Trading Options and CDS on Stocks under the Short Sale Ban

Sophie Xiaoyan Ni and Jun Pan*

July 1, 2015

Abstract

We examine the interaction between price discovery in banned stocks and the trading and prices of options and CDS during the 2008 short sale ban. We find that in banned stocks with options, (1) stocks with high put-call ratios underperform in the following five days, (2) ratios of synthetic to real stock prices have higher stock return predictability, and (3) stocks with high CDS percentage change have low subsequent returns. Our results suggest that informed investors trade derivatives in severely deteriorated market conditions, and that derivative prices are more informationally efficient than stock prices during the ban.

*Ni is from the Hong Kong University of Science and Technology (sophieni@ust.hk); Pan is from MIT Sloan School of Management and NBER (junpan@mit.edu). We benefited from comments by Charles Cao, Neil Pearson, Adam Reed, Dragon Tang, Wen-lan Qian, Kuo-chiang Wei, Ken Zhong, and participants at the HKUST seminar, Shanghai SAIF 2010 conference, the 21th CFEA held at the University of Maryland and the CICF conference 2011. Financial support from a Hong Kong RGC Research Grant (Project # 642309) is gratefully acknowledged.

1 Introduction

On September 19,2008, shortly after the bankruptcy filing of Lehman Brothers and the government $85 billion bailout of AIG, the Securities and Exchange Commission (SEC) issued an emergency ban on short sale for all financial stocks. The original motivation for SEC to institute such a ban was to prevent further price disruptions and to manage the wide-spread crisis of confidence in financial institutions; however, its effectiveness is questionable and the unintended consequences were many.[1] For example, Battalio and Schultz (2011) examine how the confusion and regulatory uncertainty generated by the imposition of the short sale ban (SSB) affected equity option markets, and find that the short sale ban is associated with dramatically increased bid-ask spreads for options on banned stocks. Grundy, Lim, and Verwijmeren (2012) reach the same conclusion on bid ask spreads and find a significant diminution in option volumes for banned stock relative to unbanned stock during the ban period. They conclude that the ban acted as an effective restriction on trading in options.

The main objective of this study is to examine whether investors use options to trade on negative information during the ban in severely deteriorated market conditions. We first examine the trading behavior in the options market during the SSB. One could think of buying a put on the SSB stock as an indirect but open channel through which any potential negative information about the underlying stock could get in. Our analysis focuses on the banned financial stocks with exchange traded options over the 14-day period between September 19 and October 8.[2] Using data from the Chicago Board of Options Exchange (CBOE) and International Securities Exchange, we construct put call ratios from put and call

[1] See, for example, the New York Times opinion piece by Arturo Bris on September 29, 2008.

[2] Over this time period, there were additions and removals from the original list; we focus on stocks that were banned through out the ban.

option volumes initiated by non-market maker public buyers to open new option positions on the SSB stocks. For each of the 14 days, we sort the SSB stocks by their put-call ratios into three groups: the top and the bottom 20% and the middle 60%. The stocks in the top 20% group are the ones for which options investors express the most negative information. They are also the most useful stocks for us to study, as the SSB has the potential to impede the incorporation of negative information into stock prices. We find that during the ban, this top 20% group underperforms the middle 60% group by 2.13% over the next three-day return and by 4.01% over the next five-day return. The differences are not only economically large, they are statistically significant, even though this test was done over a 14-day window. In contrast, the performance of the bottom 20% group, which relatively speaking options investors are relatively positive about, is not economically or statistically different from that of the middle 60% group.

By performing our analysis on a group of stocks affected by the same short sale ban and examining the predictability cross-sectionally within this group, we provide evidence that investors buy puts to trade on negative information during the ban. The cross-sectional aspect is particularly relevant, given the volatile nature of the severely degraded market at the time. It is, however, useful to perform a few robustness tests. Matching each banned stock with an unbanned stock that also has exchange traded options, we perform the same analysis on the control stocks over the same ban period and find no predictive result in either the top or the bottom 20% group. For the SSB stocks, we also perform the same analysis over the periods immediately before and after the short sale ban, and find no result of predictability.

The second objective of our study is to examine whether options prices are more informa-

tive about the future stock prices during the ban. The information signal we use is the ratio of daily synthetic stock prices to actual stock price (SS). If options prices contain information of stocks, we will see high SS is associated with high subsequent stock returns. For each trading day, we sort the SSB stocks by SS into three groups: the top and the bottom 20% and the middle 60%. We find that the SSB stocks with low SS during the ban experience low returns in following 1-2 days, and the SSB stocks with high SS have high subsequent returns. We do not find that SS of the control stocks during the ban, or the SSB stocks during the non-ban periods have any stock return predictability. Our results suggest that the increased transaction costs during the ban for banned stocks only block noise investors, and some informed traders still find ways to trade options. This leaves traces of information in the options trading and prices for banned stocks during the ban.

The third result of our study focuses on the interaction between credit default swaps and stocks during the short sale ban. Given that CDS is an insurance on the potential default of a firm, it is naturally more sensitive to negative information. It is, however, difficult to obtain trading information on CDS as it is traded over the counter. Moreover, our CDS sample is markedly smaller than the option sample: there are only 60 banned stocks with active CDS quotes. Nevertheless, our result shows that, in the presence of the SSB, it takes time for the negative information already incorporated in CDS spreads to affect stock prices.

For each banned stock, we construct its daily percentage change in CDS spreads, and use this as a CDS signal. Cross-sectionally, a firm with a more positive change in CDS is the one with more negative information. Connecting this signal to stocks, we find that over the 14-day short ban period, if the CDS signal of one banned stock is one standard deviation higher than that of another banned stock, this stock on average underperforms the other by 1.29%

over the next two-day return, and by 2.69% over the next five-day return. Moreover, this predictability is asymmetric, driven mostly by stocks with more positive percentage changes in CDS. Performing the same analysis over the periods immediately before and after the ban or on 60 unbanned control stocks during the ban, we do not find any predictability in percentage changes in CDS. The short sale ban is an important ingredient in generating the CDS predictability, which is consistent with our main result.

Conceptually, our study follows the theoretical work of Diamond and Verrecchia (1987), Miller (1977), and Chen, Hong, and Stein (2002), who state that stock prices tend to be upward-biased by short-sale prohibition or restrictions. Diamond and Verrecchia (1987) predict that when there is a short prohibition that eliminates both informed and uninformed investors, stock price will incorporate negative information with a delay.[3] While Miller (1977) and Chen, Hong, and Stein (2002) model that stocks under short constraints reflect optimistic beliefs and thus have lower future returns.

The effect of the 2008 short ban has been studied in a number of recent papers. Battalio and Schultz (2011) and Grundy, Lim, and Verwijmeren (2012) find that option market liquidity is severely affected and there is no migration of stock investors to the option market to avoid the ban. Our study focuses on the relative information efficiency of stock and option markets during the ban and shows that informed traders still bring information to the options market in the severely deteriorated market conditions. Boehmer, Jones, and Zhang (2009) examine the effect of the ban on the stock market and document that the banned stocks suffer a severe degradation in quality, as measured by spreads, price impacts, and

[3]It is, however, important to point out that the information used to gauge the speed of adjustment is in fact publicly available: both the put-call ratio and the CDS prices can be obtained in real time for a fee.

intraday volatility. Kolasinski, Reed, and Thornock (2009) find that the ban increases the informativeness of short sales, especially for stocks with listed options. Gagnon and Witmer (2009) document price differences between the U.S. and Canadian shares and trading volume migration from U.S to Canada among banking stocks during the ban. Harris, Namvar, and Phillips (2009) use a factor-analytic model to show that the ban led to substantial price inflation in the SSB stocks.

Our study is also related to Sorescu (2000), Danielsen and Sorescu (2001), and Mayhew and Mihov (2005) who focus on option introductions and investigate whether options help to relax binding short sale constraints, and whether options prices contain negative informations. Ofek, Richardson, and Whitelaw (2004) find that violations of put-call parity is asymmetric in the direction of short sale constraints, and the magnitudes are strongly related to the cost of short sale. Given that option introductions and the cost of short sale are generally endogenous, it is difficult to conclusively determine how the presence of the options market or the cost of short sale might affect the underlying stock market. Our study takes advantage of an event that was also highly endogenous, but imposed on a broad enough set of stocks for us to examine cross-sectional differences among the SSB stocks.

Our study is also related to the literature examining the cross-market information transmission between stocks and options. Among others, Easley, O'Hara, and Srinivas (1998) provide a formal framework to examine this issue and Pan and Poteshman (2006) present strong evidence that option trading volume contains information about future stock prices.[4]

[4]One important ingredient of their result is that the option volume information used in their analysis was not publicly available during their sample period. More recently and after the publication of their paper, however, the CBOE started to release such information in real time, and the predictability has decreased markedly. For example, during our very short, but special sample period, we do not find any predictability of put-call ratio for unbanned stocks.

Hu (2014)shows that stock orders from options market makers have power in predicting stock return, and stocks orders from other investors do not. Their findings indicate that this information transmission is present during normal times and the predictability is symmetric with respect to positive and negative information. Cremers and Weinbaum (2010) and Xing, Zhang, and Zhao (2010) document that options prices also contain stock directional information. We focus instead on the short sale ban, and our predictability is asymmetric with respect to the nature of information: the predictability is present only for negative information, but not for positive information.

For the CDS market, Longstaff, Mithal, and Neis (2005) document that there is no lead lag relation between CDS spread and stock prices. Acharya and Johnson (2007) find a negative cross-correlation between CDS changes and future stock returns for entities with credit deterioration and high CDS levels. In more recent studies, Norden and Weber (2009) and Tang and Yan (2011) document that stock prices lead CDS spread changes in daily frequency. However in monthly frequency, Han and Zhou (2010) find that the term structure of CDS is associated with future stock returns.

Finally, our study is related to studies examining the effect of short sale prohibitions and restrictions on stock prices. Bri, Goetzmann, and Zhu (2007) find some evidence that prices incorporate negative information faster in countries where short sales are allowed and practiced. Chang, Cheng, and Yu (2007) analyze the price effects following the addition of stocks to the short list in Hong Kong market, and find that short sale prohibitions tend to cause stock over-valuation. For studies on short restriction, Miller (1977) and Chen, Hong, and Stein (2002) model that stock prices tend to be upward-biased, whereas Diamond and Verrecchia (1987) model that price will be more efficient, especially for negative information.

Some studies use either short interest or rebate rate as a proxy for short restriction, and document that there is a negative relation between short restriction and subsequent stock returns. For example, Asquith and Meulbroek (1996), and Aitken, Frino, McCorry, and Swan (1998) use short interest as a proxy. Jones and Lamont (2002), Geczy, Musto, and Reed (2002), and DAvolio (2002) examine the predictability of rebate rate. And Saffi and Sigurdsson (2010) document that a low stock loan supply is associated with price inefficiency.

The rest of this paper is organized as follows. Section 2 provides some details on the short sale ban and the option and CDS data used in our analysis. Section 3 presents our main result with respect to option trading and future stock returns, Section 4 presents the predictive power of synthetic stock prices, and Section 5 presents the result relating CDS to future stock returns. Section 6 concludes the paper.

2 Short Sale Ban, Data and Summary Statistics

2.1 Short Sale Ban

On September 19, 2008, the SEC issued a short sale ban (SSB) on financial stocks. Initially, the ban covered 797 financial stocks selected by the SEC. On the following trading day, September 22, the SEC allowed exchanges to determine which firms would be included or excluded from the ban. Eventually, around 990 stocks were banned, with some stocks entering and exiting the ban list.

The ban was set to expire in 10 days, but could be extended to 30 days at the SEC's discretion. On October 3, immediately after the rescue plan passed the Congress, the SEC

announced that the ban would expire at 11:59pm ET October 8. The ban lasted 14 trading days, from September 19 to October 8. We choose August 19 to September 18 as the pre-ban period, and October 9 to November 8 as the post-ban period for this study.

2.2 Option Data

The data used to compute the main option trading activity are obtained from CBOE and ISE. The dataset contains daily non-market maker public customer volume for all CBOE and ISE listed options. For each option, the daily trading volume is divided into four types of trades: open buy, in which non-market makers buy options to open new positions; close buy, in which non-market makers buy options to close existing written option positions; open sell, in which non-market makers sell options to open new short positions; and close sell, in which non-market makers sell options to close out existing long options positions. Among these four types of option trades, the information content of the open buy volume is perhaps the highest, as it does not involve any pre-existing option positions or margin requirements. For this reason, our main analysis focuses on option volumes associated with open buys made by public customers. In our analysis, we also use general option volumes obtained from Option Metrics.

During the SSB period, there are 229 banned stocks and 2036 non-banned stocks with options traded on CBOE and ISE. For comparison, we match each optionable SSB stock with an optionable control stock, which is selected by minimizing the sum of the squared percentage differences of stock market capitalization, stock volume, and stock price. The matching is same as that used in Battalio and Schultz (2011), and is done for the August 19

to November 8 period.

Table 1: **Summary Statistics of Stocks with Options**

	SSB Stocks			Control Stocks		
	mean	median	std	mean	median	std
Panel A: Ban Period, Sept 19 - Oct 8						
Open Buy P/P+C (PC)	0.471	0.451	0.369	0.435	0.390	0.366
Put Volume (contracts)	713,464	71,368	2,299,883	607,386	60,804	1,955,880
Call Volume (contracts)	779,988	66,850	2,602,779	642,717	76,757	1,944,299
Option/Stock Volume	0.128	0.069	0.204	0.122	0.062	0.200
Put/Stock Volume	0.068	0.031	0.138	0.058	0.023	0.128
Call/Stock Volume	0.060	0.033	0.097	0.064	0.032	0.103
Panel B: Before Ban Aug 19 - Sept 18						
Open Buy P/P+C (PC)	0.500	0.506	0.362	0.417	0.362	0.367
Put Volume (contracts)	972,510	84,708	3,372,184	658,505	62,092	2,009,665
Call Volume (contracts)	809,980	87,708	3,015,430	712,102	73,912	2,186,903
Option/Stock Volume	0.112	0.058	0.159	0.132	0.063	0.220
Put/Stock Volume	0.058	0.024	0.090	0.058	0.023	0.105
Call/Stock Volume	0.054	0.027	0.089	0.074	0.032	0.144
Panel C: After Ban Oct 9 - Nov 8						
Open Buy P/P+C (PC)	0.478	0.455	0.365	0.421	0.372	0.360
Put Volume	733,014	76,193	2,201,612	668,849	69,368	2,072,386
Call Volume	658,743	87,571	1,904,772	606,150	83,729	1,898,124
Option/Stock Volume	0.107	0.054	0.160	0.108	0.057	0.164
Put/Stock Volume	0.059	0.022	0.113	0.052	0.022	0.098
Call/Stock Volume	0.048	0.027	0.068	0.056	0.029	0.093

Reported are the time-series averages of daily cross-sectional mean, median, and standard deviation. Open Buy P/P+C is the number of put open buy contracts initiated by public investors divided by open buy put plus call contracts of same trade type. Option/Stock Volume is 100 times the number of option contracts divided by stock volume. Call/Stock Volume and Put/Stock Volume are similar variables for call and put contracts.

Table 1 summarizes the option trading activities of the SSB and control stocks before, during, and after the short sale ban. For each variable, we compute the cross-sectional mean, median and standard deviation for every trading day and report their time series averages. In our main analysis, we use the put-call ratio (PC) as an information signal in the options market. The PC is measured as the number of put contracts open bought by public investors divided by the sum of put and call contracts of the same trade type. There is a decreased

activity in open bought put relative to call contracts for the SSB stocks during the ban. This can be seen in two ways. First, the mean and median of the PC of the SSB stocks are lower during the ban than before and after the ban. Second, the difference between the PC of the SSB and the control stocks is also lower during the ban. This result is consistent with the finding of Grundy, Lim, and Verwijmeren (2012), who show that put volume of the SSB stocks decreases during the ban.

The summary statistics of the general option volume also suggest that trading in the option market do not increase during the ban. The option volume of the SSB stocks during the ban is lower than before the ban; the decrease is more obvious for puts than calls. Though the option/stock volume of the SSB stocks is higher during the ban, the enhanced relative option volume should come from decreased stock volume, as the call and put volumes do not increase during the ban.

2.3 CDS Data

The CDS data used in this paper are from CMA via Datastream. During the short ban period, there are 395 stocks with CDS daily closing quotes, among which 60 are SSB stocks. We select 60 control stocks from the non-SSB stocks using the same matching method as before. Specifically, control stocks are selected by matching stock market capitalization, stock trading volume and stock price.

Table 2 summarizes the CDS data during, before and after the ban. The SSB stocks on average have higher CDS spread than the control stocks during the ban, and this is reflected in both the cross-sectional mean and median. For example, the average CDS spread is 629.63

Table 2: **Summary Statistics of SSB and Control Stocks with CDS**

	SSB			Control		
	mean	median	std	mean	median	std
Panel A: Ban Period, Sept 19 - Oct 8						
CDS Spread (bp)	629.63	198.86	950.54	452.91	179.86	679.55
CDS Daily Change (bp)	20.99	0.79	135.80	15.43	2.29	91.40
CDS Daily Percentage Change (%)	1.21	0.54	11.17	2.30	1.52	6.43
Panel B: Before Ban, Aug 19 - Sept 18						
CDS Spread (bp)	442.50	150.84	762.53	361.02	157.20	545.55
CDS Daily Change (bp)	7.73	0.79	125.66	-1.21	0.58	35.41
CDS Daily Percentage Change (%)	1.36	0.61	10.70	0.56	0.54	5.00
Panel C: After Ban, Oct 9 - Nov 8						
CDS Spread (bp)	916.12	248.40	1404.23	866.60	342.64	1281.19
CDS Daily Change (bp)	10.09	2.20	161.04	32.87	4.67	240.25
CDS Daily Percentage Change (%)	0.56	0.99	10.61	2.87	1.90	9.15

Reported are the time-series averages of cross-sectional mean, median, and standard deviation.

bps for the SSB stocks, compared with 452.91 bps for the control stocks. Before and after the ban, however, this relation is somewhat mixed, depending on whether the mean or median is used in the comparison. We also find that the SSB sample is more dispersed with a higher cross-sectional standard deviation. Overall, there is a general pattern of increasing CDS spreads for both the SSB and the control stocks as the broad economic condition worsens over the sample period.

3 Option trading and future stock returns

3.1 Main Results

In this section we use an option signal to investigate whether the short sale prohibition reduces the speed of stock price adjustment to negative information. During the ban, investors in the option market can still purchase puts to bet on declining stock price. If option trading

contains information, and stock prices incorporate negative information with a delay, we expect an option signal with negative information to have stronger predictability for future stock returns than an option signal with positive information. Our main empirical investigation is to test this asymmetric predictability for the SSB stocks during the SSB period. We expect this particular predictability to be less obvious for control stocks during the ban or the SSB stocks during non-ban periods.

The option signal we use is the put call ratio (PC) calculated as follows:

$$PC_t^i = P_t^i/(P_t^i + C_t^i), \tag{1}$$

where P_t^i is the number of non-market maker public investor open purchased put contracts for stock i on date t, and C_t^i is the same number for call contracts. In main the analyses, we select sample stocks with at least 50 contracts of open purchased volume to exclude the possibility that the result is driven by stocks with little option trading.

Table 3 reports the future five day returns of the portfolios sorted on put call ratios. We sort stocks into quintiles for every trading day, then compute each quintile's following five trading day cumulative returns. The first quintile includes stocks with low put call ratios, and the fifth quintile has stocks with high put call ratios. We report four different measures of returns; equal and value weighted raw returns, and equal and value weighted risk adjusted returns. When constructing the risk-adjusted returns, we use a four-factor model of market, size, value and momentum to remove the systematic component, and we estimate the factor betas using daily returns from August 2007 to July 2008.

Consistent with the argument that negative information spreads more slowly on stock

Table 3: **Returns of Stock Quintiles Sorted on Open Buy Put/Call Ratios (PC)**

	Raw. E	Raw. V	Ex. E	Ex. V	Raw. E	Raw. V	Ex. E	Ex. V
	SSB during the ban				**Control during the ban**			
Low PC	-1406.94	-1416.47	322.99	317.10	-1264.29	-1259.84	356.03	7.11
2	-1235.37	-1269.52	310.07	285.21	-1318.03	-1353.93	337.14	115.41
3	-1296.72	-1290.28	371.25	283.63	-1291.93	-1225.43	271.21	322.04
4	-1517.00	-1369.89	347.98	259.29	-1126.31	-1112.25	400.19	192.51
High PC	-1698.00	-1722.08	-10.37	25.32	-1247.07	-1285.22	338.33	237.84
3 - L	110.23	126.19	48.26	-33.47	-27.64	34.41	-84.82	314.93**
t	(1.06)	(0.99)	(0.63)	(-0.53)	(-0.36)	(0.38)	(-1.06)	(3.19)
H - 3	-401.29**	-431.80**	-481.62**	-258.31**	44.86	-59.79	67.12	-84.20
t	(-4.45)	(-5.08)	(-4.35)	(-2.42)	(0.82)	(-0.79)	(0.92)	(-1.60)
	SSB before the ban				**SSB after the ban**			
Low PC	45.22	-99.23	87.49	101.66	398.23	-98.63	70.35	0.24
2	-148.44	-14.87	68.84	52.02	94.57	107.66	-52.29	-75.94
3	-68.59	-189.47	118.83	-29.08	-8.99	-12.20	-306.34	-327.79
4	-118.40	-332.67	109.66	-147.31	92.52	37.22	-243.20	-198.89
High PC	122.73	109.44	189.03	129.72	-197.11	-17.63	-322.54	-182.06
3 - L	-113.81	-90.24	31.34	-130.74	-407.22**	86.43	-376.69**	-328.02**
t	(-1.67)	(-0.55)	(0.50)	(-1.43)	(-2.39)	(0.73)	(-2.85)	(-2.62)
H - 3	191.32**	298.91	70.21	158.80	-188.12	-5.43	-16.19	145.72
t	(3.02)	(1.77)	(1.29)	(1.52)	(-1.53)	(-0.05)	(-0.19)	(2.15)

The quintiles are formed based on open buy put call ratios on day t. The returns are in basis points from day t to $t+5$. Raw E. is the equal weighted raw returns, Raw V. is the value weighted raw return, Ex. E. is the equal weighted excess return adjusted for four risk factors, and Ex. V. is the value weighted excess returns. The t-stats adjusted for Newey West (1987) serial correlation and heteroskedasticity are in parentheses. **: significant at 5%.

prices under the SSB, we see that for the SSB stocks during the ban, the high PC quintile has the lowest future returns for all four different return measures, and the differences between the fifth and the third quintiles are all significantly negative, whereas the differences between the third and the first quintile are not statistically different from zero. For example, in equal weighted five day raw returns, the high PC quintile underperforms the third quintile by 401.29 basis points (t-stats: -4.45), whereas the return difference between the third and the first quintiles is only 110.23 (t-stats: 0.58). In contrast, we do not observe a similar pattern in the control stocks during the ban or in the SSB stocks during the non-ban periods; the high put call ratio quintiles do not have the lowest returns, and the return differences between the high and the third quintile are not statistically significantly negative.

It can be seen from Table 3 that the returns are large in magnitude; the weekly raw (abnormal) returns are in the order of -15% (3%) for the portfolios formed during the ban. These results are due to the extremely volatile market and the worsening economic condition during the ban; the average S&P500 weekly return during the same period is -9.5%. The large abnormal returns also suggest that it is difficult to find a model that captures risks during a crisis. Thus, in the following empirical analysis, we focus on the raw returns.[5]

We conduct a regression analysis to test the asymmetric predictability of the option signal using the following specification:

$$R^i_{t,t+\tau} = a + b^L\, PCL^i_t + b^H\, PCH^i_t + c\, \ln(\text{size}^i_t) + f\, R^i_{t-5,t} + g\, \text{shortInt}^i_t + \epsilon^i_t \qquad (2)$$

where $R^i_{t,t+\tau}$ with $\tau = 1, 2, \ldots, 5$ is the future τ-day cumulative raw return for stock i. In

[5]The results remain similar if common risk factor adjusted returns are used.

our test, we also use $R^i_{t+1,t+1+\tau}$ as the dependent variable to follow the procedure of skipping one day between the portfolio formation and the evaluation periods. PCL^i_t and PCH^i_t are proxies for positive and negative information signals, respectively. If stock i is in the low put call ratio (PC) quintile on date t, we assign PCL^i_t to be one, and zero otherwise. Likewise, if stock i is in the high PC quintile on date t, we assign PCH^i_t to be one, and zero otherwise. We include market capitalization (Size^i_t) as a control because size influences information efficiency and returns. $R^i_{t-5,t}$ is the return from date $t-5$ to date t. We use this lagged return to control for potential contrarian effects arising from market illiquidity. shortInt^i_t is the daily short interest divided by shares out standing. We add this variable to exclude the possibility that the predictability based on option volume is the same as the well-known predictability based on short interest.[6]

If short sale prohibition slows down the adjustment of stock prices to negative information and this negative information is contained in the trading of put options, we expect the coefficient b^H to be negative for the sample of SSB stocks during the ban. In contrast, the coefficient b^L picks up the positive side of the information content and is less affected by the ban, we expect it to be less significant than b^L. Moreover, this asymmetry between b^H and b^L would present for the SSB stocks during the ban, but not for the control stocks during the ban or the SSB stocks in non-ban periods.

Our results are summarized in Table 4. For the sample of SSB stocks during the ban, the coefficients on PCH are negative and statistically significant from day 3 to 5, whereas the coefficients on PCL are mixed in sign and not significantly different from zero. When the dependent variable is future three-day (five-day) returns, the coefficient estimate on PCH

[6]Daily short interest data are obtained from Data Explorers.

is -219.07 with t-stats -2.56 (-336.63 with t-stats -3.06). On the contrary, the estimates on PCL are all not statistically different from zero. This result indicates that relative to the average SSB stocks, those SSB stocks in the top put call ratio(PC) quintile underperform by 2.19% and 3.36% over the next three and five business days, respectively, while those SSB stocks in the bottom PC quintile do not outperform. Table 4 also shows skipping one day between portfolio formation and measurement periods does not change the result.

The right Panel of Table 4 reports the results for the control sample during the ban. We do not find any predictability from put call ratios: neither the coefficients on PCH nor those on the PCL are statistically significant. Table 4 also shows there is not much difference between the SSB and the control stocks for the coefficient estimates on control variables. In general, the estimates on size are positive and the estimates on lagged returns and short interest are negative in general.

Table 4: **Future Stock Returns and Option Trading**

	SSB stocks during the ban						**Control stocks during the ban**					
τ	*Const*	PCL_t^i	PCH_t^i	size_t^i	$R_{t-5,t}^i$	shortInt_t^i	*Const*	PCL_t^i	PCH_t^i	size_t^i	$R_{t-5,t}^i$	shortInt_t^i
Panel A: not skip one day between portfolio formation and evaluation												
1	-1700.23**	171.22	22.46	49.89	-0.14**	-0.05	-774.58**	-4.49	69.27**	11.98	-0.05**	-0.05
	(-3.39)	(1.78)	(0.42)	(1.75)	(-2.36)	(-1.79)	(-3.57)	(-0.11)	(3.05)	(0.99)	(-2.10)	(-1.51)
2	-1388.41**	56.78	-92.76	33.49	-0.17**	0.01	-980.07**	-46.44	47.45	10.77	-0.08**	-0.03
	(-2.53)	(0.48)	(-1.14)	(1.23)	(-2.59)	(0.24)	(-2.87)	(-0.58)	(1.52)	(0.61)	(-2.96)	(-1.28)
3	-1086.94	-45.51	-219.82**	24.00**	-0.13	-0.02	-1390.87**	-24.46	46.42	34.67**	-0.07**	-0.04
	(-1.64)	(-0.47)	(-2.56)	(0.67)	(-3.26)	(-0.83)	(-3.01)	(-0.30)	(1.13)	(2.30)	(-3.83)	(-1.53)
4	-1481.30**	-64.55	-176.76**	42.73**	-0.07	-0.02	-1528.74**	0.53	70.31	35.36**	-0.04	-0.05
	(-2.05)	(-0.59)	(-2.11)	(1.45)	(-1.95)	(-0.57)	(-3.62)	(0.01)	(1.24)	(2.85)	(-1.04)	(-1.82)
5	-1658.87**	-49.15	-336.63**	38.02	-0.04	-0.04	-1835.88**	45.47	87.06	34.44	-0.01	-0.03
	(-2.33)	(-0.36)	(-3.06)	(1.02)	(-1.48)	(-1.30)	(-3.36)	(0.55)	(1.43)	(1.80)	(-0.32)	(-1.21)
Panel B: skip one day between portfolio formation and evaluation												
1	-780.23**	14.21	62.35	31.63**	-0.04	-0.02	-313.69	-29.71	29.37	0.46	-0.03	-0.03
	(-3.53)	(0.26)	(1.56)	(3.25)	(-1.11)	(-0.76)	(-1.66)	(-0.77)	(1.20)	(0.03)	(-1.05)	(-1.36)
2	-277.15	-50.74	-76.48	-5.37	-0.06	-0.04	-420.08	-54.86	-6.08	3.74	-0.05	-0.04
	(-0.39)	(-0.35)	(-0.84)	(-0.23)	(-1.48)	(-1.35)	(-1.21)	(-1.00)	(-0.13)	(0.26)	(-2.46)	(-1.59)
3	-42.44	-149.04	-213.60**	-9.48	-0.03	-0.04	-832.58	-60.55	-5.21	19.20	-0.04	-0.04
	(-0.05)	(-1.10)	(-2.85)	(-0.27)	(-0.96)	(-1.24)	(-1.78)	(-0.95)	(-0.09)	(1.44)	(-1.75)	(-1.21)
4	-600.47	-154.26	-176.61**	-6.84	0.01	-0.05	-1111.86**	-28.44	9.40	26.48**	0.01	-0.04
	(-0.73)	(-1.05)	(-2.38)	(-0.17)	(0.23)	(-1.42)	(-2.85)	(-0.45)	(0.17)	(3.92)	(0.23)	(-1.65)
5	-696.98	-131.99	-313.10**	0.57	0.05	-0.06	-1318.43**	10.28	27.55	20.72	0.02	-0.06
	(-0.80)	(-0.81)	(-3.59)	(0.01)	(1.23)	(-1.72)	(-3.91)	(0.14)	(0.67)	(1.42)	(0.46)	(-1.66)

Daily cross-sectional regression of cumulative excess returns $R_{t,t+\tau}^i$ (in basis points) on the high and the low put call ratio dummies (PCH_t^i and PCL_t^i). On each day t, stocks within the respective sample are sorted by open buy put call ratios; those ranked above 80% have $PCH_t^i = 1$ and those below 20% have $LPC_t^i = 1$. Controls include the log of sizes, five day lagged returns ($R_{t-5,t}^i$), and short interest to shares outstanding ratio ($shortInt_t^i$). Fama-MacBeth t-stats adjusted for Newey and West (1987) serial correlations are reported in parentheses. ** significant at 5% level.

As a comparison, we also perform the same regression analysis for the SSB stocks from the non-ban periods. Figure 1 reports the 95% confidence interval for the coefficient estimates on PCH and PCL. To check if the predicted returns are reversed, we report the results for up to ten days returns. It can be seen that the predictability of PCH during the ban does not reverse after ten days. Right before and after the ban, PCH and PCL of the SSB stocks do not contain information about future stock returns.

3.2 Daily Coefficients

Given that the short sale ban lasts only for 14 trading days, and that the market is extremely volatile during the sample period, it is possible that the asymmetric predictability of the put call ratios of the SSB stocks is driven by a few extreme observations. To examine this possibility, we plot the daily coefficient estimates from the Fama-Macbeth regression on the high put call ratio dummy (PCH). The results are shown in Figure 2, where the dependent variables are future five-day returns. We can see that PCH can predict banned stock returns on most of the trading days during the ban. Thirteen out of fourteen coefficients on PCH are negative. Thus our finding is not driven by a few extreme observations.

It is worth noting that the only day when PCH has no predictability is the first trading day of the ban, September 19. On that day, SEC granted option market makers to sell short until 11:59 pm on the same day to facilitate the expiration of options; this suggested that option market makers would not be able to make short sales afterwards.[7] In the early morning of the second trading day of the ban, the SEC amended the ban and allowed option market makers to short sell, in view of option market can not function if market makers are

[7]See SEC Release 34-58572, September 18, 2008.

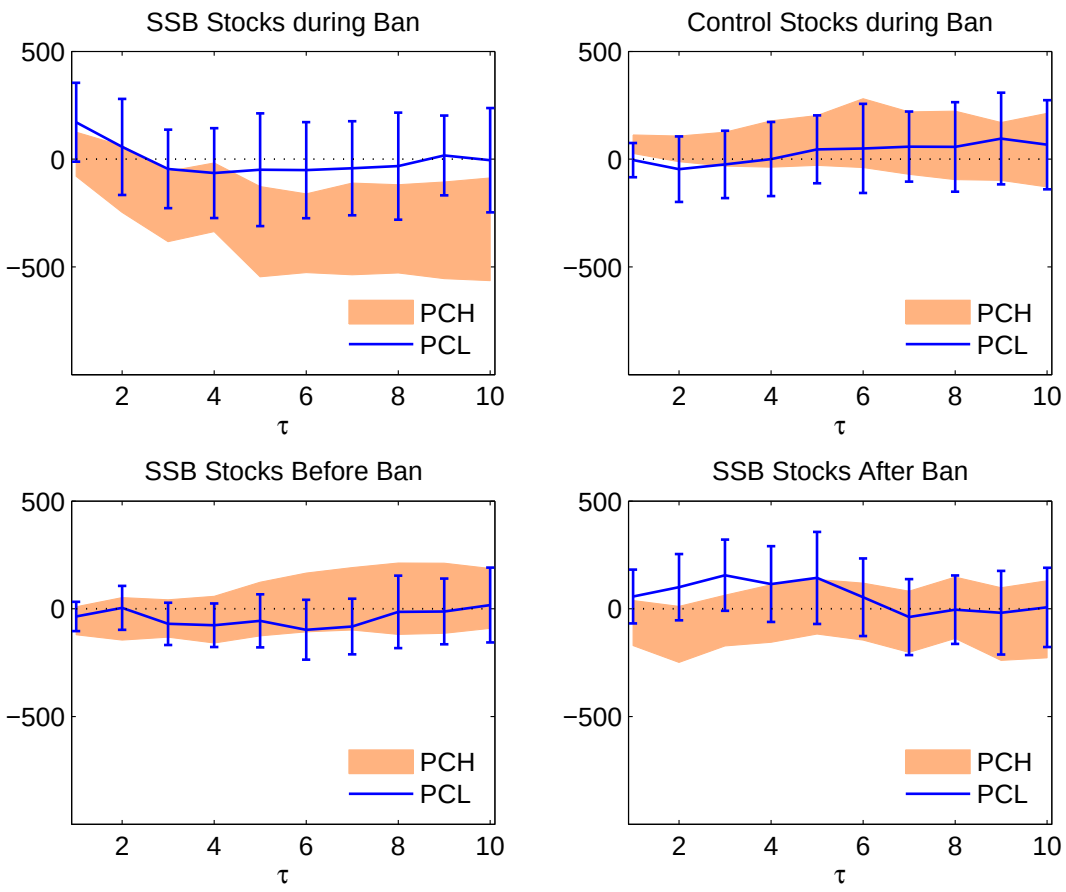

Figure 1: **95% Confidence Interval of Coefficient Estimates on PCH and PCL.** The dependents are future one day to ten day cumulative returns. The controls are log sizes, lagged five day returns and short interest relative to shares outstanding.

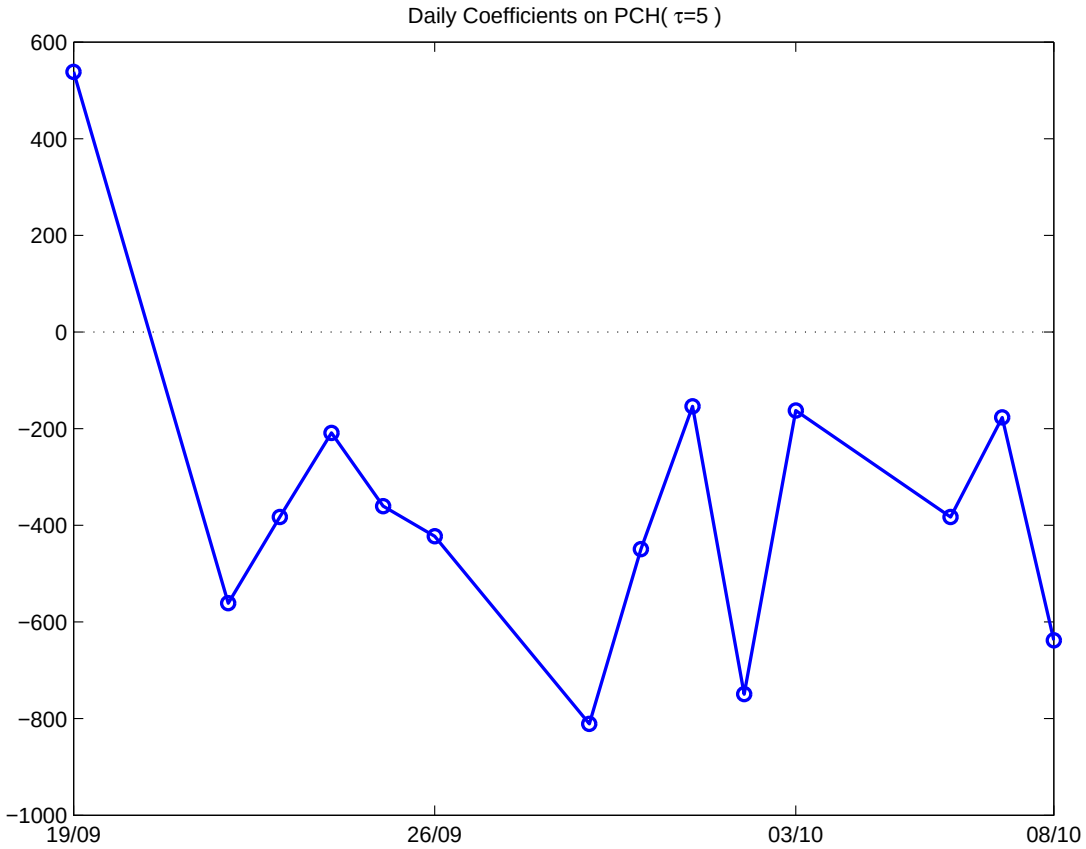

Figure 2: **Daily Coefficient Estimates on High Put Call Ratio Dummy (PCH).** The dependent is future 5 day cumulative returns in basis points. PCH is dummy for stocks ranked above 80%. Other independent variables are low put call ratio dummy, log sizes, lagged five day returns and short interest

not allowed to short.[8] The positive coefficient on PCH on the first day of the ban implies that when option market makers are prohibited from short selling, they are unwilling to sell puts to retail investors, and this option trading does not contain negative information.

3.3 Different Trade Sizes

We now examine the information content of options by breaking down open buy option volumes into different trade sizes. In the CBOE and ISE option data, each type of volume is subdivided into small, large and medium trades. Small trades are orders less than 100 contracts, large trades are orders larger than 199 contracts, and medium trades are in between.

As specified in equation (4), we regress future stock returns on the high and the low put call ratio (PC) dummies constructed from open buy volumes of different trade sizes. To generate enough observations, we include all of the stock-days with at least one contract of open buy volume. Figure 3 reports the 95% confidence interval for the coefficient estimates on the high and the low PC dummies for the SSB stocks. Similar to the main results, a prediction for different trades occurs on the high PC dummy (PCH), but not on the low PC dummy (PCL) during the ban. PCH constructed from small and large trades has stronger predictability than that constructed from medium trades, because volume from medium trades only accounts for 10% of the volume initiated by public investors, whereas the portions from small or large trades are above 40%. Figure 3 also shows that for all three types of trades, neither PCH nor PCL predicts stock returns the during non-ban periods.

[8] See 'Options Market Makers Get Relief from SEC Ban on Short-Selling', Traders Magazine Online News, September 22,2008.

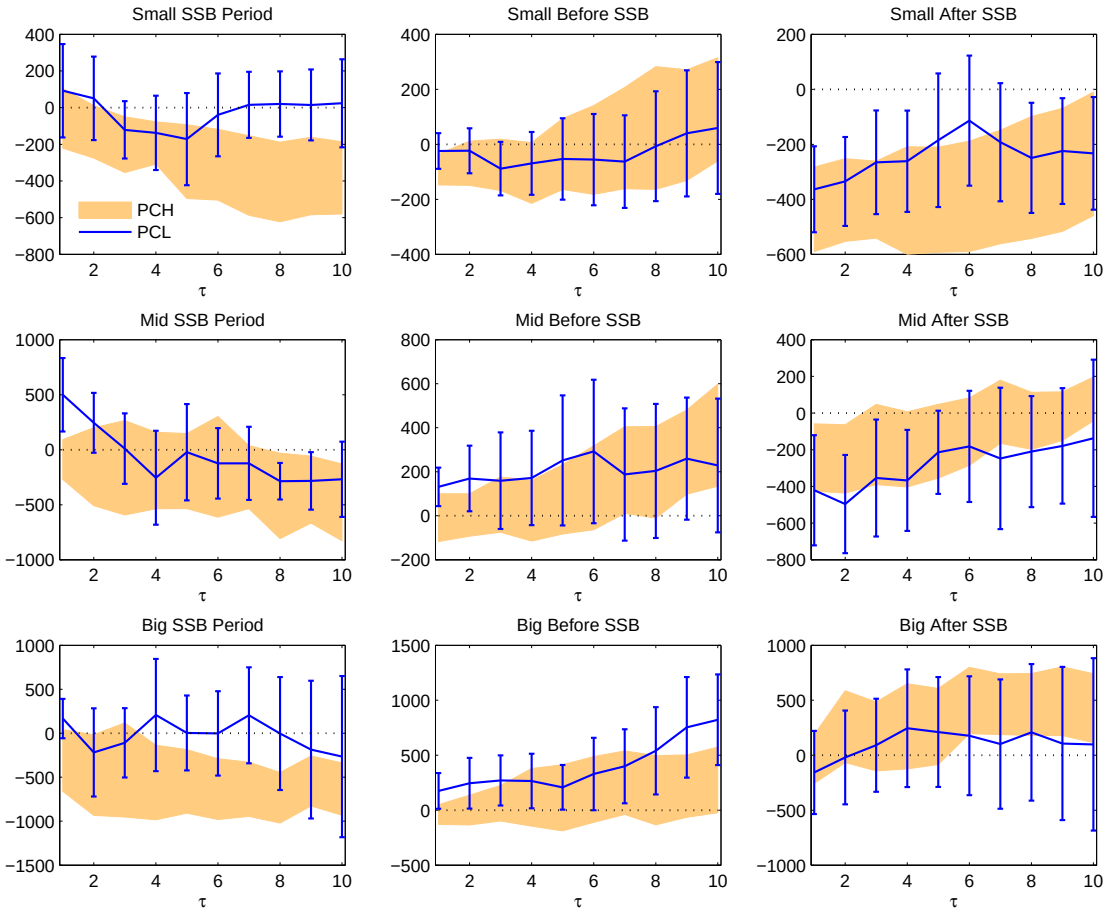

Figure 3: **95% Confidence Interval of Coefficients Estimates on PCH and PCL of Different Trade Sizes.** The dependents are the future one day to ten day stock cumulative returns in basis points. On each day t, SSB stocks are sorted by open buy put call ratios. PCH is dummy for stocks ranked above 80%, and PCL is dummy for stocks ranked below 20%. The controls are log sizes, lagged five day returns and short interest relative to shares outstanding.

4 Synthetic Stock Prices from Options Prices

In this section, we examine how the ban influences the stock directional information in options prices. The previous section presents evidence that during the ban investors buy puts to trade on negative information. As suggested by Garleanu, Pedersen, and Poteshman (2009), the demand pressure from put will increase the put price, and consequently reduce the synthetic stock prices. In our test, we use the ratios of synthetic stock price to stock price (SS) as the signal of stock price information in options prices. We calculate this as follows:

$$SS_t^i = \frac{C_t^i + K^{-r(T-t)} - P_t^i + EEP_t^i}{S_t^i} \tag{3}$$

In the above equation, C_t^i and P_t^i are the one month ATM call and put prices at 3:45 pm ET day t for stock i; S is the stock price at the same time. EEP is the early excise premium of American put.

We conduct a regression analysis to test the predictability of the signal in options prices using the following specification:

$$R_{t,t+\tau}^i = \alpha + \beta^L \, LSS_t^i + \beta^H \, HSS_t^i + c \, \ln(\text{size}_t^i) + f \, R_{t-5,t}^i + g \, \text{shortInt}_t^i + \epsilon_t^i \tag{4}$$

where $R_{t,t+\tau}^i$ with $\tau = 1, 2, \ldots, 10$ is the future τ-day cumulative raw return for stock i. HSS_t^i and LSS_t^i are proxies for the positive and the negative information signals, respectively. If stock i is in the low SS quintile on date t, we assign LSS_t^i to be one, and zero otherwise. Likewise, if stock i is in the high SS quintile on date t, we assign HSS_t^i to be one, and zero otherwise. We include market capitalization (Size_t^i), previous five day returns ($R_{t-5,t}^i$), and

short interest (shortInt_t^i) as controls.

Figure 4 plots β^L and β^H and their 95% confidence intervals. For the sample of SSB stocks during the ban, the confidence intervals of β^L are well below zero, and that of β^H are marginally above zero. For the control stocks during the ban, and the SSB stocks during non-ban periods, neither HSS nor LSS have predictive power for stock returns, suggesting that during the ban the options prices are more informative about the directional information of the banned stocks.

5 CDS and future stock returns

During the ban, investors in CDS market can still buy CDS to profit on negative information. Given that CDS is an insurance against the default of a firm, it is naturally a more sensitive to negative information, making it a good candidate for our analysis. Cross-sectionally, a firm with more positive change in CDS has more negative information. If the short sale ban reduces the speed of the stock price adjustment to negative information, and if trading affects CDS spread as documented in Tang and Yan (2011), we expect an increase in CDS to predict a low future stock return. To test this predictability, we use the following model:

$$R^i_{t,t+\tau} = a + b\,\Delta CDS^i_t + c\,\ln(\text{size}^i_t) + d\,R^i_{t-5,t} + \epsilon^i_t\,, \tag{5}$$

$$\text{where } \Delta CDS^i_t = 100\%\text{ x }(CDS^i_t - CDS^i_{t-1})/CDS^i_{t-1}\,, \tag{6}$$

where $R^i_{t,t+\tau}$ is the cumulative return of stock i from trade day t to $t+\tau$, ΔCDS^i_t is the percentage change of CDS from date $t-1$ to date t, and $R^i_{t-5,t}$ is past five day return. If the

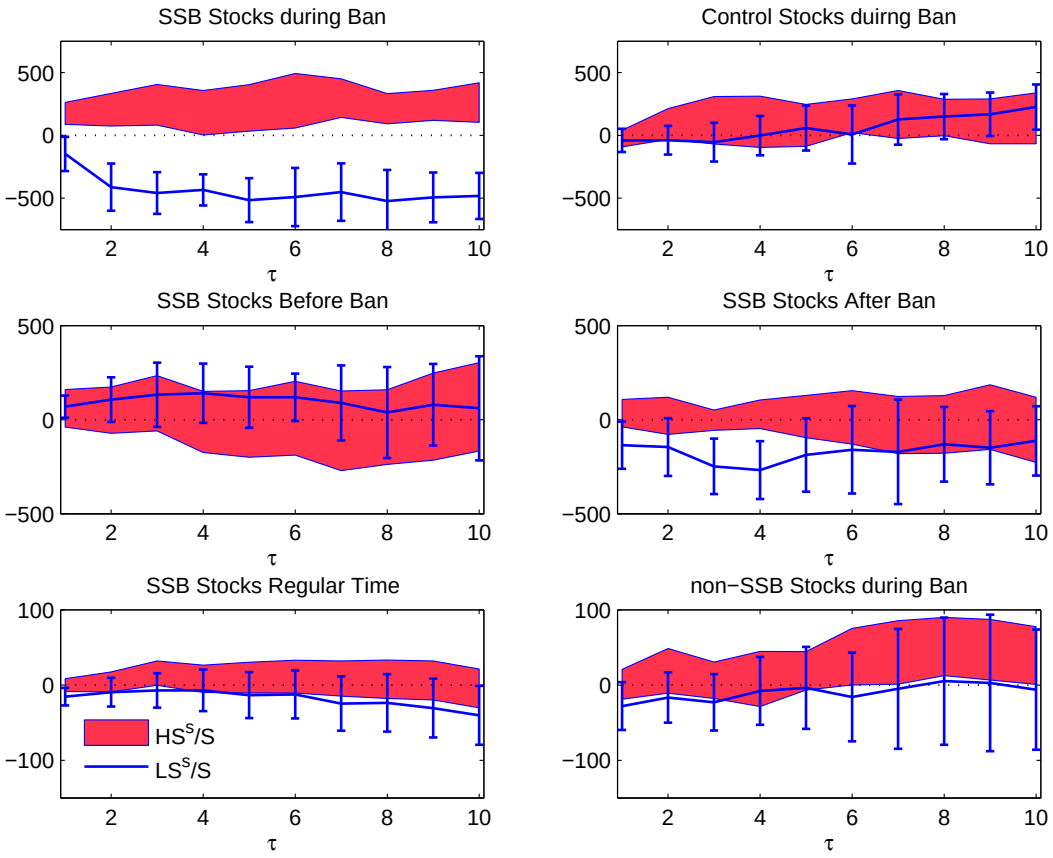

Figure 4: **95% Confidence Interval of Coefficients Estimates on $S^S H$ and SSL of Different Trade Sizes.** The dependents are the future 1 day to 10 day stock cumulative returns in basis points. On each day t, SSB stocks are sorted by open buy put call ratios. PCH is dummy for stocks ranked above 80%,

short sale ban slows down the stock price adjustment to negative information, the coefficient on ΔCDS_t^i will be negative for the SSB stocks during the ban, but not different from zero for the control stocks during the ban or the SSB stocks during the non-ban periods.

Table 5: **Future Stock Returns and Percentage Changes of CDS**

Panel A. The SSB and control stocks during the ban

	SSB stocks				Control stocks			
τ	const	ΔCDS_t^i	Size_t^i	$R_{t-5,t}^i$	const	ΔCDS_t^i	Size_t^i	$R_{t-5,t}^i$
1	-1171.27**	-8.90**	48.05	-0.12**	-574.05**	0.92	22.56**	-0.01
	(-2.59)	(-1.89)	(1.73)	(-2.25)	(-2.48)	(1.48)	(2.35)	(-0.25))
2	-1622.90**	-11.53**	58.39**	-0.15**	-850.10**	1.18	27.51	-0.04
	(-3.86)	(-2.61)	(2.05)	(-2.18)	(-2.26)	(0.90)	(1.84)	(-0.92)
3	-2056.30**	-19.34**	71.59**	-0.14**	-1169.61**	2.12	37.99**	-0.06
	(-5.40)	(-1.96)	(2.27)	(-2.47)	(-2.81)	(1.09)	(2.41)	(-1.29)
4	-2247.7**6	-24.41**	78.75**	-0.12**	-1484.21**	1.20	49.14**	-0.04
	(-4.57)	(-1.91)	(2.75)	(-2.04)	(-2.37)	(0.49)	(2.06)	(-0.70)
5	-2679.22**	-24.07**	92.1**	-0.07	-1788.24**	1.34	56.58**	-0.07
	(-5.39)	(-2.01)	(2.92)	(-1.44)	(-3.92)	(0.56)	(2.25)	(-0.98)

Panel B. The SSB stocks during non-ban periods

	Before Ban	After Ban	Regular Time
τ	ΔCDS_t^i	ΔCDS_t^i	ΔCDS_t^i
1	-5.81	0.41	-1.52
	(-1.64)	(0.10)	(-1.29)
2	-8.79	4.21	-1.98
	(-1.49)	(0.92)	(-1.40)
3	-5.92	7.82	-1.26
	(-0.57)	(1.10)	(-0.69)
4	-10.37	5.71	-1.98
	(-0.87)	(0.75)	(-0.96)
5	-8.19	4.38	-1.33
	(-0.65)	(0.68)	(-0.76)

Daily cross-sectional regression of cumulative returns $R_{t,t+\tau}^i$ on daily CDS percentage change (ΔCDS_t^i). Returns are in basis points. Controls include the log of sizes (Size_t^i) and lagged five day returns ($R_{t-5,t-1}^i$). Coefficient estimates on controls are omitted in Panel B. Fama-MacBeth t-stats adjusted for Newey and West (1987) serial correlations are reported in braces. **: significant at 5% level.

The result presented in Table 5 show that the coefficient estimates on ΔCDS are negative and statistically significant only for the SSB stocks during the ban. When the dependent variable is two (five) day future returns, the coefficient estimate is -11.53 (-24.07), implying

that a one standard deviation increase in ΔCDS is associated with a 1.29% (2.69%) return decrease in the next two (five) days. For the control stocks, the coefficient estimates on ΔCDS are not significantly different from zero. Panel B of Table 5 reports the coefficient estimates on ΔCDS for the SSB stocks during the non-ban periods. To save space we omit the estimates on the constant and control variables. As shown in Panel B, the CDS has no predictability during the non-ban periods. Right before the ban and during the normal time period from January to July 2008, the coefficients on ΔCDS are negative but not statistically significant, and during the post ban period, the coefficients are positive and not significant.

If a short sale ban impedes stock prices from incorporating negative information but does not impede positive information, we expect that increases in CDS would predict low stock returns during the ban, and that decreases in CDS would not be related to high subsequent stock returns. To test this asymmetric predictability, we use following specification:

$$R^i_{t,t+\tau} = a + b\,\Delta CDS^i_t + c\,\Delta CDS^i_t\,H^i_t + d\,H^i_t + f\,\ln(\text{size}^i_t) + g\,R^i_{t-5,t} + \epsilon^i_t\,, \tag{7}$$

where H^i_t is a dummy for high CDS change; it is one for company i on day t if its ΔCDS^i_t is above the median on day t. If the predictability of ΔCDS is asymmetric for the SSB stocks during the ban, the coefficient on the interaction term between ΔCDS and H will be negative, and the predictability of ΔCDS in equation (7) will be weaker than in equation (5).

As shown in Table 6, the coefficient estimates on the interaction term between ΔCDS and H are all negative and statistically significant. After adding the interaction term, ΔCDS no longer has predictability for the SSB stock returns. For example, when the dependent

variable is two day future returns, the coefficient estimate on the interaction term is -54.39 (t-stats: -2.09), whereas the estimate on ΔCDS is 20.84 (t-stats: 1.29). These numbers indicate that the predictability of CDS during the ban is driven by the SSB stocks with high increases in CDS, not by those with low or negative increases in CDS. This result is consistent with the premise that the short sale ban reduces the speed of stock price adjustment to negative information.

Table 6: **Future Stock Returns and High Percentage Changes of CDS**

The SSB Stocks during the Ban						
τ	const	ΔCDS_t^i	$\Delta CDS_t^i H_t^i$	H_t^i	Size_t^i	$R_{t-5,t}^i$
1	-1097.41**	19.55	-40.96**	55.17	44.39**	-0.12**
	(-2.33)	(1.67)	(-2.84)	(0.83)	(1.91)	(-2.11)
2	-1456.01**	20.84	-54.39**	-15.04	52.56**	-0.14**
	(-3.43)	(1.29)	(-2.06)	(-0.18)	(2.52)	(-1.94)
3	-1959.63**	18.25	-64.67**	77.81	66.31**	-0.13**
	(-4.81)	(1.16)	(-3.59)	(1.01)	(2.59)	(-2.42)
4	-2360.47**	18.25	-54.99**	69.43	87.40**	-0.16**
	(-4.50)**	(0.74)	(-2.14)	(0.64)	(3.30)	(-2.07)
5	-2654.81**	14.51	-68.61**	-60.51	99.04**	-0.07
	(-4.52)	(0.52)	(-2.13)	(-0.48)	(3.11)	(-1.40)

Daily cross-sectional regression of cumulative returns $R_{t,t+\tau}^i$ on CDS percentage change (ΔCDS_t^i), and its intersection with the high CDS change dummy (H_t^i). The returns are in basis points. On each day t, SSB stocks with above median ΔCDS_t^i have $H_t^i = 1$, zero otherwise. The controls include the log of equity sizes (Size_t^i) and the lagged returns ($R_{t-5,t}^i$). Fama-MacBeth t-stats adjusted for Newey and West (1987) serial correlations are reported in parentheses. ** significant at the 5% level.

6 Conclusions

In this study we focus on the short sale ban of 2008 and examine the interaction between price discovery in banned stocks and the trading of options and CDS during the 14-day period. We find that investors still use derivatives to trade on negative information when the derivative market conditions are severely deteriorated. Our results also suggest that in

the presence of a short sale ban it takes time for the negative information contained in either the options market or the CDS market to be incorporated into stock prices.

Given the volatile nature of the markets during the short sale ban, it is important for us to minimize the influence of the overall market movement on our predictive results. For this reason, we structure our test to focus within the group of stocks with the same short sale ban and examine the predictability cross-sectionally within this group. In other words, our finding of sluggishness in price impoundment is a measure of one banned stock relative to another banned stock. The only thing differentiating the paired stocks is that one has some negative information according to the options or CDS markets.

In extracting the information from the options market, we first use the trading information. Given the volatile nature of the time period and the large bid/ask spreads in the options market, this action variable could perhaps capture option information in a cleaner way. We then use options prices to show that synthetic stock prices are also more informative for future stock prices during the SSB. This result suggests that increased bid ask spreads reduce number of noise traders to the extent that options prices become more informational efficient. The results on CDS confirm that in the presence of short sale ban and large transaction costs, it takes time for the information already incorporated in CDS prices to be incorporated into stock prices.

Finally, although our original idea was simply to follow the flow of information, our result is a confirmation of the theoretical prediction of Diamond and Verrecchia (1987). In particular, our results show that the sluggishness in price impoundment is asymmetric: the information collected from either the options market or the CDS market has predictability only on the negative side, not on the positive side.

References

Acharya, V. V. and T. C. Johnson (2007). Insider trading in credit derivatives. *Journal of Financial Economics*.

Aitken, M. J., A. Frino, M. S. McCorry, and P. L. Swan (1998). Short Sales are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange. *Journal of Finance 53*, 2205–2223.

Asquith, P. and L. Meulbroek (1996). An Empirical Investigation of Short Interest. Working Paper, Harvard University.

Battalio, R. and P. Schultz (2011). Regulatory Uncertainty and Market Liquidity: The 2008 Short Sale Ban's Impact on Equity Option Markets. *The Journal of Finance 66*(6), 2013–2053.

Boehmer, E., C. M. Jones, and X. Zhang (2009). Shackling Short Sellers: The 2008 Shorting Ban. Working Paper, University of Oregon and Columbia Business School and Cornell University.

Bri, A., W. N. Goetzmann, and N. Zhu (2007). Efficiency and the Bear: Short Sales and Markets around the World. *Journal of Finance 62*, 1029–1079.

Chang, E. C., J. W. Cheng, and Y. Yu (2007). Short-Sales Constraints and Price Discovery: Evidence from the Hong Kong Market. *Journal of Finance 62*, 2097–2121.

Chen, J., H. Hong, and J. C. Stein (2002). Breadth of Ownership and Stock Returns. *Journal of Financial Economics 66*, 171–205.

Cremers, M. and D. Weinbaum (2010, 4). Deviations from Put-Call Parity and Stock Return Predictability. *null 45*, 335–367.

Danielsen, B. and S. Sorescu (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.

DAvolio, G. (2002). The Market for Borrowing Stock. *Journal of Financial Economics 66*, 271–306.

Diamond, D. W. and R. E. Verrecchia (1987). Constraints on Short-Selling and Asset Price Adjustment to Private Information. *Journal of Financial Economics 18*, 277–311.

Easley, D., M. O'Hara, and P. Srinivas (1998). Option Volume and Stock Prices: Evidence on Where Informed Traders Trade. *Journal of Finance 53*, 431–465.

Gagnon, L. and J. Witmer (2009). Short Changed? The Market's Reaction to the Short Sale Ban of 2008. Working Paper, Queen's University.

Garleanu, N., L. H. Pedersen, and A. M. Poteshman (2009, October). Demand-Based Option Pricing. *Review of Financial Studies 22*(10), 4259–4299.

Geczy, C. C., D. K. Musto, and A. V. Reed (2002). Stocks are Special too: an Analysis of the Equity Lending Market. *Journal of Financial Economics 66*, 241–269.

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

Han, B. and Y. Zhou (2010). Term Structure of Credit Default Swap Spreads and Cross Section of Stock Returns. Working Paper, University of Texas at Austina and University of Oklahoma.

Harris, L., E. Namvar, and B. Phillips (2009). Price Inflation and Wealth Transfer During the 2008 SEC Short-Sale Ban. Working Paper, University of Southern California.

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

Jones, C. M. and O. A. Lamont (2002). Short-sale Constraints and Stock Returns. *Journal of Financial Economics 66*, 207–239.

Kolasinski, A., A. Reed, and J. Thornock (2009). Can Short Restrictions Result in More Informed Short Selling? Evidence from the 2008 Regulations. Working Paper, University of North Carolina.

Longstaff, F. A., S. Mithal, and E. Neis (2005). Corporate Yield Spreads: Default Risk or Liquidity? *Journal of Finance 60*.

Mayhew, S. and V. Mihov (2005). Short Sale Constraints, Overvaluation, and the Introduction of Options. Working Paper, SEC and Texas Christian University.

Miller, E. (1977). Risk, Uncertainty, and Divergence of Opinion. *Journal of Finance 32*, 1151–1168.

Newey, W. K. and K. D. West (1987). A Simple Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator. *Econometrica 55*, 703–708.

Norden, L. and M. Weber (2009). The Co-Movement of credit default swap, bond and stock markets: an empirical analysis. *European Financial Management 15*, 529–562.

Ofek, E., M. Richardson, and R. F. Whitelaw (2004). Limited Arbitrage and Short Sales Restrictions: Evidence from the Options Markets. *Journal of Financial Economics 74*, 305–342.

Pan, J. and A. Poteshman (2006). The Information in Option Volume for Future Stock Prices. *Review of Financial Studies 19*, 871–908.

Saffi, P. A. C. and K. Sigurdsson (2010). Price Efficiency and Short Selling. *Review of Financial Studies*, forthcoming.

Sorescu, S. (2000). The Effect of Options on Stock Prices: 1973 to 1995. *Journal of Finance 55*, 487–514.

Tang, D. and H. Yan (2011). Price Impact of CDS Trading. Working Paper, Hong Kong University and University of South Carolina.

Xing, Y., X. Zhang, and R. Zhao (2010, 6). What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns? *Journal of Financial and Quantitative Analysis 45*, 641–662.