The information content of short selling and put option trading: When are they substitutes?*

This Draft: August, 2017

Abstract

Using January 2005 – June 2007 trading data for all NYSE stocks we identify the informational patterns and impact of exogenous shocks in short sales and option trades upon stock price changes. We find that short sales have more predictive power than put option trades. However, if short selling volume is low put options trading does have predictive power and thus may be a substitute used by informed investors.

Key words: Short selling; Put option trades; Informational patterns; Price discovery

JEL Codes: G12; G14

The information content of short selling and put option trading: When are they substitutes?*

Xiaohu Deng
Tasmanian School of Business and Economics
The University of Tasmania
Hobart, TAS 7001, Australia
xiaohu.deng@utas.edu.au

Lei Gao
Department of Finance
Iowa State University
Ames, IA 50011, USA
lgao@iastate.edu

David M. Kemme
Department of Economics
The University of Memphis
Memphis, TN 38152, USA
dmkemme@memphis.edu

* We would like to thank Alex Kurov, Lucjan Orlowski, Jacob Kleinow, Thomas Poppe, and seminar participants at the University of Memphis, Midwest Finance Association 2015 Annual Meeting, and Financial Management Association 2015 Annual Meeting for helpful comments. All mistakes and errors remain ours.

1. Introduction

Two major venues that mostly informed investors use, short sales and put options trading, are both found to contain privileged and negative information (e.g. Chakravarty, Gulen, and Mayhew, 2004; Cao, Chen, and Griffin, 2005; Diether, Lee, and Werner, 2009; Hao, Lee, and Piqueira, 2013; and etc). Nevertheless, whether short sellers and put option traders are equally informed is not clear. Further, whether or not informed trading in short sales and put option trades are essentially substitutes is also an open question. We provide answers to these questions.

Early theory (Black, 1975; Easley, O'Hara, and Srinivas, 1998) suggested that informed traders participate in both option and short equity markets. Subsequent empirical studies supported to varying degrees the presence of informed trading in both markets, which then in turn may be revealed in the equity market. However, the evidence regarding which market is the primary venue for the most informed traders is still mixed. Anthony (1988) analyzed the relationship between option and stock markets and shows that call option trading volume predicts trading in the stock market on the next day. But Chan, Chung, and Fong (2002) found that informed investors prefer to trade directly in the stock market. Studies directly comparing the informativeness of option traders *and* short sellers are few.

Short sales are driven by public and private information. However, put option trades can be driven not only by information but also by liquidity shocks and hedging needs (Chesney, Crameri, and Mancini, 2015). For this reason, we expect that a number of short sales and put option trades are not made by the same group of investors. Compared to put options trades, short sales, in turn, should contain different information content. Moreover, as short sales are mostly information driven, and put options trades are driven by different reasons, we conjecture that short selling contains more information, i.e. predictive power, than put option trades, i.e. causality flows form short selling to put option trading and stock price changes. We find this to be true in general, but under certain circumstances put option trading has more predictive power. We quantify the contribution to price discovery for these two groups of informed investors.

Using January 2005 – June 2007 trading data for all NYSE stocks, we determine the information precedence of short sales and put option trading. We extend Hasbrouck's (1991) bivariate VAR model of stock market trades to also include put option trades and short sales, and determine the optimal model by lag length tests on the independent variables, and Wald tests of the vector of coefficients of each independent variable rather than t-tests of individual coefficients. This approach confirms Granger causality tests and combined, determines the direction of information flows, or predictability. Then, with these orderings we specify a Choleski decomposition which allows us to identify the VAR and calculate impulse response functions (IRFs). These responses to shocks in short sales and put option trades and their persistence in each market allow us to compare the informational patterns of short sales and put option trades. We repeat this for subsamples based on short and put option trading intensity.

In general, the VAR results suggest short sales can predict future stock returns, yet options cannot. This is consistent with the recent finding that option trades do not contain as much information as short sales (see, Hao, Lee, and Piqueira, 2013; Muravyev, Pearson, and Broussard, 2013). The impulse response functions indicate that stock prices respond negatively to a shock in short sales for one to two days, and do not exhibit any statistically significant response to the shock in put option trades. This then suggests that short sales contain information that takes longer to incorporate into stock prices than put option trading.

According to our finding and the empirical evidence from the recent literature (e.g. Hao, Lee, and Piqueira, 2013), short sales contain more information. However, the literature suggests put options can be informed under some circumstances, such as when selling stock is expensive or there are some other restrictions to sell stocks short[1]. To test whether market conditions influence whether put options and short sales can be substitutes, we analyze several subsamples. We partition our sample by volume of short sales and put option trades, re-estimate the VAR and IRFs. For heavily-shorted stocks, short sales always have predictive power for future stock returns. However, we do not find that put option trades of also heavily-shorted stocks has any significant predictive power for future stock returns, regardless of the amount of put options traded on the same underlying stocks. However, an important finding is that for lightly-shorted stocks, put option trades show predictive power for future stock returns. This can be due to short sales constraints so that most of informed traders reroute to put option trading venue (Figlewski and Webb, 1993). This finding holds only when put option trading is intensive and short selling is not.

The impulse responses further confirm that short sales contain more information. The impulse responses for subsamples show the similar subsample variations. For heavily-shorted stocks, stock returns to the shock in short sales exhibit a negative

[1] Non-comprehensive list includes Figlewski and Webb (1993), Danielsen and Sorescu (2001), and Blau and Wade (2011).

response. Stock returns to the shock in put option trades exhibit no significant response regardless of the amount of put options are traded. For lightly-shorted stocks, the stock returns show a temporary negative response to the shock in put option trades for about a day, conditional on the fact that put option trading is intensive (high put-to-stock ratio). When put option trading is not intensive, stock returns show no response to option trades. However, the stock returns still exhibit significant and negative responses to the shock in short sales regardless of the amount of shares sold short. These results combined suggest that short sales contain more information in general and expedites the price discovery process,[2] and put option trading is an alternative channel for informed investors to trade under certain conditions, i.e., if short selling is limited.

The effect of option trading on price discovery is less clear. Easley, O'Hara, and Srinivas (1998), Chakravarty, Gulen, and Mayhew (2004) and Cao, Chen, and Griffin (2005) find evidence to support Black's (1975) thesis that option trading contains information, while a more recent study by Muravyev, Pearson, and Broussard (2013) uses disagreement events in which the stock and options markets disagree about the stock price, and argue that option trading doesn't provide an economically meaningful contribution to price discovery. Another recent work by Johnson and So (2012) find that the option to stock volume ratio (O/S) reflects private information; Hu (2014) find that stock order imbalance induced by option order imbalance predicts future stock returns in a cross section model. Our finding that put option trading contains information only when short selling is limited supports and complements the literature discussed above as to whether this effect exists.

[2] See, e.g. Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009) and Boehmer and Wu (2013).

Our results extend and complement both streams of literature, by providing evidence that short sales have predictive power for stock price revisions, the temporal pattern of that predictive and under certain conditions put options trading does as well. The VAR and IRF results suggest that the role short selling plays in the price discovery process is much more important than put option trading.

The next section of the paper presents data and sample selection. Section 3 presents our methodology. Section 4 discusses main empirical results. Section 5 analyzes the subsamples and the cases in which put option trading may substitute for short selling. Section 6 concludes.

2. Data and sample

The empirical analysis in this study employs several different data sources. Because we are interested in how the markets adjust to shocks in fundamentals and the equilibrating process may be lengthy, especially for smaller companies, we use daily data rather than intra-day data. We employ 4 variables to proxy trading activity: daily short ratio, daily stock turnover, daily stock returns, and daily put option volume scaled by stock volume (P/S ratio). In order to calculate the daily short ratio, we first obtain intraday short selling data from Reg SHO. The Reg SHO dataset provides intraday short volume for all stocks traded on NYSE during January 3, 2005 to July 6, 2007. We aggregate intraday short volume into daily volume for each stock in our sample, then we calculate the daily short ratio as the daily short volume scaled by stock trading volume. Daily stock returns and turnover are obtained from CRSP. Daily put option volume is retrieved from Option Metrics, which contains data on all US exchange-listed equities and market indices, as well as all US listed index and equity options. We require every underlying stock in our sample to have at least 100 active trading days in any of the venues, and our sample covers 442 NYSE listed stocks that have active trading in both markets. Our sample is one of the largest in most relevant studies (comparable to 467 stocks in Grundy, Lim, and Verwijmeren (2012) and much larger than 45 NYSE stocks in Hao, Lee, and Piqueira (2013) and 39 stocks in Muravyev, Pearson, and Broussard (2013)). All the variables are defined in Appendix 1.

Table 1 provides a summary of descriptive statistics of all variables in our sample. Panel A presents the summary statistics with a balanced sample, in which all the observations are dropped if any variable is missing[3]. Panel B presents the summary statistics for an unbalanced sample setting, in which each variable has its actual number of observations during the sample period. The summary statistics in both panels provides similar statistics. Consistent with prior literature, the average daily stock trading volume is larger than the highest option daily put volume. In addition, the average daily short volume is about 15.6% (15.2% for the balanced sample) of the average daily stock trading volume, also as found in the prior literature (e.g. Hao, Lee, and Piqueira, 2013).

[Insert Table 1 about here]

3. Methodology and model

While existing studies have discussed the informational ordering of multiple markets, they do not quantify the size or duration of adjustments to new information, and do not provide formal Granger causality tests on the informational ordering of multiple

[3] All variables in our study are truncated at 1% and 99% levels.

markets and the optimal lag length tests when employing the VAR model. Thus, our first task in determining the informational ordering is to calculate pair-wise Granger causality tests and block exogeneity tests on daily stock returns and daily trading volume of stock, options, and short markets. The prerequisite for calculating the impulse response functions is to identify the model, either with structural constraints or alternatively a recursive ordering. Because theory does not provide guidance on structural constraints, we identify the model via Choleski decomposition based on the recursive ordering determined by the series of Granger causality tests. Given these, we then determine the optimal lag length, estimate the VAR, and calculate the impulse response functions. We present the model and the sample characteristics step by step in the following subsections.

3.1. Pre-analysis

3.1.1. Stationarity

Before all formal tests, it is important to understand the statistical properties of all variables in our sample. Stationarity rules out spurious correlation and is a desirable characteristic for the variables in a VAR model.

Therefore, for each of the four series we conduct panel unit root tests including Levin; Lin; Chu, Pesaran and Shin; ADF-Fisher; and PP-Fisher unit root tests on all 4 variables. All unit root tests reject the null hypothesis of the existence of a unit root, suggesting that all series in our sample are stationary (results are presented in Appendix 2).

3.1.2. Granger causality

After confirming the mean stationarity of all 4 variables, we conduct a series of pair-wise Granger causality tests, a block exogeneity test and Wald tests to determine the informational ordering of the equity trading, put option trades, and short sales.

Pair-wise Granger causality tests are presented in Appendix 3, and Table 2 reports the results of the block exogeneity test. From pair-wise Granger causality tests, there is bi-directional causality between all variables except P/S ratio. In addition, the exogeneity tests reported in Table 2 suggests, at best, a weak linkage between put option and equity trading. Therefore, we order the variables based on the relative significance of the causality tests. According to the causality tests statistics, the informational ordering is stock return, stock turnover, short ratio, and put ratio.

[Insert Table 2 about here]

3.2. The model

In effect, we expand Hasbrouck's (1991) bivariate VAR model to a four variable VAR, identified via a Choleski decomposition and then estimate the impulse response functions[4]. We may write the structural VAR as:

$$Bx_t = \gamma_0 + \sum_{i=1}^{p} \gamma_1^p . x_{t-p} + \varepsilon_t \qquad (1)$$

To identify the model we define the restricted B matrix as:

$$B = \begin{bmatrix} 1 & b_{12} & b_{13} & b_{14} \\ 0 & 1 & b_{23} & b_{24} \\ 0 & 0 & 1 & b_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix}; \text{ and}$$

[4] Note we may also employ generalized IRFs which are invariant with respect to the ordering. But, to the extent we can employ information from the Granger causality tests and the Wald Tests the Choleski decomposition is preferred. We order variables based on the significance of the Granger causality statistics.

$$\gamma_0 = \begin{bmatrix} b_{10} \\ b_{20} \\ b_{30} \\ b_{40} \end{bmatrix}; \qquad x_t = \begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \end{bmatrix};$$

$$\gamma_1^p = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{14} \\ \vdots & \ddots & \vdots \\ \gamma_{41} & \cdots & \gamma_{44} \end{bmatrix}^p \; and \;\; \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix};\ \text{where}$$

p is the lag length and x_{1t} is daily P/S ratio, x_{2t} is daily short ratio, x_{3t} is daily stock turnover, and x_{4t} is daily stock return for a particular stock on day t. (See variable definitions in Appendix 1).

The order of the individual variables in this vector is determined as above and correspondingly, we then impose the restrictions of the Choleski decomposition that defines the individual elements of the B matrix:

$$b_{21} = b_{31} = b_{32} = b_{41} = b_{42} = b_{43} = 0.$$

Multiplying by B^{-1} provides the reduced form VAR

$$x_t = A_0 + \sum_{i=1}^{p} \gamma_1^i x_{t-1} + e_t \qquad (2),$$

where

$$A_0 = B^{-1}\,\gamma_0,\ A_i = B^{-1}\gamma_1^p, \text{ and } e_t = B^{-1}\varepsilon_t.$$

From Enders (2009), equation (2) can be estimated by OLS. The results confirm the Granger causality tests, and we can then determine the system optimal lag length. By employing optimal lag length tests and comparing AIC (Akaike Information Criterion) and SIC (Schwartz Information Criteria), we find that the optimal lag length for estimating our VAR is 10.

Impulse response functions allow us to examine the dynamic response of x_t to the shock in ε_t. Assuming the stability conditions are met we can rewrite equation (2), the VAR, as a vector moving average equivalent (e.g. Swanson and Granger, 1997):

$$x_t = \bar{x} + \sum_{i=0}^{p} A_i \, e_{t-i} \qquad (3),$$

and since $e_t = B^{-1}\varepsilon_t$ we can write

$$x_t = \bar{x} + \sum_{i=0}^{p} A_i \, B^{-1}\varepsilon_t \qquad (4).$$

Letting $\emptyset_i = A_i B^{-1}$ we can write

$$x_t = \bar{x} + \sum_{i=0}^{p} \emptyset_i \, \varepsilon_t \qquad (5).$$

The sixteen elements of $\emptyset_0$ are the impact multipliers of a shock, or the instantaneous responses to a change in ε_t, and the elements of $\emptyset_1$ are the one period response of a change in ε_t. Similarly, for i = 2, 3, …, p. Plotting these provides the impulse response functions, which depict the response of any element of x_t to a shock in any of the other elements. We assume analytic standard errors to calculate the +/-2s bounds for the impulse response functions.

4. Empirical results

4.1. Baseline results

The estimated coefficients of the VAR with an optimal lag length of 10 lagged trading days confirm the Granger causality tests and the informational roles of short selling and put option trading. Then, and more importantly, by identifying the VAR via Choleski decomposition we can calculate the impulse response functions and know the magnitude, statistical significance, and duration of the impact of an informational or unexpected shock in one market on the others. In the following subsections, we provide the VAR results, the identified VAR, and impulse response functions.

From the prior literature (e.g., Diamond and Verrecchia, 1987; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; *inter alia*) and our Granger causality and block exogeneity test results, short sales have greater predictive power for stock returns, i.e., contain more information, than put options. Regarding the informational role of put option markets, the pair-wise Granger causality tests, and block exogeneity tests above do not provide clear evidence of predictive power. Now we provide additional evidence as to whether informed trading is present in put options markets.

Table 3 presents the VAR results of estimating equation (2) with optimal lag length of 10 days. Panel A presents the estimates of the VAR model, and Panel B reports the Wald tests of coefficients in the daily stock returns equation.

[Insert Table 3 about here]

In Panel A, each column presents a model of each variable in the VAR as the dependent variable. For space reasons the coefficients of only the first three lags are reported even though our Wald tests are for 10 lags.[5] In column 1, we find that the lagged

[5] Full results are reported in Appendix 4.

short ratios have predictive power for future returns to the extent that the coefficients of some individual lags are statistically significant. However, lagged put ratios are not statistically significant. This is consistent with the previous Granger causality tests.

While examining individual coefficients is informative, a more appropriate test of an individual variable's predictive power in any equation is the Wald test for the vector of lagged coefficients. These results are presented in Panel B. We find that in the daily stock returns equation the vectors of coefficients of daily stock returns, daily stock turnover, and daily short ratio lagged 10 periods are statistically significantly different than 0, confirming the presence of informed trading in the short selling market. However, the vector of coefficients for put option trades 10 lagged periods is not significantly different from zero, consistent with Panel A results. The combined results in this subsection suggest that the information content of short selling is greater than put options trading to the extent that short selling has significant predictive power for future stock prices and put options does not.

To summarize, the identified VAR together with Wald test results in this subsection indicate the presence of informed trading in short selling market, which is consistent with prior research (see, e.g. Chan, Chung, and Fong, 2002; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009; Boehmer and Wu, 2013; Hao, Lee, and Piqueira, 2013; and etc). However, baseline results in this subsection do not find evidence of informed trading in the option markets (strong evidence as defined by the Wald test). To examine the nature of informed trading in short selling and put option trading, we now calculate impulse response functions based on the identified VARs in the following subsection.

4.2. Impulse response functions

To better understand the strength and significance of the informational flows between both markets we now examine the effect of exogenous informational shocks that occur in one market upon all other markets, i.e., the impulse response functions. These provide an explicit measure of the magnitude and duration of the responses to the informational shocks. The results illustrate the temporal nature of the market adjustments and the significance of short selling are important to the price discovery process. The role of put options trading on price discovery is negligible.

Figure 1 reports the impulse responses of stock returns to a one standard deviation shock in short selling and put option trading. We find that stock prices exhibit a statistically significant and negative response to the shock in short selling around the first two trading days, and then becoming statistically insignificant. This is consistent with the finding of Diether, Lee, and Werner (2009) that increased short selling activities can predict negative abnormal future returns. The persistence of the response is evidence that short sellers have access to superior information ahead of the market.

[Insert Figure 1 about here]

In contrast to the response of stock prices to the shock in short selling, the response to the shock in put option trades does not show any significant response. The literature relating informational flows from options markets to the stock market is not conclusive. Easley, O'Hara, and Srinivas (1998) shows that informed traders trade in both equity and option markets. Several empirical studies such as Chakravarty, Gulen, and Mayhew (2004), and Cao, Chen, and Griffin (2005) also find supporting evidence on the presence of informed trading in option markets. However, Chan, Chung, and Fong (2002) do not find evidence that option trading volume has predictive power on future returns. The more recent study from Muravyev Pearson and Broussard (2013) finds that the option trading does not contribute to the equity price discovery process. So far our findings, in general, support the latter stream of literature.

Together with the results in previous sections, it appears that short selling contains more information, and the information content of put options seems negligible. We understand that informed trading might happen at an intra-daily frequency. While it might be the case, it cannot change our general findings as our findings suggest that short selling still has predictive power for future stock returns for days.[6] In the next section, we qualify our general results by examining subsamples defined by trading intensity in short selling and put options.

5. Can put option trading substitute for short selling in price discovery?

So far we find no evidence that put options have significant predictive power for future stock prices, but as noted above many authors suggest put options can be informed under some circumstances such as when selling stock is expensive or there are restrictions to short selling. Yet Grundy, Lim, and Verwijmeren (2012) find evidence that the short selling ban in 2008 restricts put option trading, suggesting that put options may not provide a substitute for short sales in the transmission of information to stock price revisions.

[6] We also include contemporaneous variables in our model to control the intraday effect of informed trading, and the results don't change.

To examine this possibility we partition our sample by short selling (short ratio) and put option trades (put ratio), and we conduct the same analysis for different subsamples. We assign stocks with average daily short ratio above median short ratio to high short group, and those stocks below median to low short group. We employ the same approach to assign stocks to high and low put group. Table 4 reports the VAR results for different subsamples. Panel A reports one-way sorting VAR results for four different sample: stocks with high put ratios, stocks with low put ratios, stocks with high short ratios, and stocks with low short ratios. The coefficients of lagged short ratios are statistically significant for all subsamples, but the coefficients of lagged put ratios are significant only for the low short group. Thus in most cases short sales contain more information than put options regardless whether put option buyers are involved or not. However, when short sales are not heavily present, put options trading may serve as a substitute for short selling.

Double sorting results from Panel B are consistent with this finding. In Panel B, lagged put options variables are not significant for most subsamples but are significant for the high put/low short sample, and the magnitude of the coefficients are larger than those for lagged short sales. This further explains the interaction between informed short selling and put options, as put options have no predictive power for future returns even if a stock is lightly shorted when put options are low for a particular stock.

[Insert Table 4 about here]

The impulse response functions for each put/short subsamples formed by double sorting are depicted in Figure 2. As expected, stock prices exhibit a statistically significant response to the shock in short sales for all subsamples although the persistence differs for different subsamples. The only case in which stock prices exhibit a statistically significant response to the shock in put options is the high put/low short subsample, which reflects the VAR results. In Panel B of Figure 2, stock prices exhibit a statistically significant response to the shock in put options trading on about the fifth day after the shock and then dissipate permanently. Compared to the response to the shock in short sales lasting more than a few days for all subsamples, the response to the shock in put options is only significant conditional on lightly shorted stocks.

[Insert Figure 2 about here]

In sum, the results in this section provide one explanation for the different findings in the literature regarding the substitutability of short selling and put option trading. For the full sample we find that put options trading is not a substitute for short sales regardless of short selling constraints, which is consistent with Grundy, Lim, and Verwijmeren (2012). However, under certain circumstances, when put options traders are heavily involved but short sellers are not[7], put options do have predictive power for future stock prices and thus likely contribute to the price discovery process (consistent with Figlewski and Webb, 1993; Danielsen and Sorescu, 2001; and Blau and Wade, 2011).[8]

6. Summary and conclusion

[7] This can be due to short selling constraints or stock characteristics, and we are not examining the underlying reason for these.

[8] As shown in IRFs results for low short/high put subsample, the response of stock prices to the shock in put option trading is only significant for one day.

In this paper we use January 2005 – June 2007 trading data on short selling and option markets to identify (1) the presence of informed trading across markets, (2) the size and significance of the length of time that specific information shocks prevail in each market, and (3) how two trading venues and informed traders interact with each other in each market..

Existing studies find mixed evidence on the presence of informed trading in short selling and options markets. By employing Granger causality and block exogeneity tests and a VAR, we find evidence of informed trading in short selling and evidence of informed trading in the put options market when short ratio is low. The impulse response functions show the exact magnitude and length of time for the responses to exogenous hypothetical shocks to dissipate. In general, we find that stock prices respond negatively to the shock in short selling for the first one to three days and then become insignificant. Our results suggest that put options trading may play a role in stock price discovery process to the extent that short selling is limited. Options are mostly used as hedging purposes rather than arbitrage for both companies and institutional traders. While noise traders might use options to arbitrage as if they have the private information on the underlying stocks, our results suggest informed investors do trade in both short selling and the put options market. Informed trading present in short selling is more pervasive vis-a-vis trading in the put options markets.

Reference

Anthony, J. H., 1988. The interrelation of stock and options market trading volume data. *Journal of Finance, 43*(4), 949-964.

Ayers, B. C., Li, O. Z., Yeung, P. E., 2011. Investor trading and the post-earnings-announcement drift. *The Accounting Review, 86*(2), 385-416

Barber, Brad M., Terrance Odean, Ning Zhu., 2009. Do retail trades move markets? *Review of Financial Studies, 22*(1), 151-186.

Black, F., 1975. Fact and fantasy in the use of options. *Financial Analysts Journal, 31*, 36-4161-72.

Blau, B.M., Wade, C., 2013. Comparing the information in short sales and put options. *Review of Quantitative Finance and Accounting, 41*(3), 567-583.

Boehmer, E., Jones, C.M., Zhang, X., 2008. Which shorts are informed?. *Journal of Finance, 63*, 491–527.

Boehmer, E., Wu, J. J., 2013. Short selling and the price discovery process, *Review of Financial Studies, 26*, 287-322.

Cao, C., Chen, Z., Griffin, J., 2005. Informational content of option volume prior to takeovers. *Journal of Business, 78*, 1073–1109.

Chakravarty, S., Gulen, H., Mayhew, S., 2004. Informed trading in stock and option markets. *Journal of Finance, 59*, 1235–1257.

Chan, K., Chung, Y.P., Fong, W., 2002. The informational role of stock and option volume. *Review of Financial Studies*, *15*, 1049-1075.

Chesney, M., Crameri, R., Mancini, L., 2015. Detecting abnormal trading activities in option markets. *Journal of Empirical Finance, 33*, 263-275.

Cohen, L., C. Malloy, L. Pomorski., 2012. Decoding inside information. *Journal of Finance, 68*(3), 1009–1043.

Diamond, D.W., Verrecchia, R. E., 1987. Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics, 18*, 277–311.

Diether, K., Lee, K., Werner, I., 2009. Short-sale strategies and return predictability. *Review of Financial Studies, 22*, 2531-2570.

Danielsen, B. R., Sorescu, S. M., 2001. Why do option introductions depress stock prices? An empirical study of diminishing short-sale constraints. *Journal of Financial and Quantitative Analysis*, 36, 451–484.

Easley, D., O'Hara, M., Srinivas, P. S., 1998. Option volume and stock prices: evidence on where informed traders trade. *Journal of Finance, 53*, 431–465.

Enders, W., 2009. *Applied econometric time series (11e)*. John Wiley Sons.

Figlewski, S., Webb, G.,1993. Options, short sales, and market completeness. *Journal of Finance, 48*, 761–777.

Grundy, B. D., Lim, B., Verwijmeren, P., 2012. Do option markets undo restrictions on short sales? Evidence from the 2008 short-sale ban. *Journal of Financial Economics, 106*(2), 331-348.

Gervais, S., Odean, T., 2001. Learning to be overconfident. *The Review of Financial Studies, 14*(1), 1-27.

Hao, X., Lee, E., Piqueira, N., 2013. Short sales and put options: Where is the bad news first traded?. *Journal of Financial Markets, 16*(2), 308-330.

Hu, J., 2014. Does option trading convey stock price information?. *Journal of Financial Economics, 111*(3), 625-645.

Johnson, Travis L., and Eric C. So., 2012. The option to stock volume ratio and future returns. *Journal of Financial Economics, 106*(2), 262-286.

Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. *The Journal of Finance, 63*(1): 273-310.

Kumar, A., Lee, C., 2006. Retail investor sentiment and return co-movements. *The Journal of Finance, 61*(5): 2451-2486.

Muravyev, D., Pearson, N. D., Broussard, J. P. 2013. Is there price discovery in equity options? *Journal of Financial Economics, 107*, 259-283.

Odean, Terrance. 1998a. Volume, volatility, price, and profit when all traders are above average. *Journal of Finance, 53*(6), 1887-1934.

Pan, J., Poteshman, A.M., 2006. The information in option volume for future stock prices. *Review of Financial Studies, 19*(3), 871–908.

Swanson, N. R., Granger, C. W., 1997. Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions. *Journal of the American Statistical Association, 92*(437), 357-367.

Tables

Table 1: Descriptive statistics

This table reports summary statistics for all traded call/put options volume, the underlying stock return, the underlying stock trading volume, and short volume across all trading days during January 2005 – June 2007. Panel A reports the summary statistics for the variables with a balanced sample. Panel B reports the summary statistics for the variables with an unbalanced sample.

Panel A: Balanced sample							
Variables	N	Unit	Mean	Median	Max	Min	STD
Rt	184,924	basis points	4.751	2.309	400.0	-376.5	135.8
STOCKVOLt	184,924	1,000 shares	2,021	1,318	13,497	39.69	2,039
SHORTVOLt	184,924	1,000 shares	315.6	216.4	1,789	13.20	292.5
PUTVOLt	184,924	1,000 shares	1.053	0.236	14.26	0.002	1.950
TURNt	184,924		0.009	0.007	0.467	0.000	0.008
PUTt	184,924		0.001	0.000	0.196	0.000	0.003
SHORTt	184,924		0.156	0.164	0.133	0.333	0.143
Panel B: Unbalanced sample							
Rt	191,997	basis points	4.854	2.262	400.0	-376.5	136.0
STOCKVOLt	195,385	1,000 shares	2,096	1,346	13,497	39.69	2,153
SHORTVOLt	197,050	1,000 shares	325.8	221.1	1,789	13.20	305.2
PUTVOLt	200,723	1,000 shares	1.142	0.251	14.26	0.002	2.094
TURNt	200,723		0.010	0.007	0.467	0.000	0.010
PUTt	195,385		0.001	0.000	0.196	0.000	0.003
SHORTt	195,385		0.155	0.164	0.133	0.333	0.142

Table 2: Block Exogeneity Wald Test

This table reports the Block exogeneity Wald test results for daily stock return, stock turnover, short ratio, call to stock ratio, and put to stock ratio. Each column represents the results when dependent variables are daily stock returns, stock turnover, short ratio, call to stock ratio, and put to stock ratio. *, **, and *** indicate significance at the 1%, 5%, and 10% levels.

	Rt	TURNt	SHORTt	PUTt
	Chi-sq	*Chi-sq*	*Chi-sq*	*Chi-sq*
Rt		185.3^{***}	114.8^{***}	81.32^{***}
TURNt	77.32^{***}		139.0^{***}	35.36^{***}
SHORTt	43.70^{***}	50.15^{***}		70.15^{***}
PUTt	8.68	49.09^{***}	75.60^{***}	

Table 3: Vector autoregressive results

This table reports the results of VAR model for daily stock return, stock trading turnover, put ratio, and short ratio. The results are estimated with 10 lags. Panel A reports the estimates of first 3 lags. Panel B reports the Wald test of coefficients for the full ten lags on all independent variables. *, **, and *** indicate significance at 10%, 5%, and 1% level.

Panel A: VAR results

	1	2	3	4
	Rt	TURNt	SHORTt	PUTt
Lagged Variables				
Rt-1	-0.009***	-0.006***	0.13***	-0.001**
Rt-2	-0.022***	-0.004***	0.233***	0.000
Rt-3	-0.001	-0.004***	-0.083*	0.000
TURNt-1	0.037***	0.355***	0.718***	0.001
TURNt-2	-0.022***	0.118***	-0.396***	-0.001
TURNt-3	0.002	0.066***	-0.224*	-0.001
SHORTt-1	-0.001**	-0.000	0.357***	0.001***
SHORTt-2	0.000	-0.001***	0.059***	0.000
SHORTt-3	0.000	0.000	0.145***	0.001***
PUTt-1	-0.009	0.045***	1.431***	0.175***
PUTt-2	-0.033	0.014	3.496***	0.130***
PUTt-3	-0.026	0.012	-7.449***	0.056***
Adj R-squared	0.002	0.548	0.682	0.525
F-statistic	6.495	3,038	5,380	2,768
Akaike AIC	-5.917	-7.882	-0.288	-10.30

Panel B: Wald tests of coefficients

	Null Hypotheses	*Chi-sq*	*P-value*
Rt-i (i=1,2,…,10)	all coefficients of daily stock return from lag 1 to lag 10 are zero.	247.7	0.000
TURNt-i (i=1,2,…,10)	all coefficients of daily stock trading volume from lag 1 to lag 10 are zero.	58.17	0.000
SHORTt-i (i=1,2,…,10)	all coefficients of daily short volume from lag 1 to lag 10 are zero.	34.71	0.000
PUTt-i (i=1,2,…,10)	all coefficients of daily put volume from lag 1 to lag 10 are zero.	10.15	0.427

Note: the optimal lag length for VAR is between 10 and 15 based on the optimal lag length tests and AIC/SIC test statistics. The results are similar when we employ the VAR when the lag length is allowed to vary between 10 and 15.

Table 4: Vector autoregressive results portioned by short selling and put option trading

This table reports the results of VAR model for daily stock return, stock trading turnover, put ratio, and short ratio partitioned by short ratio and put ratio with the dependent variables as daily stock return. Panel A reports the results based on one-way sorting on short selling and put option trading, and Panel B reports the results based on two-way sorting on short selling and put option trading. The results are estimated with 10 lags and we report the estimates of first 3 lags. *, **, and *** indicate significance at 10%, 5%, and 1% level.

Panel A: One-way sorting results

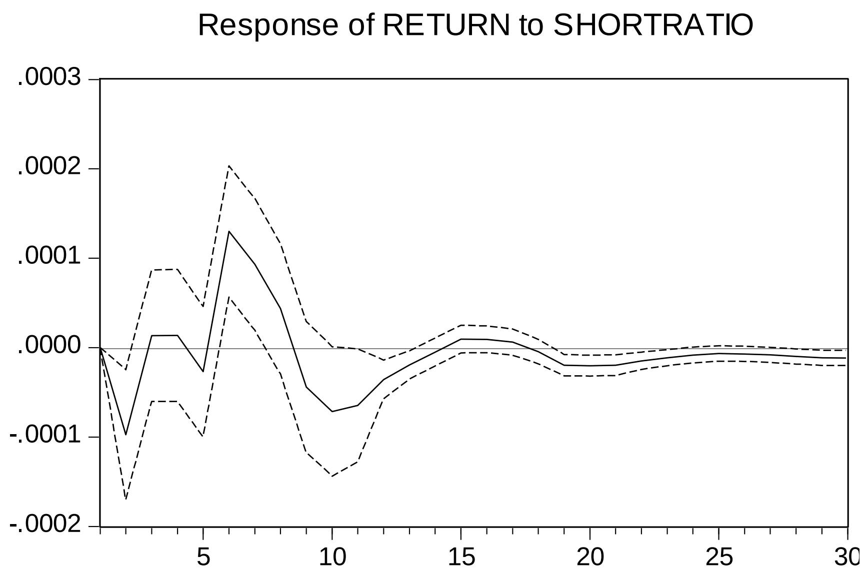
Lagged variables	High put	Low put	High short	Low short
Rt-1	0.003	-0.022***	-0.005	-0.023***
Rt-2	-0.012***	-0.032***	-0.015***	-0.038***
Rt-3	0.000	-0.002	0.002	-0.009**
TURNt-1	0.015	0.076***	0.012	0.061***
TURNt-2	-0.011	-0.033***	-0.015	-0.044***
TURNt-3	-0.021*	0.028**	-0.009	0.014
SHORTt-1	-0.001*	-0.001*	-0.001***	-0.013***
SHORTt-2	0.000	0.000	0.000	-0.002**
SHORTt-3	0.000	0.000	0.000	-0.001
PUTt-1	0.002	0.002	-0.022	-0.198***
PUTt-2	-0.014	-0.035	0.001	-0.227***
PUTt-3	-0.038	0.139	-0.013	-0.127
Adj R-squared	0.002	0.005	0.004	0.019
F-statistic	3.817	7.758	5.533	32.27
Akaike AIC	-5.827	-6.013	-5.822	-6.064

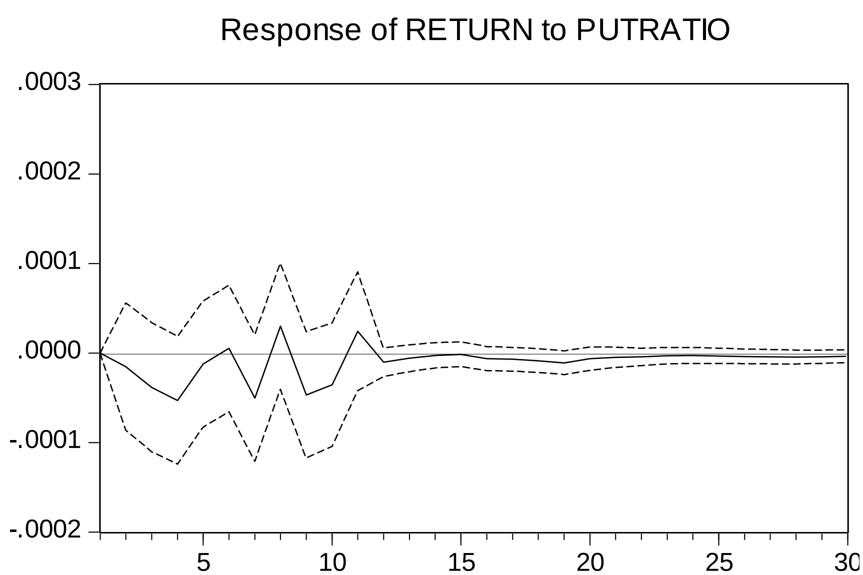
Panel B: Two-way sorting results

Lagged variables	High put		Low put	
	High short	Low short	High short	Low short
Rt-1	0.004	-0.004	-0.015**	-0.039***
Rt-2	-0.008	-0.025***	-0.021***	-0.049***
Rt-3	-0.001	-0.004	0.007	-0.014***
TURNt-1	-0.002	0.032*	0.043***	0.094***
TURNt-2	-0.004	-0.040**	-0.023	-0.049***
TURNt-3	-0.029*	-0.014	0.013	0.046**
SHORTt-1	-0.001**	-0.016***	-0.005***	-0.011***
SHORTt-2	0.000	-0.002*	-0.001	-0.002**
SHORTt-3	0.000	0.000	-0.001	-0.003**
PUTt-1	0.023	-0.167*	-0.123	0.255
PUTt-2	-0.000	-0.166*	0.023	-0.001
PUTt-3	-0.021	-0.167*	0.155	0.229
Adj R-squared	0.003	0.017	0.007	0.024
F-statistic	3.051	13.43	5.844	21.36
Akaike AIC	-5.738	-5.983	-5.926	-6.141

Figures

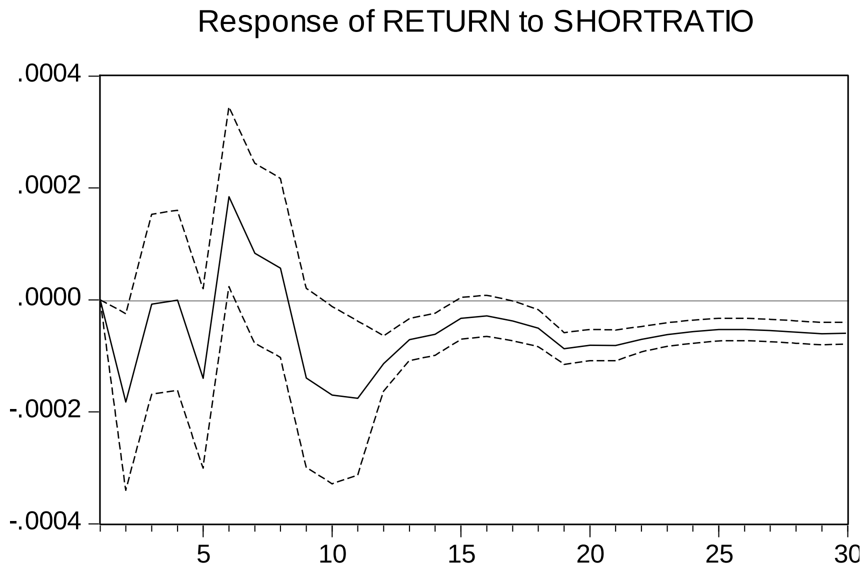
Figure 1: Accumulated impulse responses of stock return to a Choleski one standard deviation shocks in the activities of short selling/put options

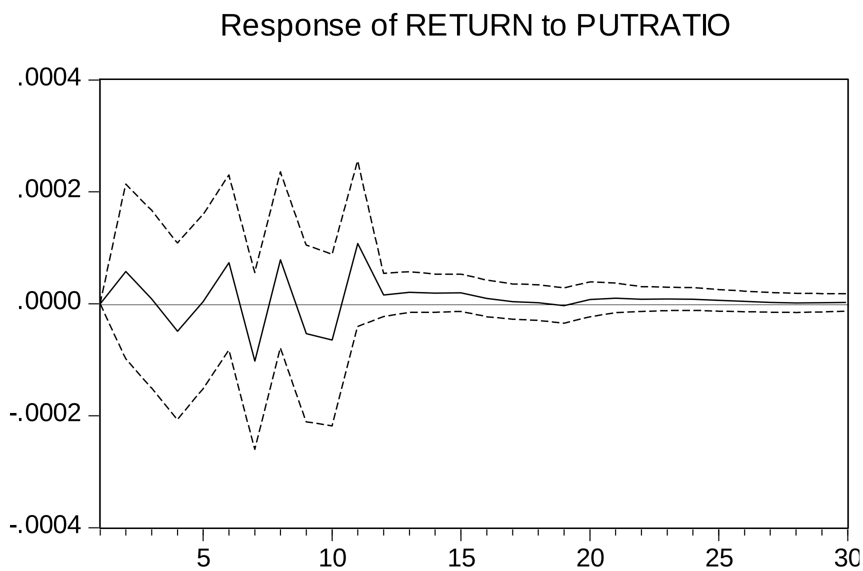




This figure exhibits the impulse responses of daily stock return to one standard deviation shocks in daily short ratio and put to stock ratio based on the VAR estimation in Table 3. The solid line denotes the impulse-response function and the dotted lines are +/- 2s bands.

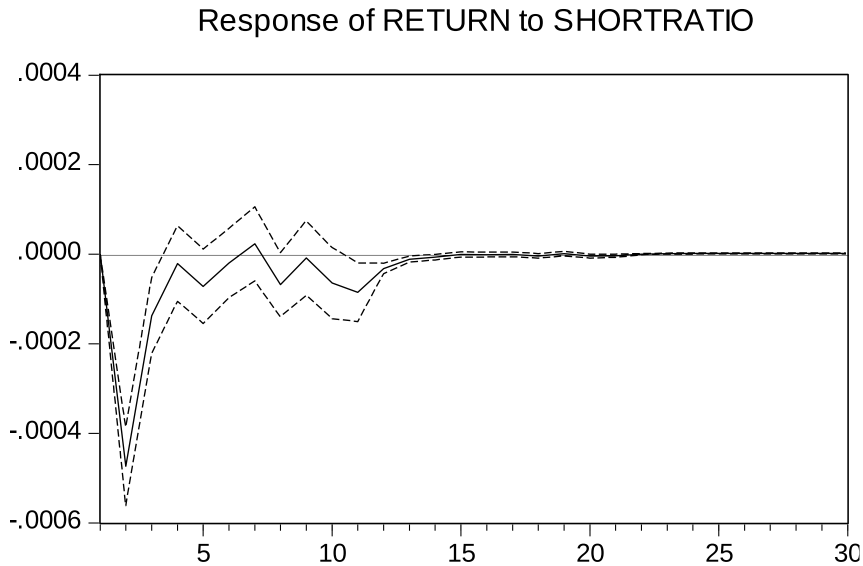
Figure 2: Impulse responses of stock return to a Choleski one standard deviation shocks in the trading activities of short selling/put options: partitioned by shorts selling and put option trading

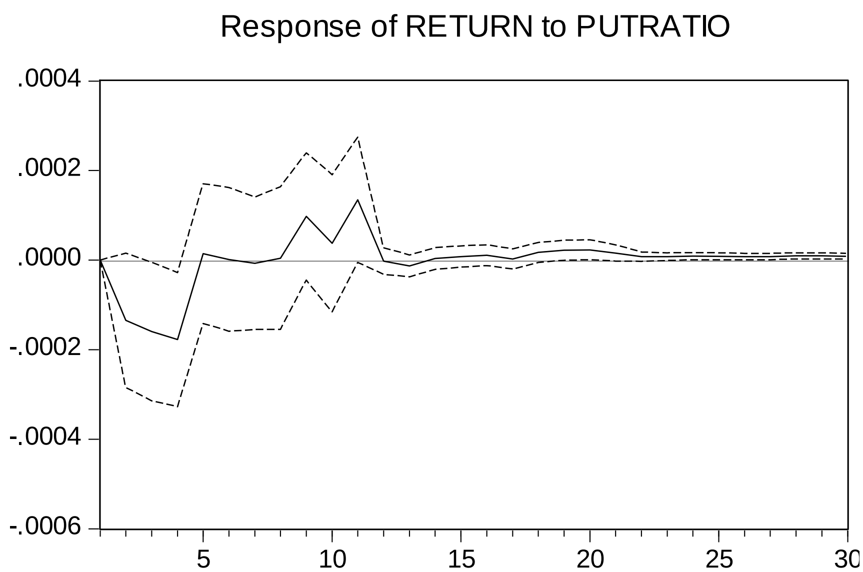




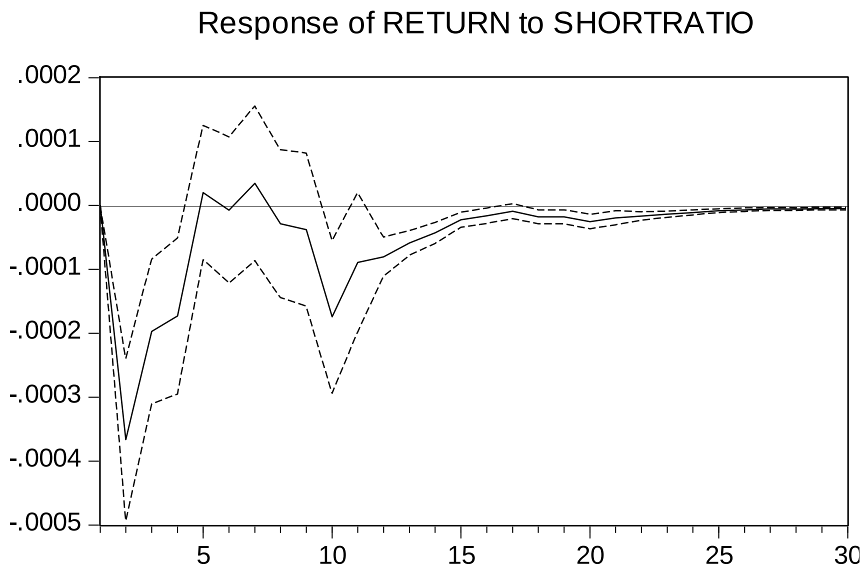
Panel A: Impulse responses for the stocks with both high put and high short ratios

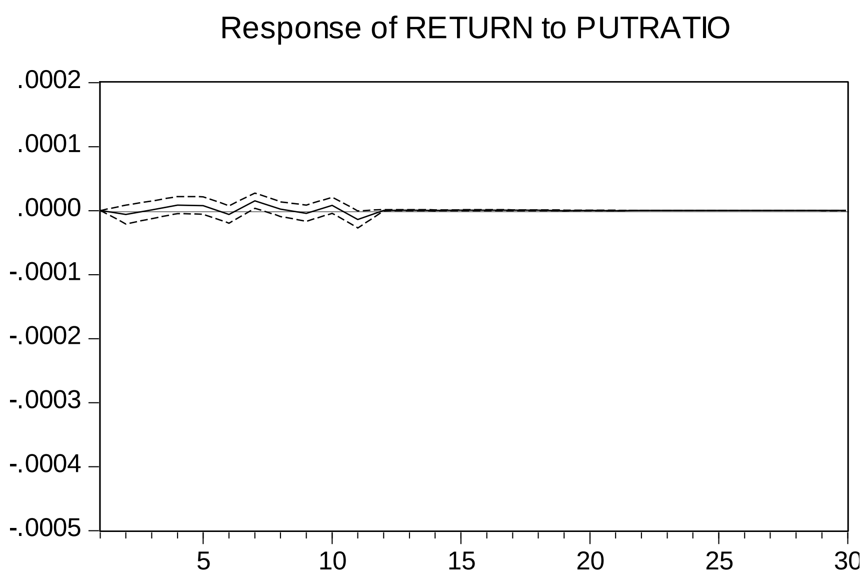
Figure 2, cont'd



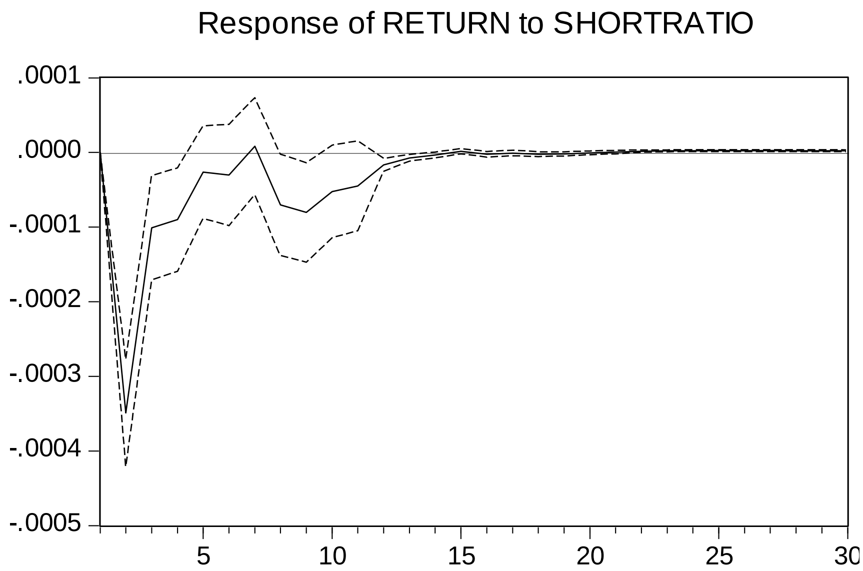


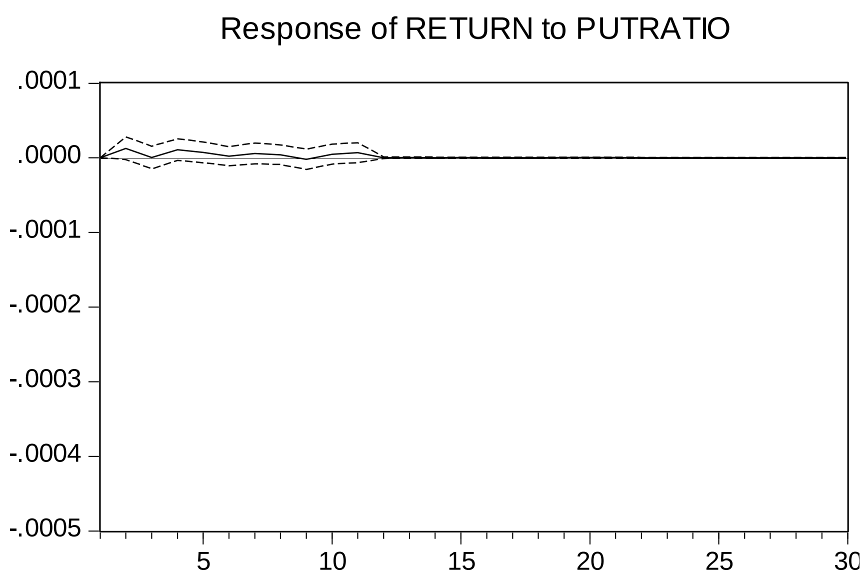
Panel B: Impulse responses for the stocks with both high put and low short ratios





Panel C: Impulse responses for the stocks with both low put and high short ratios





Panel D: Impulse responses for the stocks with both low put and low short ratios

This figure exhibits the impulse responses of daily stock return to one standard deviation shocks in daily short ratio and put to stock ratio based on the VAR estimation in Table 4, partitioned by put-to-stock ratio and short ratio. Panel A exhibits the responses for the stocks with both high put and short ratios, Panel B exhibits the responses for the stocks with high put and low short ratios, Panel C exhibits the responses for the stocks with low put and high short ratios, and Panel D exhibits the responses for the stocks with low put and low short ratios. The solid line denotes the impulse-response function and the dotted lines are +/- 2s bands.

Appendix

Appendix 1: Variable Definitions

Variable name	Definition	Data source
Rt	Daily return (basis point)	CRSP
STOCKVOLt	Daily stock trading volume	CRSP
SHORTVOLt	Daily short volume	NYSE Reg SHO
PUTVOLt	Daily put option trading volume	Option Metrics
PUTt	Put to stock ratio, defined as daily put volume scaled by daily stock trading volume	
SHORTt	Short ratio, defined as aggregate daily short volume scaled by daily stock trading volume	
TURNt	Daily stock turnover	

Appendix 2: Panel unit root tests

This appendix presents the results of panel unit root tests for all key variables used in VAR estimation. Each row presents the results of the unit root tests for the indicated variable. Levin, Lin, Chu test is used for testing common unit root processes; Pesaran and Shin, ADF-Fisher, and PP-Fisher tests are used for testing the individual unit root processes. The numbers in parentheses are p-values.

	Levin, Lin Chu t-stats	Pesaran and Shin W-stat	ADF-Fisher Chi-sq	PP-Fisher Chi-sq
Rt	-165.1	-236.7	41,126	63,318
p-value	(0.000)	(0.000)	(0.000)	(0.000)
STOCKVOLt	-159.4	-125.2	25,199	51,648
p-value	(0.000)	(0.000)	(0.000)	(0.000)
SHORTVOLt	-156.8	-117.1	24,149	50,490
p-value	(0.000)	(0.000)	(0.000)	(0.000)
PUTVOLt	-119.5	-124.8	28,657	50,993
p-value	(0.000)	(0.000)	(0.000)	(0.000)

Note: The null hypothesis for each unit root test here is the data follows a unit root process. For each variable every test can reject the null hypothesis.

Appendix 3: Pair-wise Granger causality tests

This appendix presents the results of Pair-wise Granger causality tests for all key variables used in VAR. The first column states the null hypothesis of the underlying Granger causality of each pair of variables. Test statistics and p-value are reported in the last two columns.

Null hypothesis	Obs	F-Statistic	Prob.
TURN does not Granger Cause R	190,787	8.950	<0.001
R does not Granger Cause TURN		22.06	<0.001
SHORT does not Granger Cause TURN	235,861	5.221	<0.001
TURN does not Granger Cause SHORT		84.32	<0.001
SHORT does not Granger Cause R	179,769	7.055	<0.001
R does not Granger Cause SHORT		25.59	<0.001
PUT does not Granger Cause R	93,356	0.674	0.749
R does not Granger Cause PUT		2.714	0.003
PUT does not Granger Cause STOCKVOL	124,061	32.82	<0.001
STOCKVOL does not Granger Cause PUT		45.05	<0.001
PUTVOL does not Granger Cause SHORT	123,246	40.94	<0.001
SHORT does not Granger Cause PUT		47.37	<0.001

Appendix 4: Vector autoregressive results

This appendix reports the results of VAR model for daily stock return, stock trading turnover, put ratio, and short ratio. The results are estimated with 10 lags. *, **, and *** indicate significance at 10%, 5%, and 1% level.

	1	2	3	4
	Rt	TURNt	SHORTt	PUTt
Lagged Variables				
Rt-1	-0.009***	-0.006***	0.13***	-0.001**
Rt-2	-0.022***	-0.004***	0.233***	0.000
Rt-3	-0.001	-0.004***	-0.083*	0.000
Rt-4	-0.014***	-0.003***	-0.073	-0.000
Rt-5	-0.015***	-0.001	-0.081*	0.000
Rt-6	-0.016***	-0.001*	0.174***	0.001***
Rt-7	-0.009***	-0.000	-0.117**	-0.000
Rt-8	0.007**	0.001	-0.064	-0.000
Rt-9	0.009***	-0.000	-0.240***	-0.000
Rt-10	0.016***	-0.001	-0.184***	-0.000
TURNt-1	0.037***	0.355***	0.718***	0.001
TURNt-2	-0.022***	0.118***	-0.396***	-0.001
TURNt-3	0.002	0.066***	-0.224*	-0.001
TURNt-4	-0.006	0.073***	-0.030	0.001*
TURNt-5	-0.001	0.058***	0.015	0.000
TURNt-6	0.019**	0.047***	0.016	-0.000
TURNt-7	0.003	0.034***	0.175	-0.001
TURNt-8	-0.012	0.047***	0.092	0.000
TURNt-9	0.003	0.036***	-0.315**	-0.001*
TURNt-10	0.012*	0.057***	0.066	0.003***
SHORTt-1	-0.001**	-0.000	0.357***	0.001***
SHORTt-2	0.000	-0.001***	0.059***	0.000
SHORTt-3	0.000	0.000	0.145***	0.001***
SHORTt-4	-0.000	-0.000	0.072***	-0.000**
SHORTt-5	0.000***	-0.000	0.034***	-0.000***
SHORTt-6	0.000	0.000*	0.005	-0.000

Appendix 4, cont'd

	1	2	3	4
	Rt	TURNt	SHORTt	PUTt
Lagged Variables				
SHORTt-7	-0.002	0.000^{**}	0.046^{***}	0.000^{***}
SHORTt-8	-0.001	-0.000	0.088^{***}	-0.000^{***}
SHORTt-9	-0.001	-0.000^{**}	0.051^{***}	0.000^{***}
SHORTt-10	-0.001	0.000^{*}	0.083^{***}	-0.000^{***}
PUTt-1	-0.009	0.045^{***}	1.431^{***}	0.175^{***}
PUTt-2	-0.033	0.014	3.496^{***}	0.130^{***}
PUTt-3	-0.026	0.012	-7.449^{***}	0.056^{***}
PUTt-4	-0.001	-0.021^{**}	-2.569^{***}	0.068^{***}
PUTt-5	0.013	0.007	0.053	0.066^{***}
PUTt-6	-0.032	0.002	3.355^{***}	0.048^{***}
PUTt-7	0.031	0.024^{**}	1.861^{***}	0.064^{***}
PUTt-8	-0.030	-0.030^{***}	2.548^{***}	0.048^{***}
PUTt-9	-0.009	-0.001	1.201^{***}	0.087^{***}
PUTt-10	0.037	-0.004	0.398	0.037^{***}
Adj R-squared	0.002	0.548	0.682	0.525
F-statistic	6.495	3,038	5,380	2,768
Akaike AIC	-5.917	-7.882	-0.288	-10.30