Option Market Manipulation

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May 14, 2024

Abstract

Since the introduction of exchange-based trading in 1973, there has been ongoing interest in determining the impact of option trading on underlying stock prices, and vice-versa. In this paper, we study the behavior of the option and stock markets, in presence of stock market manipulations. We merge intra-day manipulation data from SMARTS, Inc with option market data from both OptionMetrics and ISE. We detect a clear and strong trend in the option trading, with the option liquidity that peaks at the violation day. Short-term and out-of-the-money expiration options are mostly linked to stock market manipulations while we do not observe any extra manipulations for Friday expirations.

Keywords: Market Manipulation, Options, Option Trading.

JEL classification: G14, G18.

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Financial support from the AGAUR - SGR 2017-640 grant are gratefully acknowledged.

1 Introduction

How the option market behaves before, during and after the underlying stock market experiences a possible manipulation? Are call or put options more prone to be linked to manipulated stock prices? What about their moneyness and time to maturity? Do option traders only benefit from a manipulated stock price increase/decrease or both movements might be beneficial for them?
Since the inception of equity options trading in 1973, the financial world has witnessed a surge in the popularity and participation of options traders in various markets. Alongside this growth, concerns have emerged about the possibility that some traders may engage in manipulative activities, specifically targeting stock prices to amplify their profits from options trades. Such practices, if widespread, could have far-reaching consequences for market dynamics and investor confidence. This paper aims to investigate the validity of these concerns and shed light on the potential uneconomic impact of stock price manipulation on the option market and by options traders.

The complex nature of this inquiry renders it a challenging, yet crucial, element in comprehending the intricacies of the option market, the stock market, and their interrelated trading dynamics. Among others, the complexity lies in detecting the possible market manipulations, and how these might impact on the options market. Due to the importance of the topic, we are indeed not the first one trying to clarify these questions. The relationship between the stock and the option markets is commonly examined by analyzing three distinct channels: i) price and/or volume pressure and trading frictions, ii) information, and iii) potential market manipulation. The first two channels present almost opposite views, while the third one is often considered the consistently present but difficult-to-document residual channel. With respect to the price and/or volume pressure, Goncalves-Pinto et al. (2020) and Goncalves-Pinto and Sala (2023) show that different proxies for informed option trading cannot predict the spread between actual and synthetic stock returns around firm-specific news. Confirming a large strand of the literature (e.g. Stephan and Whaley (1990); Chan et al. (1993); Vijh (1990); Chan et al. (2002); Muravyev et al. (2013) and Collin-Dufresne et al. (2021)) this evidence goes against the existence of an incremental informational channel in the option market. According to this literature, the drivers of price movements are mainly market microstructure elements, such as price and/or volume pressure, or various market frictions.

The opposite view taken by the other strand of the literature (e.g.: Pan and Poteshman (2006); Ni et al. (2008); Cremers and Weinbaum (2010); Xing et al. (2010); Hu (2014); Lin and Lu (2016); Ge et al. (2016); Cremers et al. (2022)) presents evidence of an information channel among the two markets, with the option market usually leading the stock market.

Finally, as a residual explanation to most of the above papers, there is the less explored but always mentioned manipulation channel. Ni et al. (2005) show that stock prices "pin"' at option strike prices on option expiration dates. The authors motivate this phenomenon primarily through the hedge rebalancing by options market makers, and secondly advancing some evidence of price manipulations. The hedge rebalancing price pressure for stock and future price is also carried forward by Golez and Jackwerth (2012), and Ni et al. (2021)). Filippou et al. (2023) document that shortly before options' expiration dates traders might want to push the stock price to the "Max Pain" price, which is defined as the stock price that minimizes the total payoff of all options with that expiration date. Other related papers present evidence of stock prices manipulations by institutional investors like hedge funds (Ben-David et al. (2013)) and mutual funds (Carhart et al. (2002). Hillion and Suominen (2004) report evidence that some traders might want to influence the closing price placing large trades right before markets close. From a stock option perspective Randall and Heron (2009) find that 13.6% of the 39,888 stock option grants to top executives during the period 1996–2005 were backdated or otherwise manipulated while Augustin et al. (2019) perform an event study to analyze the pervasiveness of informed trading activity in target companies' equity options before the announcements of 1,859 U.S. takeovers. Still linked to corporate events, Augustin et al. (2023) study how private information affects investors' options trading strategies ahead of corporate news events. Finally, and from a pure theoretical perspective, Allen and Gale (1992) provide a theoretical framework for a utility maximizer investor to manipulate stock prices while Danger et al. (2019) shows different market manipulation schemes on option expiration dates.

Two main common elements among these papers are: i) their analysis of the impact of the option market on the stock market, and ii) their treatment of manipulations as a residual element without thorough investigation. Building upon these observations, our paper introduces two novel approaches. Firstly, we take a divergent path by investigating how the stock market may influence option markets. Specifically, we scrutinize the behavior of the option market before, during, and after potential manipulation of underlying stock prices. Secondly, to detect potential manipulation, we integrate US intraday manipulation data from SMARTS, Inc., with option market data from OptionMetrics and ISE. Our analysis spans the period 1/1/2007-31/12/2018, both included. This matched dataset allows us to map what happens on the option market when a potential manipulation is detected. The SMARTS dataset defines and detects - under several metrics - possible market manipulation, while the optionmetrics dataset contain all necessary information to analyze the eventual spillover effects on the options market. Specifically, to merge the datasets, we first consider all declared NYSE and NASDAQ intra-day manipulations registered in the SMARTS dataset, then we discard all stocks without written stock options. It is worth noticing that the algorithms used by SMARTS to detect possible stock price manipulations are not arbitrary measures introduced in this paper for this analysis, but are the work of more than 30 years of industry surveillance experience, refined and utilized on a daily basis by different leading regulatory authorities. Through this merged dataset we can study the option market activity around manipulations. As a snapshot for our analysis, Figure 1 depicts the option market liquidity before, during and after potential manipulations. Specifically, it depicts on the y axis the daily sum of all call and put equity options traded, and on the x axis the time series of the registered manipulation day, where time t is the potential manipulation day and we consider a 5-days time window around the potential manipulation day. From Figure 1 we document how equity options linked to potentially manipulated stock prices first exhibit a clearly increasing volume during the week preceding the stock price manipulation (from $t-5$ to t). Then, after the manipulation day (t), the trading volume of the manipulated equity options almost reverts to the original value registered one week before the manipulation (from t to $t+5$). Overall, from the figure, we can infer a strong increase in interest from option traders to trade around potential manipulation events. It's crucial to underscore that our manipulation dataset goes beyond merely capturing volatility. Specifically, the SMART dataset employs a 30-minute rolling window to detect

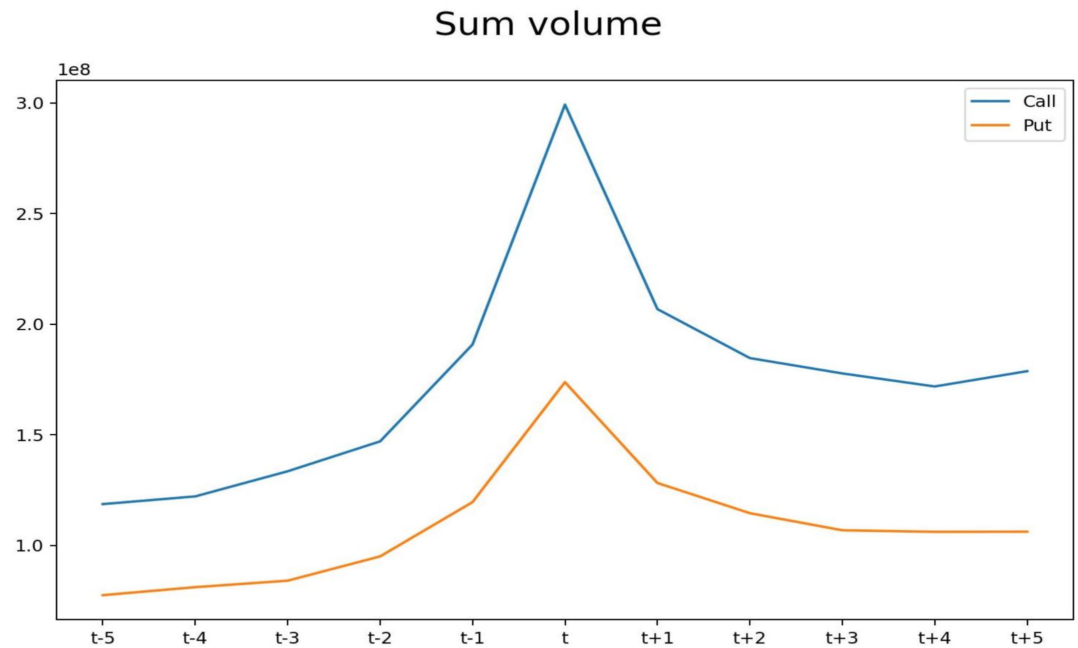


Figure 1: **Daily volume of put and call option traded.** This figure represents the daily sum of call (blue) and put (orange) volumes around a manipulation day, where t is the manipulation day.

significant deviations in stock price, volume, bid-ask spread, or other stock characteristics exceeding three standard deviations. These deviations persist for a period before returning to their original values. This behavior contrasts sharply with the patterns exhibited by volatile stocks. Contrary to volatility, which is both mean-reverting and highly persistent (see Engle (1982)), the violation events identified by the SMART dataset pertain to stocks exhibiting highly suspicious behavior, such as sudden, unexpected price jumps, which remain at elevated or reduced levels for a duration before reverting.

Also, as we document in the empirical section, the average level of the VIX and VXN indexes are both increasing before and *after* manipulation, while the amount of option traded before and after manipulation is very close to half. This clearly discards the fact that option traders are only moved by volatility-related concerns.

As a robustness, and for both calls and puts, we encounter the exact same pattern once we refine our analysis and we disentangle the total option liquidity dataset into a more granular open-buy volume, open-sell volume, close-buy volume and close sell volume. This result, along many others, are presented in Section 5.

As documented by Augustin et al. (2023), the optimal option trading strategy for a rational and possibly informed investor is the one that combines the best moneyness and option tenure to maximize the investor's expected return. While Augustin et al. (2023) provide a theoretical framework on how informed investor can best leverage their information and create a database of possibly interesting trading events, here we empirically check their theory departing from a dataset of potentially manipulated stock prices. As such, in our empirical analysis, we are able to more precisely document the types of options tenure and moneyness that are mostly related to potentially manipulated stock prices.
In terms of moneyness, we investigate if the trading options linked to manipulated stock prices have mostly short, medium or long-term expiration. Equally, we investigate which option moneyness is mostly traded by informed investor. Both the option tenure and moneyness allow the investor to maximize her trade, and are conditional to the clarity of the information. In absence of information uncertainty, a rational investor willing to maximize her welfare would prefer to trade in very short-term and OTM options. In fact, the clearer the information, and the less an investor needs to pay extra money trading long-term options. Equally, for the moneyness, the less the information uncertainty, and the higher the likelihood that an investor is able to select an option that is not OTM but has the potentiality to go ITM. Nevertheless, as we will document in the empirical part, frictions play an important role in detecting the optimal trading strategy, as a possibly profitable DOTM option might not be the optimal moneyness due to its very high frictions, which make it very expensive and - very often - not even traded.

Our findings shows that not all options are equal and some of them are most closely related to manipulated stock prices. Specifically, short-term and OTM options are the most traded options in presence of potential stock price manipulations. We also document a clear pattern for both call and put ITM (OTM) options to increase (decrease) in price before manipulation, thus violating a basic principle of market manipulation, while returning to a random behavior after manipulations. While a lot is known about the stock characteristics linked to market manipulation, less is known to those stocks that also have options and are linked to manipulations. We thus provide information about the characteristics of the stock manipulated that has equity options. As such, we provide a framework for regulators and policy makers to better monitor how option trading activities might be linked to manipulated stock prices and vice-versa.

The remainder of the paper is organized as follows. Section 2 provide a theoretical intuition on to why option traders might benefit from both positive and negative stock price manipulations. Section 3 list and explain the hypothesis that we will test. Section 4 presents the dataset. Section 5 presents the empirical results of our hypothesis. Lastly, Section 6 concludes the paper.

2 Stock price manipulations and option trading

One of the most challenging part to detect option manipulations is that option traders are very flexible as they can benefit from the price of the stock underlying the option to be manipulated either up or downward. Among others, two are the main drivers that might determine the direction of the stock price manipulation, namely i) the type of settlement of the option and ii) the position of the option traders. Regarding the option's settlement, if options are cash settled, both long and short might have the incentive to manipulate the stock market. Depending on the option style, such a manipulation might be upward (e.g. for a short put option trader or a long call option trader) or downward (e.g. for a short call option trader or a long put option trader). Differently, for physically settled options only who is short might have the incentive for a stock price manipulation (Danger et al. (2019)).

With respect to the position of the option trader, long positions only benefit from one position but things are less immediate for option writers as the same trader might differently benefit from both up and downward price manipulations. Let us first analyze long option positions, as the dynamics are simpler. Before expiration, call (put) holders benefit from high (low) stock prices, as the call (put) options payoff increases as the stock price is greater (lower) than the pre-determined and fixed strike prices.[1] As such, a call (put) holder only benefits

[1]We only consider plain vanilla call and put options, which are financial contracts with a fixed strike price and time to expiration.

from an upward (downward) stock price manipulation.

Short positions are more counterintuitive, as traders might have the incentive to have both high or low prices. Let's consider the case of call options. A call option writer collect a premium upfront and is obliged to pay the call option holder in case in which the stock price exceed the strike price. Clearly, a call option writer might be tempted in keeping the price low and, specifically, lower than the strike price of interest. Equally though, option writers might benefit from a price increase. Specifically, for an out-of-the-money call writer, if the stock price is close enough to the strike price, and just prior to option expiration, the writer might have the incentive to manipulate upward the underlying market. If the buyer of an option is incentivized to exercise it due to the writer's purchases (causing the option to go in-the-money), then the option writer will be assigned a short position at a price higher than the current market price. This short position can help the writer offset any purchases made in the underlying asset market, resulting in a profit from the difference between the strike price and the writer's average purchase price of the underlying asset. Such a trading scheme can be formally described as:

$$\alpha = A_o(K - S_T) + A_p(S_T - \bar{S}) + A_s(\tilde{S} - S_T) \tag{1}$$

where A_o, A_p, A_s are the amount of options, stock purchased and stock sold, respectively, S_T is the price of the stock at manipulation and $\bar{S}, \tilde{S}$ are the weighted average prices of the stock purchased and sold, respectively. The last piece of equation $A_s(\tilde{S} - S_T)$ is nonzero only when the option writer buys more stock than needed. Assuming for simplification that the option writer buys the right amount of stock to cover her option position, $A_o = A_p$ it follows that:

$$\alpha = A_o(K - \bar{S}) \tag{2}$$

which shows that if the option writer is able to buy the right amount of stock (A_o) at an average price $\bar{S}$ that is below the strike price K, then she will be able to profit from this trading scheme. By put-call parity, put options work equally just flipping the entire concept.

The presented trading schemes underpin a clear "uneconomic" trading behavior. According to the fundamental principle of supply and demand, any non risk-lover buyer aims to acquire an asset at the lowest available price, while a seller aims to sell it at the highest possible price. Any deviation from this basic principle implies that the trades were intended to send price signals to the market, such as for the purpose of manipulation, instead of obtaining the best price. In the case being examined, the underlying trades are considered "uneconomic" because the trader seeks to purchase the asset at a high price, rather than a low price, in order to become a seller at the strike price, K. It might in fact be more profitable to buy the stock at a high rather than a low price if this trade satisfies the condition $K - \bar{S} > 0$.

This analysis shows how difficult is the analysis to detect option market manipulations without a signal of an effective stock price manipulation. We overcome this issue by changing the viewpoint, and departing from a dataset of possibly manipulated stock prices.

3 Hypothesis

HYPOTHESIS 1: Manipulated stocks with written stock options exhibit:

1. *An increasing trading volume during the week preceding the manipulation day;*
2. *A decreasing trading volume during the week subsequent to the manipulation day.*

From Grossman and Stiglitz (1980) we know that it makes economical sense for investors to pay a cost to collect private information. This is especially true around corporate events (e.g. scheduled events like earning announcements) when volatility tends to increase and trading might be more profitable. Not surprisingly, it is especially when investors have stronger incentives to gather private information and trade on such information that the volume of the asset of interest increases. Moreover, informed investors often prefer to build up and down their trading position overtime and not just in one time, not to have a too strong market impact on the market liquidity and/or to give less information to other market's participants. As such, we should expect that, in presence of stock price manipulations, the trading volume of the equity options linked to the manipulated stocks should increase overtime, peak at the manipulation day and decrease overtime to the original levels after manipulations happened.

HYPOTHESIS 2: Short-term options are more likely than medium and long-term options to be related to manipulated stocks.

As anticipated in the Introduction, the optimal option trading strategy for a rational and informed investor is the one that combines the best moneyness and option tenure to maximize the investor's expected return. As such, options tenor is one of the key variables in the cost-effectiveness trade-off of options trading. In presence of private information, or if an investor is confident in her ability to move the market price, a rational profit maximizing investor would increase her expected profit by trading in short-term options. Intuitively, the sharper the signal, and the more an investor is willing to take the risk of having a contingent claim that expires soon, this to maximize her leverage without loading on unneeded costs. Specifically and all else equals, option prices always increases in price with their time to maturity, as longer maturities options give the holder a higher likelihood for the asset to end up ITM. As such, if an investor posses clear and reliable information, would prefer to trade in short term options, as this would prevent her not pay extra money buying unneeded longer term options. We could then conjecture that options trading in presence of manipulated stock prices should be more oriented toward short than to medium and long maturities.

HYPOTHESIS 3: Out-of-the-money (OTM) options are more likely then other moneyness to be related to manipulated stocks.

Equally important to the options tenure, there is the options moneyness. As such, and similarly to hypothesis 2, also the option moneyness enters into the profit-cost trade-off. It is in fact only in presence of clear information, thus with no information uncertainty, that informed options trader would take the risk of trading in the cheaper but potentially more profitable OTM options. OTM options often represent the optimal moneyness for informed option traders because i) cheaper than ITM options, and ii) more liquid than the DOTM options. First, all else equal, ITM options are in fact more expensive than OTM options as, being already ITM, have clearly a higher likelihood to end up ITM. As such, in the absence of information uncertainty, an informed or strategic option trader would accept to take the risk of trading OTM options and thus save some money. Secondly, what often prevents traders to trade into even more speculative DOTM options is their higher frictions, once compared to OTM options. Specifically, frictions impact DOTM options under two domains, i) in terms of bid-ask spread, and ii) in terms of minimum option price. The highly speculative nature of DOTM options makes many investors reluctant to trade them, which is reflected in their bid-ask spread being much wider than less speculative options (e.g., OTM, ATM, ITM options). Secondly, each exchange set some minimum option price to remove options with extremely low prices and guarantee an optimal trading activity. For example, for the CBOE, the minimum price variant is $0.05 (nickel) for series trading under $3.00 and $0.10 (dime) for series trading $3.00 and above.[2] ADD A STATISTICAL ANALYSIS HERE Moreover, Augustin et al. (2023) show that DOTM are quite always above the minimum price, even though their fair value would be lower. This difference is often explained justified by some premium (downside risk, illiquidity) etc, which makes DOTM options even more expensive than what they are, thus making them economically not optimal. Taken all together, it is not rare that DOTM are not even trade, as their too low price and/or frictions make them un-interesting for option traders.

It is worth noticing how the same impacts are not applicable to ITM and DITM options, as their higher intrinsic values, together with the absence of minimum tick for options (again due to their high prices), makes them more attractive to option traders. ITM options can then be traded by those investors for which frictions are too important, to still achieve a positive return, although with a lower leverage. The role of DITM option is mostly relegated to synthetically replicate DOTM options, as DITM are less cost sensitive, while a proper calibration would allow the option trader to obtain the same benefit (although at a higher cost) than directly trading in possibly non liquid DOTM options. Clearly, such synthetic positions require a high level of sophistication, together with a higher capital to invest in the strategy (very high margins, above all for put option synthetic replications), which make DITM options hardly traded products.[3]

In summary, we should expect informed investor to mostly trade in OTM options, followed by ITM options and we should expect a very low trading in DOTM and DITM options.

HYPOTHESIS 4: Friday expiration and the third Friday of the month are more likely to be related to stock manipulations.

As a first step we consider if there is a particular expiration day that is more prone to option manipulations. Among all days we put an emphasis on Fridays and, above all on the third Fridays of the month. Often named as "triple witching days", the 3rd Fridays of the

[2]Beginning on or about 01/26/07, some option classes will have different MPVs

[3]Moreover, as documented by Augustin et al. (2023), as of today, there is almost no publicly reported civil obligations initiated by the SEC that involved the use of synthetic option positions.

quarterly cycle (March, June, September, December), are notoriously important trading days in the derivatives market are as futures contracts, index options, and options futures contracts all expire simultaneously in the a.m. settlement window. Due to the combination of these expiring activities, the "triple witching days" are often seen as more prone to option market manipulations.

HYPOTHESIS 5: Big and liquid stocks are less likely to be related to manipulated stocks. Or, similarly although differently, small and illiquid stocks are more likely to be related to manipulated stocks.

Douglas

HYPOTHESIS 6: After a stock price manipulation, the underlying stock price is prone to reversal, while option prices follow a random walk.

Douglas

HYPOTHESIS 7: Stock and option price manipulations are likely related to scheduled events.

The period around the release of material corporate news is one in which investors should exhibit stronger incentives to gather private information and trade on this information. If these incentives would exist, investors would be equally interested in using their superior information both in the stock and the option market. If this hypothesis is true we should expect an increasing number of manipulations from $t-5$ to t in the stock market and a reduction in the bid-ask spread for the option market. While the former event is immediate, the tightening of the bid-ask spread is linked to a common option trading strategy of informed investors that tend to sell overpriced straddles and strangles (thus involving both OTM put and call options at different strike prices) to take advantage of scheduled event. In presence of scheduled events, in fact, retail investors are prone to buy overpriced call and put options. As a consequence, the seller of the strategy might pocket in the extra money due to the overpriced. It is in fact true that scheduled events might increase the volatility, but the volatility has to be higher than expected to generate money. Also, around scheduled events like earning announcements option investors in search for stocks with an expected abnormal volatility tend to clusters. Typically, and even more so recently, the long side is taken by retail investors which typically overestimate the future volatility and tend to overpay for what they buy, incur in very large bid-ask spreads, and do not respond optimally to the announcements dynamics (Silva et al. (2023). **Check option behavior (volume and bid ask spread)**

HYPOTHESIS 8: Stocks with equity options are more prone to manipulation.

A natural question for the analysis is weather equity with written equity options are more subjected to manipulation.

TO ADD: all hypothesis linked to panel regression analysis. What about the Loriano's paper?

4 Dataset

For our empirical analysis we match intra-day manipulation data from SMARTS, Inc (in 2010 SMARTS, Inc has been acquired by NASD) with option market data from both OptionMetrics and ISE, and stock characteristics from CRSP Compustat. Specifically, we explore a manipulation data sample sourced from SMARTS, Inc., and Capital Markets CRC (CMCRC) situated in Sydney. SMARTS and CMCRC gather information about alleged manipulation instances across more than 50 global stock exchanges, serving as valuable resources for regulatory bodies in those nations. The SMARTS surveillance software, developed in the late 1980s, is employed by over 50 of the world's foremost stock exchanges. In 2010, NASD acquired the system. Rather than merely pinpointing irregular trading activities, the SMARTS system excels at detecting manipulations, as evidenced by its widespread use by major stock exchanges worldwide for this very purpose. Nowadays, the metric proposed by SMARTS often stand as the established industry benchmark for uncovering manipulative trading practices. It is important to note that the SMARTS algorithms are not arbitrary measures introduced in this document; instead, they represent the culmination of over 30 years of industry surveillance experience, refined and utilized by leading regulatory authorities.

The manipulation cases under our scrutiny pertain to suspected instances, rather than confirmed and legally enforced cases. The process of enforcement can span several years following the identification of a suspected case, with many cases possibly never reaching the enforcement stage, contingent upon an assessment of anticipated costs and the uncertainties associated with legal proceedings. Repeated instances of manipulation are more prone to face enforcement actions compared to isolated cases, primarily because of the increased likelihood of a favorable outcome in litigation.

In our study, we utilize instances of continuous trading manipulation as a stand-in for market manipulation, covering the period from 2007 to 2018 for the US market (NYSE and NASDAQ).

Specifically, aligning with the availability of manipulation dataset, the investigation's timeline is constrained to span the period 2007-2018. Our analysis follows two approaches. First, we only consider a stock to be manipulated under the Continuous Trading Manipulation (CTM) metric which, based on specific rules, detects an abnormal 30-minute change of liquidity, returns, and transaction costs. It is worth noticing that the CTM is not just capturing volatility, as volatility is well-known to be strongly persistent and mean reverting (Engle (1982)). Differently, the CTM is related to those prices that experience sudden unexpected jumps, stay at high or low jump level for some time, and then revert back. Specifically, jumps have to be at least more than three standard deviations away from the average 30 minutes behavior of the market for the same time window, and for at least three out of the five indicators of liquidity, returns, and transaction costs in consideration.[4] If these alerts were solely indicative of abnormal trading activity, one would expect to observe concurrent fluctuations in adjacent time intervals, such as the surrounding 30-minute windows. This irregular activity wouldn't be confined to a single 30-minute window and would not subsequently return to the usual pattern of trading.

Next, for robustness, we consider all cases in which, under all available metrics, we detect a manipulation. All the specific rules, and the calculations of the manipulation metrics that follow from them, are summarized in the Appendix A. It is worth noticing that, on a total of 250,306 detected manipulations, XXXXX follows under the CTM metric, which represents a XXXXX of the total sample. Also, the 250,306 detected CTM manipulations happened in 2,922 single days, which implies and average of 86 manipulations for each of the single day. Considering all manipulations metrics we have instead 2990 single days, which shows the ro-

[4]The five indicators are i) Total trading value over the past 30 mins ii) Total trading volume over the past 30 mins, iii) Return over the past 30 mins, iv) Average effective spread over the past 30 mins, and v) Average quoted spread over the past 30 mins.

bustness of the CTM among all indicators.

Next, we match the manipulation data sample with the option data. Specifically, from the manipulation data sample we only consider those stocks with written equity options. We then obtain, from Optionmetrics, all available closing bid and closing ask option prices, option volumes and open interest.
Still in terms of options, we obtain from ISE a more granular volume dataset. Specifically, for all written stock options, we retrieve all end of day opening buy, closing buy, opening sell and closing sell volumes data. From this dataset we only keep options prices with i) strictly positive volumes, ii) strictly positive and non-missing bid prices, iii) non-missing ask prices whose value is strictly greater than the relative bid prices.

Finally, for all those stocks with written options, we obtain from CRSP Compustat some basic stock characteristics. Specifically, we obtain the book value, sale, market value, market-to-book value, current total asset, total asset and current total liabilities.

Having the dataset of manipulated stock prices and the relative options written on them we first match them and then only consider what happens 5 days before and after the manipulation day. This allows us to work with a smaller dataset and perform basic event studies. Next, we report some basic summary statistics of the options written on the manipulated stocks. In particular, divided by year, Tables 1 and 2 represent basic summary statistics of the call and put option prices and volume around the manipulation period (from $t-5$ to $t+5$), respectively. They also present the number of TICKER and PERMNO available for each year. From both table some interesting results emerge. First, while the number of TICKERS available is rather constant, the number of PERMNO is growing overtime, also reflecting the liquidity of the option markets that increased overtime. Secondly, for both call and put options, price mean, median and standard deviation are first decreasing up to 2012 and then strongly increasing as we approach the year 2018 (year with a particular high values for all price statistics). The same statistics related to the volume of the options traded show a peak related to the period 2008-2009 followed by an strong decrease in value overtime as volumes are less than half than their peak values. For both call and put options, in fact, mean and standard deviation of the volume of options traded peak at around the years 2010 and 2011, and tend to decrease right after. Third, in terms of prices, for both the mean and the median, values tend to be always higher for the call options, aside for the years 2008 and 2009.

MEANING?

The same holds true for the mean and standard deviation of the option volumes. Finally, things are mixed for the standard deviation of prices as no option style appear to dominate the other.

MEANING?

Year	TICKER	PERMNO	Price Mean	Price Median	Price StDev	Vol. Mean	Vol. Median	Vol. StDev
2,007	3,703	564	6.99	3.20	11.32	463.47	58.00	2,264.40
2,008	3,417	564	4.80	2.15	8.06	573.69	71.00	2,312.72
2,009	3,767	709	3.90	1.85	7.23	902.00	70.00	6,870.75
2,010	2,754	533	3.66	1.84	5.53	765.95	65.00	6,932.97
2,011	3,274	645	3.84	1.80	6.01	607.78	58.00	5,899.47
2,012	3,255	651	3.45	1.70	5.57	462.41	55.00	1,939.71
2,013	3,543	768	5.22	2.20	10.71	391.06	47.00	1,505.31
2,014	4,200	954	4.92	2.00	9.74	399.15	50.00	1,792.30
2,015	4,380	1,017	6.07	2.08	13.84	372.84	43.00	1,923.60
2,016	4,067	960	4.57	1.75	12.02	400.30	44.00	2,303.11
2,017	4,231	1,146	8.44	2.45	26.68	348.88	40.00	1,477.51
2,018	4,145	1,321	13.38	2.95	41.74	296.03	35.00	1,335.43

Table 1: **Call options summary statistics.**

Year	TICKER	PERMNO	Price Mean	Price Median	Price StDev	Vol. Mean	Vol. Median	Vol. StDev
2,007	3,703	509	4.92	2.60	7.16	490.50	71.00	1,873.84
2,008	3,417	508	6.51	3.35	9.48	750.99	82.00	3,353.06
2,009	3,767	605	3.88	1.77	7.00	760.41	71.00	4,594.35
2,010	2,754	466	2.80	1.46	4.13	544.54	68.00	2,625.80
2,011	3,274	547	3.64	1.77	6.32	452.13	57.00	2,006.08
2,012	3,255	548	2.69	1.42	4.20	368.41	52.00	1,337.87
2,013	3,543	656	3.35	1.34	9.26	294.49	41.00	1,287.80
2,014	4,200	787	4.34	1.74	9.71	266.96	41.00	1,123.89
2,015	4,380	862	4.37	1.93	7.50	267.71	34.00	1,344.31
2,016	4,067	761	3.95	1.65	8.93	260.41	33.00	1,437.91
2,017	4,231	883	4.38	1.70	9.88	260.80	33.00	1,092.98
2,018	4,145	1,100	9.67	2.28	27.33	211.02	28.00	1,175.44

Table 2: **Put options summary statistics.**

To gain more insight on the dataset used for the analysis we represent the above tables. The upper panel of Figure 2 compares the prices and volumes metrics of call and put options. The lower panel of Figure complements it, by adding the standard deviation into the picture. Finally, and in terms of exchanges, we document that out of the 250,306 registered

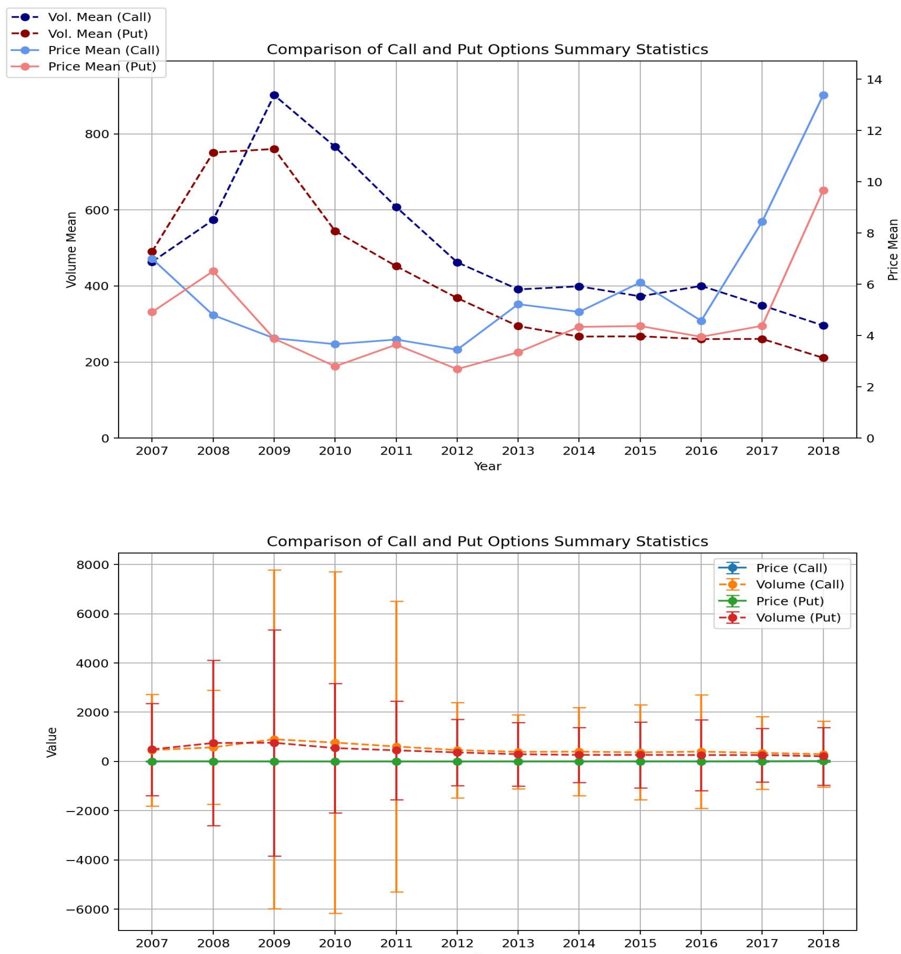


Figure 2: **Yearly summary statistics of put and call option.** The upper panel represents the yearly price and volume means, divided for call and put options. The lower panel represents again the yearly price and volume means, but equipped also with their standard deviations.

manipulations, 71.37% (178,650) of them are linked to the NYSE, while the remaining 28.63% (71,569) to the NASDAQ. As a side note, it is interesting to know that, given our dataset, the NYSE is the market with the highest number of manipulations, followed by the Shenzhen stock exchange, and Tokyo stock exchange. **shell we say something about this? are NYSE**

stocks more prone to NASDAQ in general?

5 Empirical Results

5.1 HYPOTHESIS 1: Volume Trend

Departing from Figure 1 already presented in Section 1, we now dig further into the volume and we differentiate between i) call and put options ii) open and close volume iii) buy and sell trades. The result of this analysis is depicted in the top and bottom panel of Figure . Specifically, the

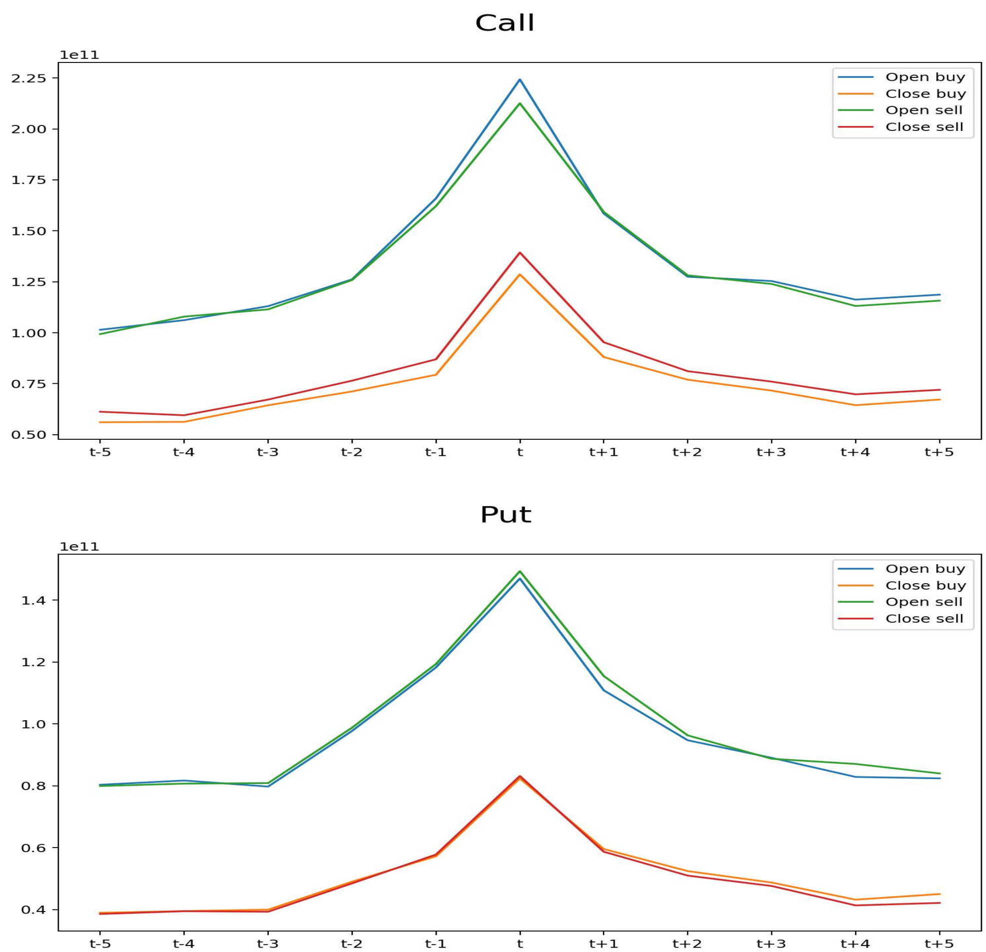


Figure 3: **Daily volume of call option traded divided by trading position.** The upper panel of this figure represents the daily sum of Call open (blue) and close (orange) buy volumes around a manipulation day, where t is the manipulation day. Equally, it represents the Call open (green) and close (red) sell volumes around a manipulation day.

top panel of Figure represents the volumes of all manipulated call options around manipulation but divided as open buy (blue line), open sell (green line), close buy (orange line) and close sell (red line). We repeat the same analysis in the bottom panel of Figure this time for the volume of all put options around manipulation. As it clearly emerges from both panels of the figure, the volume specific results strongly confirm the pattern presented in Figure 1. Both for call and put options, the volume is monotonically increasing from $t-5$ to t, it peaks at t and decreases to almost the same initial level at $t+5$. These findings are aligned with Chakravarty (2001) which first documents the Barclay and Warner (1993) stealth-trading hypothesis[5] that informed traders might prefer to split up their trades to reduce as much as possible their price impact. The main logic behind stealth trading is to gradually and partially trade to profit before the trades fully reveal (the possibly private) information Barclay and Warner (1993) and Admati and Pfleiderer (1988)). If nothing, the only difference between call and put option volumes lie in the higher total overall volume of call options both at the peaks and at at the starting levels. Indeed, our findings have to be considered as conservative, as informed or strategic traders can disguise their activity and hide their operativity by splitting their trades across exchanges, across markets and/or across different financial assets (e.g, stocks, options, synthetic products, CDS etc.). Finally, it is worth noticing that, while the option volume goes down, the market volatility remains high, thus showing an unwinding of options positions even in presence of expensive option markets. Would the manipulation dataset only capture volatility, this would revert to its original level after manipulation. This event confirm that the SMART dataset captures much more than just volatility and that option traders might be moved by uneconomic factors, as their trade interest is not driven by volatility. Such an event can be inferred from Figure 4, which represents the average volatility of the VIX and VXN indexes around manipulation dates. While the VIX has an increase that is almost perfectly monotonic, the VXN experience a very small drop from $t+1$ to $t+2$ and then restart being increasing.

[5]Stealth-trading refers to trades that are neither too large nor too small, to prevent to excessively move the price and to keep under control the expensiveness of the trades, respectively.

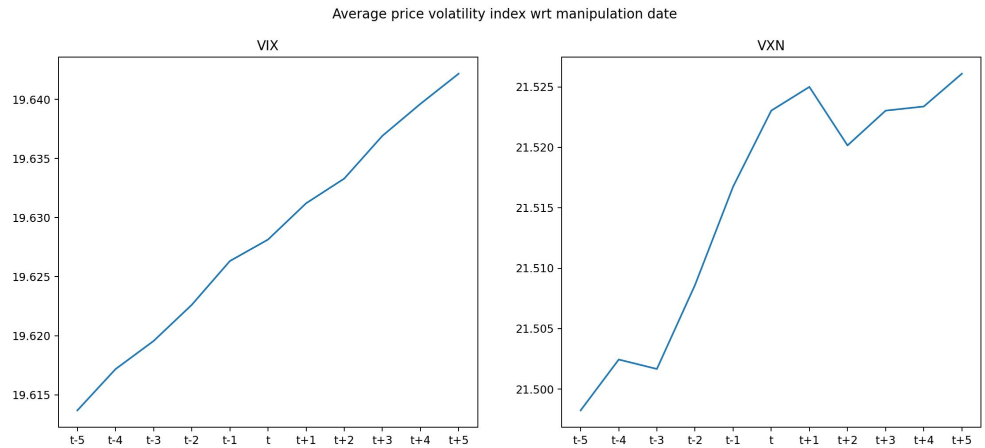


Figure 4: **Average volatility around manipulation events.** The left panel depict the average value of the VIX index around manipulation events. The right panel repeat the analysis, but for the VXN index.

5.2 HYPOTHESIS 2: Option Maturities

Tables 4 and 6 present summary statistics regarding which kind of call option maturities are mostly traded before and after the manipulation date, respectively. In terms of maturities, we consider an option to be short-term if expiration is within 30 days, medium-term is greater than 30 days but within 90 days, and long-term if is greater than 90 days. Tables consider two different time windows. One time window goes from $t-5$ to $t+5$. Another window divides the two time period into pre-manipulation 4 and post-manipulation 6. For all maturities we present the sum of options traded over the entire time period (sum), the same sum but in percentage (sum %), the sum only over the pre or post manipulation period (% Only Pre and % Only Post, respectively) Table 4 shows how most of call options traded before the manipulation day are

Table 3: Pre-manipulation Statistics

Maturity	Sum	Sum (%)	Mean	Sum (%, period)	STD
Short-term	62,175,110.67	17.63	389.71	36.88	1,736.80
Medium-term	56,539,521.67	16.03	290.96	33.53	1,216.48
Long-term	49,885,196.83	14.15	156.35	29.59	1,184.41
TOTAL	168,599,829.17	47.82		100.00	

Table 4: **Pre-manipulation Call maturities.** ADD HOW THEY ARE COMUPTED.

Table 5: Post-manipulation Statistics

Maturity	Sum	Sum (%)	Mean	Sum (%, period)	STD
Short-term	67,163,421.80	19.05	420.98	36.50	1,737.08
Medium-term	64,192,659.40	18.21	330.34	34.89	1,217.12
Long-term	52,647,945.80	14.93	165.01	28.61	1,184.44
TOTAL	184,004,027.00	52.18		100.00	

Table 6: **Post-manipulation Call maturities.** ADD HOW THEY ARE COMUPTED.

short-term options (36.88%), followed by medium (33.53%) and long-term options (29.59%). If we split the total trading among pre- and post-manipulation, we still have that most of options traded are short-term options (17.63%), followed again by the medium- (16.03%) and long-term options (14.15%). Finally, by splitting the total amount of options traded in the 10 days among pre and post, it emerges from Table 6 how most of trading happens post manipulation (52.18% vs. 47.82%), and how the majority of post-manipulation options traded are again short-term options (19.05%), followed by medium (18.21%) and long-term options (14.93%). The above findings are economically aligned with the natural trade-off existing between the degree of uncertainty of the information and the time horizons of the trade. Specifically, the lower the uncertainty of the signal received by the investors, the more a profit maximizing investor wants to trade in short-term options in order to maximize her return. This because in absence of uncertainty (or with a low level), the investor wants to maximize her expected return by trading in short-term option without the need to pay extra money for longer term options. Longer terms options are in fact more expensive, as they provide the investor with more time for the option go in the ITM area, and would be an unnecessary extra cost for the investor. Tables 8 and 10 confirm the above findings for put options. As for the call

Table 7: Pre-manipulation Statistics

Maturity	Sum	Sum (%)	Mean	Sum (%, period)	STD
Short-term	39,300,057.83	18.06	308.61	37.36	1,242.50
Medium-term	35,858,304.33	16.48	235.97	34.09	1,020.24
Long-term	30,041,798.83	13.80	144.78	28.56	589.57
TOTAL	105,200,161.00	48.34		100.00	

Table 8: **Pre-manipulation Put maturities.** ADD HOW THEY ARE COMUPTED.

Table 9: Post-manipulation Statistics

Maturity	Sum	Sum (%)	Mean	Sum (%, period)	STD
Short-term	41,787,183.00	19.20	328.14	37.17	1,242.65
Medium-term	39,769,397.20	18.27	261.70	35.38	1,020.56
Long-term	30,862,830.80	14.18	148.73	27.45	589.58
TOTAL	112,419,411.00	51.66		100.00	

Table 10: **Post-manipulation Put maturities.** ADD HOW THEY ARE COMUPTED.

options, most of pre-manipulation trading involves short-term options, which values that are also slightly higher than for the call options (18.06% and 37.36% against 17.63% and 36.88%). Once more, trading is slightly more tilted toward the post-manipulation period (51.66% vs 48.34%), with again the short-term maturities being the preferred options.

5.3 HYPOTHESIS 3: Option Moneyness

Next we study the moneyness of the options involved with the stock being manipulated. Tables 12 and 14 show the trading interest divided by moneyness. To make the picture simple we fist only consider OTM and ITM options and include all ATM options in the ITM classification. In the appendix we show how results are still robust including ATM options, as they account for a minority of the options traded in this market. Specifically, we consider a call option to be OTM whenever its moneyness is < 1 and ITM whenever is $\geqslant 1$. We consider a put option to be OTM whenever its moneyness is > 1 and ITM whenever is $\leqslant 1$. Throughout the paper, we define moneyness as S_t/K, where S_t is the actual value of the underlying and K the option strike price.

From the tables it emerges how the OTM options are, by far, the most traded options both before and after the manipulation. With a 34.4% of OTM options trade (vs. 10% ITM) and a 77% (vs. 23%), this is true both if we split the dataset, and if we compact it, for the pre-manipulation period. The same holds even stronger for the post-manipulation period, with a 46.3% of OTM options trade (vs. 9.2% ITM) and a 82.9% (vs. 17.1%)

Next, we increase the granularity of the moneyness, considering also deep-in-the-money (DITM) and deep-out-the-money (DOTM) options. Specifically, we consider a call option to

Table 11: Prevalence Statistics

Time	Sum	Sum %	Sum % Period	Mean	Vol
ITM	15787284.67	0.10087346	0.229621983	4.981340858	102.9894933
OTM	52966083.17	0.343579364	0.770378017	18.28094194	212.0997571
TOTAL	68753367.83	0.444452825	1		

Table 12: **Pre-manipulation Call moneyness.** ADD HOW THEY ARE COMUPTED.

Table 13: Post Statistics

Time	Sum	Sum %	Sum % Period	Mean	Vol
ITM	14672950.4	0.092078127	0.170968298	4.699781259	129.9111015
OTM	71149688	0.463469049	0.829031702	24.31435149	297.3662689
TOTAL	85822638.4	0.555547175	1		

Table 14: **Post-manipulation Call moneyness.** ADD HOW THEY ARE COMUPTED.

be DITM whenever its moneyness is > 1.15, ITM when $\leqslant 1.15$ and $\geqslant 1$, OTM when < 1 and $\geqslant 0.85$, and DITM when < 0.85. Equally, we consider a put option to be DOTM whenever its moneyness is > 1.15, OTM when $\leqslant 1.15$ and > 1, ITM when $\leqslant 1$ and $\leqslant 0.85$, and DITM when < 0.85. To provide a more comprehensive picture, we also consider the options expiration into the analysis.

First we consider the pre-manipulation distribution of all put options linked to manipulated stock and divided per moneyness and time to maturity. From **?** it emerges how OTM options are the mostly linked (48.27%) to manipulated stock prices and, in particular, the short-term ones (25.34%). With an almost equal quantity, OTM options are followed by DOTM (24.49%) and ITM (23.70%) options. For the DOTM options there is almost an equal divisions among short-medium and long-term maturities, while for ITM options are again the short-term options that take the biggest share. Finally, DITM options account for a small fraction of the total (3.54%).

Next we consider the same analysis, but for call options. Table 18 shows the pre-manipulation distribution of the call options linked to manipulated stock and divided per moneyness and time to maturity. Confirming previous results, also for the pre-manipulation call options it

Table 15: Statistics Table

	Moneyness	Short-term	Medium-term	Long-term	Total
DITM	Sum	491,283	531,571.83	1,173,149.67	2,196,004.5
	Sum %	0.0106	0.0079	0.0169	0.0354
ITM	Sum	5,917,378.33	3,810,945.83	2,974,715.83	12,703,040
	Sum %	0.1248	0.0641	0.0481	0.2370
OTM	Sum	12,214,012.17	7,427,938.33	5,779,399.67	25,421,350.17
	Sum %	0.2534	0.1310	0.0984	0.4827
DOTM	Sum	4,411,348.33	3,627,216	6,249,400.17	14,287,964.5
	Sum %	0.0842	0.0609	0.0998	0.2449

Table 16: **Pre-manipulation Put moneyness and maturity.**

Table 17: Statistics Table

	Moneyness	Short-term	Medium-term	Long-term	Total
DITM	Sum	241,878.5	1,101,066,667	8,503,713,333	1,202,356.5
	Sum %	0.0044	9.31E-05	0.0103	0.0148
ITM	Sum	7,183,959,167	4,231,346,667	3,169,622,333	14,584,928.17
	Sum %	0.1137	0.0570	0.0415	0.2121
OTM	Sum	16,255,055.17	11,928,296	9,245,967,167	37,429,318.33
	Sum %	0.2666	0.1710	0.1247	0.5623
DOTM	Sum	4,249,087,333	3,814,217,833	7,473,459,667	15,536,764.83
	Sum %	0.0631	0.0516	0.0961	0.2108

Table 18: **Pre-manipulation Call moneyness and maturity.**

emerges how short term OTM options are the mostly linked to stock manipulations, followed almost equally by short- and medium-term ITM and DOTM options (here, differently than put options we have slightly more ITM than DOTM options), while DITM options cover only a very small fraction of the entire dataset (1.48%).

WHEN DONE, ADD THE POST MANIPULATION CALL DATA.

HYPOTHESIS 4: Friday expiration

In this Section we study if manipulations are linked to some specific expiration day. In particular, Friday expiration and the third Friday of the month could be possibly more prone to manipulation. Table XXXX ADD TABLE shows that, in terms of expiration, there is not a particularly day that stands out as all days share an equal amount of approximately 20% of the total expiration. Specifically, out of a total amount of 1,022,448 detected manipulations, 215,997 happen to be on Friday (21%), and 56,610 happen to be on the third Friday of the month (5.5%).

ADD TABLE WITH ALL DAYS - and check results

5.4 HYPOTHESIS 5: Stock Characteristics

Next we consider the stock characteristics of the manipulated stock prices. Table 19 show the average stock characteristics for the period into consideration. Specifically, it presents the current total asset (CTA), total asset (AT), book value, total current liabilities (TCL), sale, market value (MktVal) and market-to-book value (MtB). **ask for help as I'm not good in reading this data.**

Year	Count	CTA	AT	Book Val	TCL	Sale	MktVal	MtB
2,007	294,623	5,992.44	72,298.21	10,514.04	4,880.17	20,321.51	24,859.84	4.52
2,008	380,245	5,325.78	99,282.53	10,401.59	4,455.39	19,943.07	14,233.59	1.75
2,009	405,032	5,755.92	90,745.48	11,579.74	4,316.03	18,248.40	19,748.70	2.11
2,010	381,112	8,687.99	107,198.19	15,373.39	6,742.80	25,016.88	24,525.60	2.50
2,011	499,304	8,480.66	91,115.52	14,935.45	6,500.41	25,435.94	23,813.14	4.55
2,012	686,257	8,419.15	87,567.96	14,625.72	6,266.24	24,266.52	24,209.65	7.28
2,013	881,946	8,804.74	82,895.67	15,030.83	6,264.81	23,595.60	34,928.15	6.01
2,014	1,372,585	8,877.02	75,183.77	14,333.35	6,576.45	24,482.92	37,254.89	2.84
2,015	1,747,198	7,752.07	56,332.18	11,745.70	5,646.17	19,295.63	34,895.19	2.75
2,016	1,386,870	9,100.16	75,084.31	13,952.81	6,637.19	20,640.47	39,709.22	3.63
2,017	1,449,294	8,832.88	40,525.06	10,040.20	6,645.99	21,063.09	46,721.52	2.57
2,018	2,186,886	10,361.45	55,253.94	11,929.77	7,904.91	24,472.26	60,906.75	5.57

Table 19: **Stock Characteristics for the entire dataset.**

To better understand the trading behavior of options investors and the profile of the stocks options linked to manipulated stock prices, we divide the above table into call an put options. Specifically, Tables 20 and 21 presents the underlying' characteristics for those companies for which there is been trading of call and put options during the event study, respectively.

Year	Count	CTA	AT	Book Val	TCL	Sale	MktVal	MtB
2,007	149,617	5,909.90	71,300.09	10,386.41	4,813.35	20,074.55	24,502.60	4.58
2,008	192,523	5,271.72	98,086.50	10,290.89	4,407.90	19,748.26	14,091.22	1.74
2,009	206,180	5,676.30	89,433.06	11,419.69	4,256.91	18,026.96	19,459.56	2.14
2,010	194,800	8,532.28	105,130.01	15,102.29	6,625.72	24,634.29	24,058.77	2.47
2,011	255,601	8,306.64	89,129.20	14,633.08	6,368.07	24,924.34	23,321.54	4.50
2,012	350,431	8,316.57	86,148.07	14,408.76	6,194.09	23,903.71	23,851.58	7.17
2,013	451,441	8,626.05	81,025.29	14,737.01	6,137.77	23,121.49	34,246.11	6.24
2,014	705,596	8,721.38	73,968.93	14,071.25	6,463.22	24,000.19	36,383.69	2.93
2,015	897,708	7,602.27	54,911.45	11,497.30	5,544.51	18,886.15	34,097.30	2.75
2,016	708,321	8,965.23	73,655.73	13,709.15	6,545.12	20,302.18	38,941.14	3.46
2,017	842,740	8,521.22	39,667.03	9,884.59	6,472.04	20,553.56	44,200.41	2.07
2,018	1,115,011	10,194.03	54,433.49	11,732.65	7,773.54	24,055.40	59,801.38	5.37

Table 20: **Stock Characteristics Call options only.**

Year	Count	CTA	AT	Book Val	TCL	Sale	MktVal	MtB
2,007	145,006	6,078.11	73,328.07	10,645.67	4,949.52	20,576.32	25,229.33	4.46
2,008	187,722	5,381.42	100,509.16	10,515.16	4,504.26	20,142.86	14,379.80	1.76
2,009	198,852	5,838.78	92,106.13	11,745.68	4,377.54	18,477.98	20,048.84	2.08
2,010	186,312	8,851.59	109,360.60	15,656.84	6,865.75	25,416.90	25,015.47	2.53
2,011	243,703	8,663.59	93,198.82	15,252.58	6,639.49	25,972.51	24,330.85	4.60
2,012	335,826	8,526.00	89,049.59	14,852.12	6,341.34	24,645.12	24,582.37	7.40
2,013	430,505	8,992.76	84,857.01	15,338.93	6,398.42	24,092.76	35,642.21	5.78
2,014	666,989	9,041.46	76,468.93	14,610.59	6,696.08	24,993.59	38,180.44	2.75
2,015	849,490	7,910.32	57,833.56	12,008.13	5,753.58	19,728.34	35,737.71	2.75
2,016	678,549	9,240.66	76,575.57	14,207.06	6,733.16	20,993.61	40,510.38	3.80
2,017	606,554	9,264.58	41,717.20	10,256.30	6,887.05	21,771.03	50,223.52	3.26
2,018	1,071,875	10,535.26	56,107.40	12,134.81	8,041.38	24,905.90	62,057.25	5.79

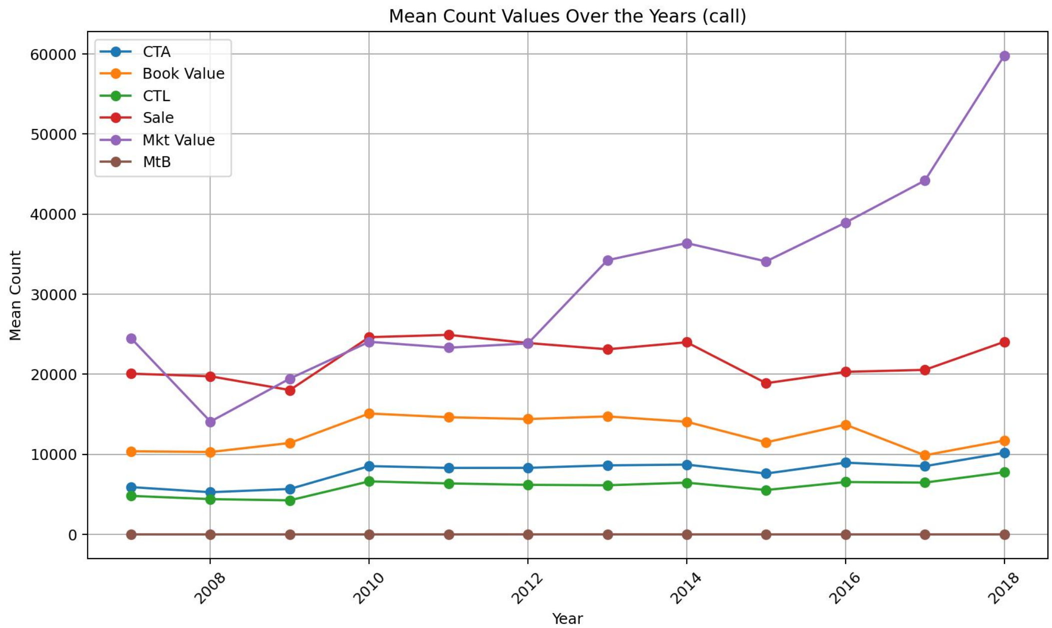
Table 21: **Stock Characteristics Put options only.**

To visualize the above tables, the upper and lower panel of Figure 5 depict the mean values, presented in Tables 20 and 21, respectively. The figures give us an even better representation of the stock characteristics which, as expected, are almost unchanged among call and put options. This lack of difference confirms us that, all else equal, a possibly informed trader can profit from both call and put options, without making a difference on the stock price characteristics when deciding if to use call or put options. While the choice of using call or put is not impacted, clearly some characteristics matter, as both figures and the table provide a clear picture on the stock characteristics of the possibly manipulated underlying. It is well-known that small and illiquid stocks are more prone to manipulations as small trades can highly move the market. As anticipated, a similar story holds also for the option market, where nevertheless a trader always has to consider the trade-off between illiquidity costs and the returns one can gather from the option manipulation.

5.5 HYPOTHESIS 6: Stock Price Reversal and Option Prices Trends

This Section is divided in two parts. First, we explore if the manipulated stock prices present a price reversal. Second, we study how option prices behave before, during and after the manipulation event.

Specifically, we first explore the overall behavior of the underlying prices around the ma-



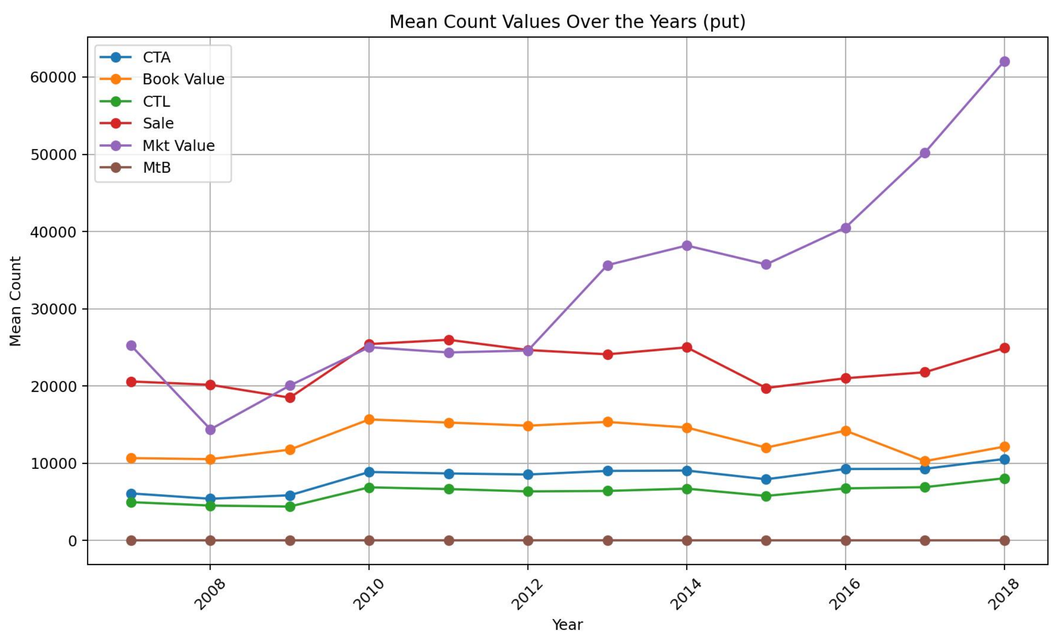


Figure 5: **Stock Characteristics:** the upper (lower) panel represents the characteristics of the possibly manipulated stock prices where call (put) options have been traded during the window $t-5$ to $t+5$.

nipulation day and, in particular, we check if these prices present some sort of price reversal, a typical pattern present in case of stock prices manipulation. Figure 6 depicts the Δ price of all the possibly manipulated options' underlying around manipulation, where Δ price is defined as the actual minus previous price of the underlying. Considering a windows of 5 days around manipulation we thus have 4 and 5 data points before and after manipulation, respectively. Interestingly, Figure 6 depicts a clear stock price reversal after time t, a common stock price

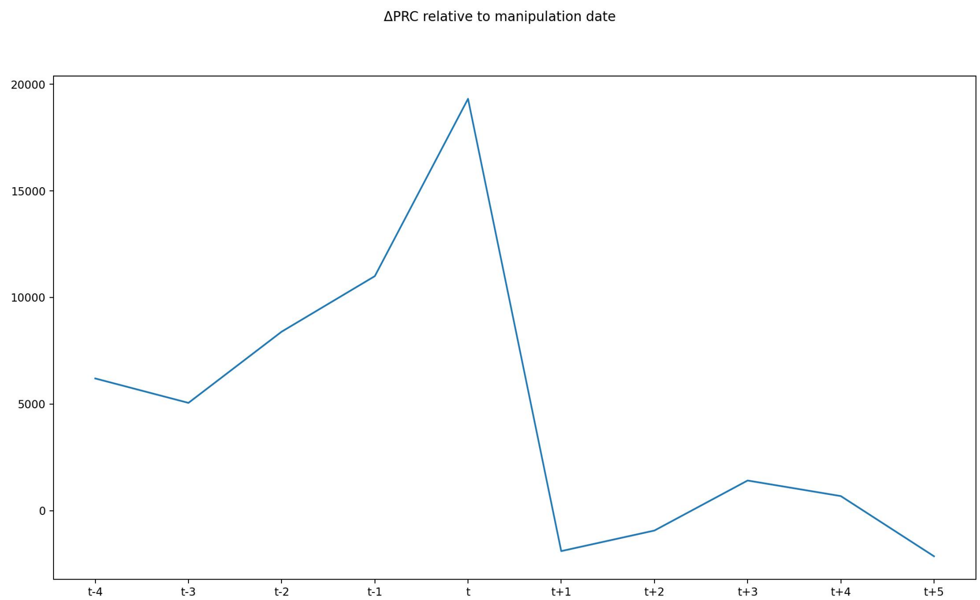


Figure 6: **Delta Underlying Price.** The figure represents the delta price of the options underlying around manipulation.

behavior for manipulated stocks. In line with the efficient market theory, while the Δ price appears to be monotonically increasing before t, it shows a higher degree of randomness after it.

Next, we focus on the option price trend, first aggregating all options (only divided into call or put), then classifying the option given their moneyness. Figure 9 depicts the average price of all call options into our sample around the manipulation day. From the figure it emerges a big price jump just before time t, while the average price is mostly random and without a clear trend after it. Next, Figure 5.5 depict the average call option price around manipulation for all ITM and OTM call options with manipulated stock prices. Specifically, the left (right) panel depict the ITM (OTM) average call option price. Here, the trend is remarkably clear, as the average call option price for the ITM call options is increasing up to time t, it corrects

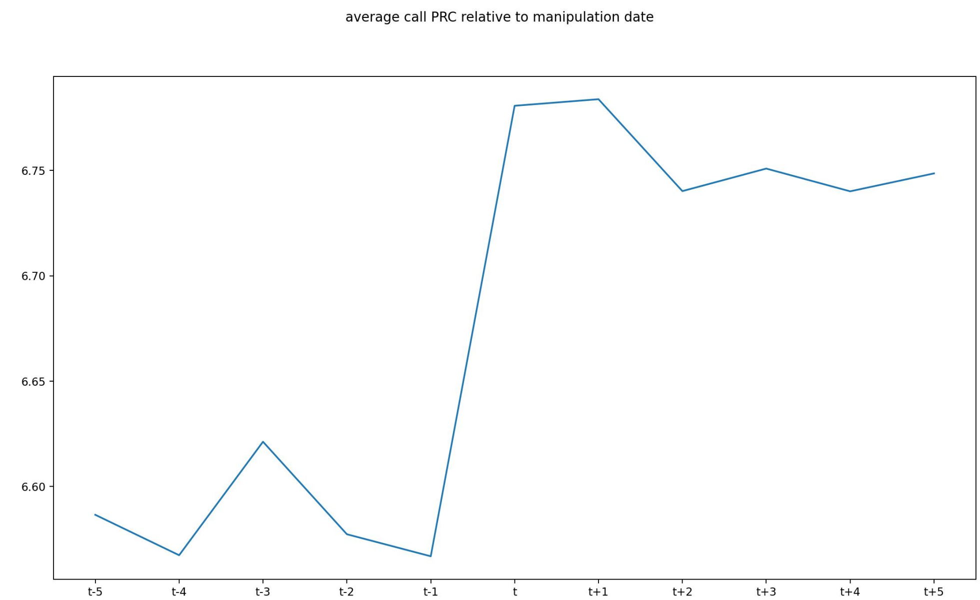


Figure 7: **Average Call option price.** The figure represents the average Call option price around manipulation.

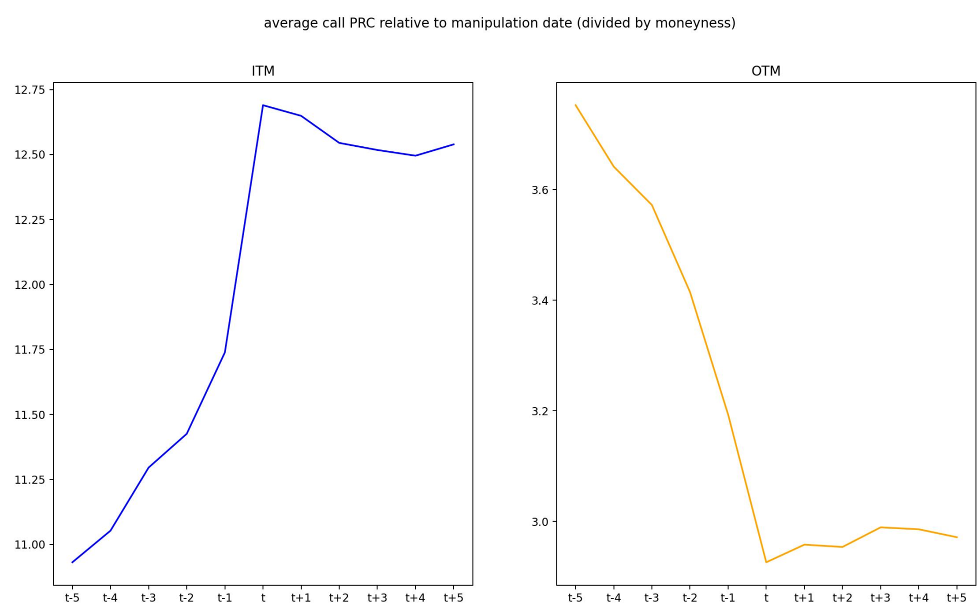


Figure 8: **Average Call option price.** The figure represents the average Call option price around the manipulation and divided by moneyness. The left (right) panel depicts the average price for ITM (OTM) options.

right after and appears to be fully random up to $t+5$. Differently, for the OTM average call option price the trend is strongly downward up to time t, when the price turns back to a higher degree of randomness. As expected, the ITM average call option price are remarkably higher than their OTM counterpart.

We now repeat the same analysis but for put options. Figure 9 show the average put option price, of all options traded, around the manipulation period. Similar to the average call option

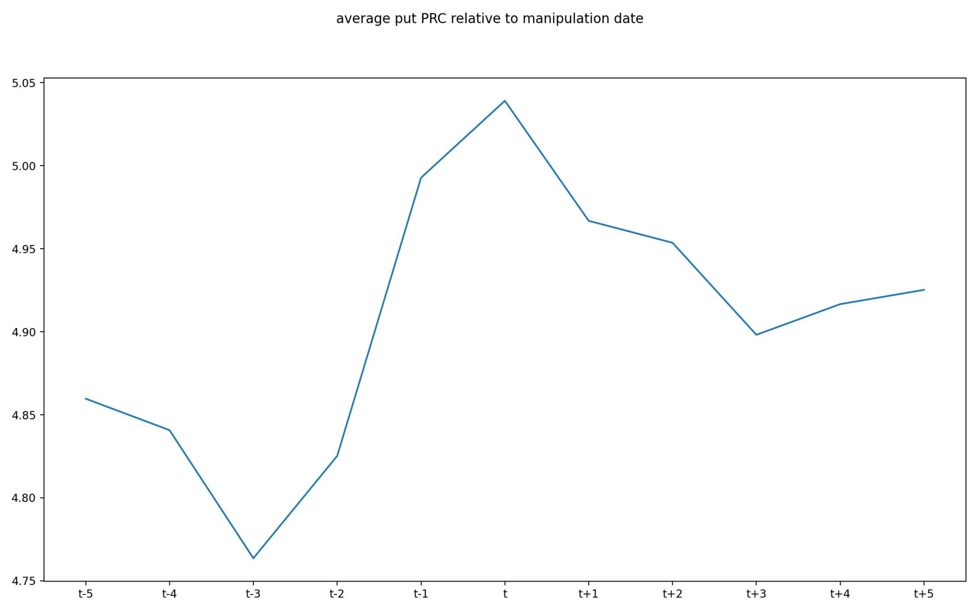


Figure 9: **Average Put option price.** The figure represents the average Put option price around the manipulation.

prices, the price shows an positive trend. Differently than the call option case here the price does not jump but moves up over time and then reverts back to a more random state. As we did for the call options, we next focus on the option moneyness in Figure 10. The ITM and OTM average put option price depicted in Figure 10 follow a similar pattern than the the average call option price represented in Figure . Specifically, both in terms of magnitude and shape, the behavior of the ITM and OTM average put prices is similar to the ITM and OTM average call prices. For the magnitude, the average call (put) option price grows of approximately \$1.7 (\$2.0) from \$11 to \$12.7 (from \$8.2 to \$10.2) If nothing, the average call option prices, both

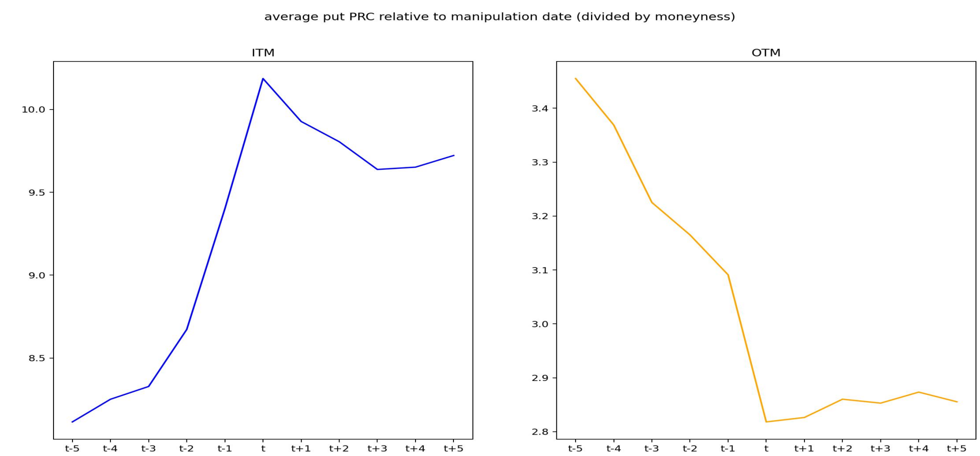


Figure 10: **Average Put option price.** The figure represents the average Put option price around the manipulation and divided by moneyness. The left (right) panel depicts the average price for ITM (OTM) options.

ITM and OTM, have from $t-5$ to t a steeper price change than the average put option prices. The price behavior after t is instead very similar for call and put options, both ITM and OTM, as prices appear without a clear trend and more prone to follow a random walk. Clearly, and once more, the ITM average put option price are way greater than the relative average OTM put option price.

HYPOTHESIS 7: Scheduled Events.

This test focuses on the time window around the release of scheduled firm-specific news. Specifically, it uses earnings announcements as scheduled news.[6] Earnings announcement dates are from I/B/E/S and then are matched with both the stock and option datasets presented in Section 4. Figure 11 represents the number of manipulation around scheduled events. The picture clearly show an almost monotonically increasing number of manipulations, with an important jump in the day prior to the earning announcements. In fact, while from $t-5$ to $t-2$ the average number of manipulations is present but still low, this quantity almost double from $t-2$ to $t-1$, and explodes from $t-1$ to t, just prior to the announcement day.

HYPOTHESIS 7: Stocks with Equity Options.

From a total of 8,192 firms that have seen manipulated at least once from the period 2007-

[6] As the SEC requires the reporting of the earning within 35 and 60 days after quarter and year end, it is common in the literature to use earning announcements as pre-scheduled and non-discretionary events. Although very rare, violations of this timing is often accompanied with negative market reactions Bagnoli et al. (2002).

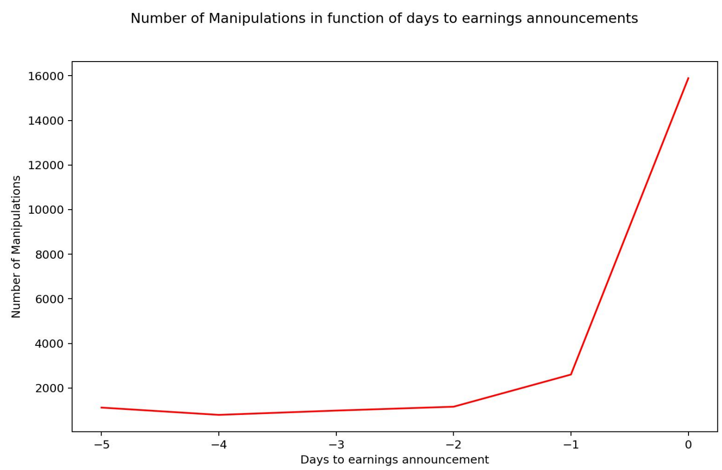


Figure 11: **Number of manipulations around earning announcements.**

2018, only 843 of them (10.2%) do not have equity options. For this analysis we only consider CTM manipulations. As such, firms can suffer more than one manipulation per day, and some of them experienced up to 4 cases of manipulations in a single day. Things are very similar if we enlarge the spectrum of possible manipulation metrics, as in this case we have 10,412 firms that have been manipulated at least once, and 91.9% of them have written equity options. Each of these firms

6 Conclusion

TO DO

7 Bibliography

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A Appendix

A.1 Continuous Trading Manipulation 30 mins Number of Alerts

Provided by SMARTS, Inc. and Capital Markets CRC (CMCRC) in Sydney, the Continuous Trading Manipulation (CTM) metric detects abnormal 30-minute change of liquidity, returns and transaction cost based on the following rules:

- For every 30-minute window (j) after opening of the current trading day (t), calculate the following metrics for every security in the market.

    1. Total trading value over the past 30 mins
    2. Total trading volume over the past 30 mins
    3. Return over the past 30 mins
    4. Average effective spread over the past 30 mins
    5. Average quoted spread over the past 30 mins

- For every security in the market, calculate the average value of the above metrics for each 30-minute window (j) over the past 30 trading days (t-1 to t-31).

- For the j^{th} 30-minute window of the current trading day (t)

    1. For security i, calculate the Security Delta ($\text{SD}_{i,j,t,m}$) as the difference between metric m for the current window (j) and the average metric value for the same window (j) over the past 30 trading days. (Note that for the trading volume and trading value metric, the difference is calculated as the percentage change.)
    2. Calculate the average value of Delta ($\text{D}_{i,j,t,m}$) across all Market Delta securities ($\text{MD}_{j,t,m}$). Note that for the 30-minute return metric, index returns is used to calculate the average delta.
    3. Calculate the difference between ($\text{SD}_{i,j,t,m}$) and ($\text{MD}_{j,t,m}$) for the current trading day (thus having a Current Security Delta, formally $\text{CSD}_{i,j,t,m}$) and the average daily difference over the past 30 trading days (having and Historical Security Delta, formally $\text{HSD}_{i,j,t,m}$)
    4. If there are 3 or more metrics with $\text{CSD}_{i,j,t,m}$ that is more than 3 standard deviations away from $\text{HSD}_{i,j,t,m}$, increase the number of Continuous Trading Manipulation alert by one.

A.2 Moneyness including ATM options

	Time	Sum	Sum (%)	Mean	Sum (%, period)	STD
ITM	prev	51,359,119.00	14.57%	204.34	30.46%	1,483.21
ATM	prev	7,793,334.50	2.21%	304.15	4.62%	1,219.51
OTM	prev	109,447,375.67	31.04%	276.41	64.92%	1,262.11
TOTAL	prev	168,599,829.17	47.82%		100.00%	
ITM	post	52,763,703.80	14.96%	209.93	28.68%	1,447.39
ATM	post	9,069,360.40	2.57%	353.95	4.93%	1,292.05
OTM	post	122,170,962.80	34.65%	308.55	66.40%	1,657.79
TOTAL	post	184,004,027.00	52.18%		100.00%	

Table 22: **Pre and post manipulation Call moneyness.** ADD HOW THEY ARE COMUPTED.

	Time	Sum	Sum (%)	Mean	Sum (%, period)	STD
ITM	prev	32,373,598.83	14.88%	232.41	30.77%	1,231.40
ATM	prev	4,161,953.83	1.91%	238.32	3.96%	854.96
OTM	prev	68,664,608.33	31.55%	208.04	65.27%	788.21
TOTAL	prev	105,200,161.00	48.34%		100.00%	
ITM	post	30,652,663.80	14.09%	220.06	27.27%	1,551.55
ATM	post	5,159,825.60	2.37%	295.45	4.59%	1,133.85
OTM	post	76,606,921.60	35.20%	232.10	68.14%	954.43
TOTAL	post	112,419,411.00	51.66%		100.00%	

Table 23: **Pre and post manipulation Put moneyness.** ADD HOW THEY ARE COMUPTED.

Value	Time	Short-term	Medium-term	Long-Term	Total
sum	DITM	3,302,979.33	3,530,663.67	5,381,200.00	12,214,843.00
sum (%)	DITM	2.48%	2.65%	4.04%	9.17%
sum (% period)	DITM	27.04%	28.90%	44.05%	100.00%
mean	DITM	266.18	266.18	127.88	
vol	DITM	2,098.50	1,360.70	2,513.97	
sum	ITM	3,807,256.17	2,634,470.33	1,351,608.00	7,793,334.50
sum (%)	ITM	2.86%	1.98%	1.02%	5.85%
sum (% period)	ITM	48.85%	33.80%	17.34%	100.00%
mean	ITM	395.07	367.48	153.30	
vol	ITM	3,560.75	2,602.28	1,502.27	
sum	ATM	2,053,890.67	1,090,149.33	562,680.67	3,706,720.67
sum (%)	ATM	1.54%	0.82%	0.42%	2.78%
sum (% period)	ATM	55.41%	29.41%	15.18%	100.00%
mean	ATM	239.27	248.21	100.12	
vol	ATM	1,728.31	1,529.37	632.56	
sum	OTM	30,143,614.50	27,893,990.50	19,239,447.67	77,277,052.67
sum (%)	OTM	22.64%	20.95%	14.45%	58.03%
sum (% period)	OTM	39.01%	36.10%	24.90%	100.00%
mean	OTM	421.10	350.85	164.85	
vol	OTM	1,610.76	1,345.18	765.86	
sum	DOTM	6,437,553.83	9,683,410.17	16,049,359.00	32,170,323.00
sum (%)	DOTM	4.83%	7.27%	12.05%	24.16%
sum (% period)	DOTM	20.01%	30.10%	49.89%	100.00%
mean	DOTM	541.52	300.47	190.97	
vol	DOTM	2,794.07	1,170.01	1,040.03	

Table 24: **Pre manipulation Call time and moneyness.** ADD HOW THEY ARE COMUPTED.

Value	Time	Short-term	Medium-term	Long-Term	Total
sum	DITM	2,900,617.00	3,446,034.50	3,205,786.33	9,552,437.83
sum (%)	DITM	3.45%	4.09%	3.81%	11.35%
sum (% period)	DITM	30.37%	36.07%	33.56%	100.00%
mean	DITM	464.54	464.54	210.23	
vol	DITM	3,284.46	1,630.84	1,029.16	
sum	ITM	2,079,053.83	1,398,893.50	684,006.50	4,161,953.83
sum (%)	ITM	2.47%	1.66%	0.81%	4.94%
sum (% period)	ITM	49.95%	33.61%	16.43%	100.00%
mean	ITM	299.45	263.89	131.04	
vol	ITM	2,351.73	3,000.10	1,562.85	
sum	ATM	1,041,129.33	549,966.00	217,528.00	1,808,623.33
sum (%)	ATM	1.24%	0.65%	0.26%	2.15%
sum (% period)	ATM	57.56%	30.41%	12.03%	100.00%
mean	ATM	171.58	172.30	70.90	
vol	ATM	966.88	1,418.37	498.02	
sum	OTM	18,365,324.17	15,353,413.00	9,751,401.83	43,470,139.00
sum (%)	OTM	21.81%	18.24%	11.58%	51.63%
sum (% period)	OTM	42.25%	35.32%	22.43%	100.00%
mean	OTM	306.65	256.82	146.29	
vol	OTM	958.33	938.15	529.66	
sum	DOTM	5,916,151.17	7,919,797.33	11,358,520.83	25,194,469.33
sum (%)	DOTM	7.03%	9.41%	13.49%	29.93%
sum (% period)	DOTM	23.48%	31.43%	45.08%	100.00%
mean	DOTM	321.58	193.30	134.65	
vol	DOTM	1,279.60	752.88	530.20	

Table 25: **Pre manipulation Put time and moneyness.** ADD HOW THEY ARE COMUPTED.