(-2.398)**	(-2.230)**	(0.247)	(-2.161)**	(-4.281)***	(-2.720)***	(-2.547)**	(-2.359)**
RREL		0.266	0.616	-0.383	0.590	0.028		0.448	0.775	-0.228	0.803	0.231
		[0.570]	[1.244]	[-0.671]	[1.164]	[0.062]		[0.949]	[1.556]	[-0.394]	[1.559]	[0.499]
		(0.628)	(2.104)**	(-0.653)	(1.638)	(0.660)		(0.966)	(2.656)***	(-0.357)	(2.204)**	(0.465)
DFSP		-2.750	-3.282	-0.729	-2.518	-3.247		-2.818	-3.362	-0.760	-2.497	-3.252
		[-1.816]*	[-2.180]**	[-0.367]	[-1.638]	[-2.119]**		[-1.825]*	[-2.191]**	[-0.377]	[-1.586]	[-2.091]**
		(-2.839)***	(-3.757)***	(-0.424)	(-2.250)**	(-3.394)***		(-3.174)***	(-4.467)***	(-0.444)	(-2.396)**	(-3.396)***
TMSP		0.011	0.021	-0.240	0.026	-0.047		0.062	0.064	-0.197	0.077	0.010
		[0.034]	[0.068]	[-0.752]	[0.083]	[-0.151]		[0.201]	[0.206]	[-0.622]	[0.251]	[0.031]
		(0.041)	(0.077)	(-0.851)	(0.098)	(-0.184)		(0.228)	(0.243)	(-0.647)	(0.295)	(0.036)
DIV		3.520	3.390	3.862	3.816	3.409		3.567	3.430	3.920	3.855	3.408
		[2.627]***	[2.535]**	[2.909]***	[2.828]***	[2.548]**		[2.614]***	[2.519]**	[2.902]***	[2.813]***	[2.501]**
		(3.011)***	(4.005)***	(3.130)***	(3.003)***	(3.123)***		(3.194)***	(4.363)***	(3.437)***	(3.116)***	(3.197)***

LR_m		0.104	0.118	0.093	0.083	0.041		0.111	0.123	0.098	0.093	0.055
		[1.073]	[1.209]	[0.970]	[0.853]	[0.417]		[1.060]	[1.170]	[0.949]	[0.890]	[0.526]
		(1.093)	(1.619)	(1.026)	(0.891)	(0.545)		(1.086)	(1.557)	(1.016)	(0.920)	(0.659)
GOI	0.142	0.133	0.111	0.125	0.125	0.143	0.031	0.037	0.030	0.034	0.039	0.046
	[2.777]***	[2.528]**	[2.119]**	[2.359]**	[2.391]**	[2.725]***	[1.626]	[1.723]*	[1.413]	[1.583]	[1.801]*	[2.094]**
	(2.864)***	(3.161)***	(2.916)***	(2.818)***	(2.925)***	(3.525)***	(1.679)*	(1.729)*	(1.512)	(1.651)	(1.864)*	(2.175)**
VRP			0.592						0.609			
			[2.730]***						[2.819]***			
			(6.993)***						(7.479)***			
CFNAI				0.017						0.018		
				[1.484]						[1.520]		
				(1.452)						(1.476)		
CAY					0.407						0.452	
					[2.000]**						[2.198]**	
					(2.710)***						(2.943)***	
BDI						0.038						0.039
						[2.735]***						[2.760]***
						(3.404)***						(3.497)***
Wald statistic	[7.710]***	[19.042]***	[23.987]***	[20.787]***	[21.949]***	[23.435]***	[2.643]	[16.270]**	[21.734]***	[17.966]**	[20.103]***	[20.439]***
	(8.201)***	(37.150)***	(91.480)***	(55.270)***	(28.944)***	(22.725)***	(2.821)*	(22.725)***	(108.074)***	(36.469)***	(23.354)***	(39.748)***
Adj. R^2(%)	3.44	7.34	14.63	10.26	9.10	14.17	0.65	5.59	13.36	8.64	7.88	12.65

Panel B: Out-of-sample predictability analysis

Row	Comparison	*OOS R^2*	*ENC-NEW*	*MSE-F*	*MSPE-adjusted*
1	*GOI* vs. *const*	-0.01%	1.131*	-0.823	0.835
2	(*GOI, RREL*) vs. *const*	-0.00%	1.939**	-0.014	1.133
3	(*GOI, VRP*) vs. *const*	4.35%	3.844***	3.184**	1.579*
4	(*GOI, BDI*) vs. *const*	14.75%	12.343***	12.112***	2.505***
5	(*GOI, VRP, RREL*) vs. *const*	10.17%	7.440***	7.926***	2.275**

6	(*GOI, VRP, BDI*) vs. *const*	15.81%	14.679***	13.148***	2.427***
7	(*GOI, RREL, BDI*) vs. *const*	15.43%	12.069***	12.769***	2.607***
8	(*GOI, VRP, RREL, BDI*) vs. *const*	19.70%	17.935***	17.168***	2.671***

Panel C: Analysis for Sharpe ratios of returns

Row	Predictors	*N*[*l*]	*Sharpe ratios*	*B*[*p*]
1	*GOI*	43	0.85	0.27
2	*GOI, RREL*	41	0.71	0.42
3	*GOI, VRP*	40	0.86	0.26
4	*GOI, BDI*	44	0.82	0.29
5	*GOI, VRP, RREL*	39	1.20	0.05
6	*GOI, VRP, BDI*	36	0.79	0.33
7	*GOI, RREL, BDI*	45	0.73	0.39
8	*GOI, VRP, RREL, BDI*	36	0.99	0.15