Option Market Behavior Around the Stocks' 52-Week Highs and Lows

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This paper extends the research on informed trading in the options market by investigating the reaction of the option market to mispricing in the underlying stock around the 52-week highs and lows. The implied volatility spread, which captures the demand for put options relative to call options, is used to examine the behavior of the options market around the stock price extremes. Regression and quintile analysis are performed to test for the stock return predictability of the implied volatility spread. The results show that comparatively expensive call options predict positive stock returns and comparatively expensive put options predict negative stock returns around the 52-week highs and lows. The predictability is stronger for stocks with a higher probability of informed trading and the results are more significant around the 52-week lows. The evidence implies traders can take advantage of the predictability of the implied volatility spread to develop gainful trading strategies. This is the first paper to examine the relative demand of put and call options around the 52-week highs and lows. This research sheds new light on how the option market and the stock market are segmented and where informed investors trade.

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1. Introduction

Information about the stock's 52-week highs and lows is one of the most widely available features of historical stock prices. Several news outlets highlight the stocks that have reached their 52-week highs and lows. While this technical information does not suggest changes in fundamental value, it draws investor attention. Previous empirical research suggests that investors use this form of technical information to make trading decisions. For example, Huddart, Lang and Yetman (2009) find an increase in trading volume and positive abnormal returns once the stock breaches the previous period's high and low price limits; George and Hwang (2004) find that the nearness to the 52-week high price has more powerful predictive information regarding future stock returns relative to past returns; Heath, Huddart and Lang (1999) find that the attainment of the high or low stock price extremes affects managers' decisions on exercise of executive options and Baker, Pan and Wurgler (2009) find that the pricing of mergers and acquisitions are impacted by the stock price extremes.

Further, the trading behavior around stock price extremes may be associated with psychological heuristics such as the adjustment and anchoring bias proposed by Tversky and Kahneman (1975) as well as the prospect theory proposed by Kahneman and Tversky (1979). For example, investors may make a decision to buy (sell) a stock based on the proximity of the price to the 52-week low (52-week high) while blithely ignoring the stock's fundamentals. In such a scenario, the price extremes act as anchors in investment decision making. George and Hwang (2004) also conjecture that the price extremes influence the investors' reaction to new information. Specifically, investors are inclined to underreact to good (bad) news when the current price is near (far from) the 52-week high. Conversely, Li and Yu (2012) show that whenever the historical high is used as an anchor, investors tend to overreact to good (bad) news when the stock price is neighboring its historical high (low). Such behavioral biases can cause mispricing by generating trend continuation (momentum) and reversals for individual stock returns. Overall, the evidence shows that stock prices potentially deviate from their fundamental values around the stock price extremes and the numerous puzzling stock return patterns around the stock price extremes seemingly defy the efficient market hypothesis.

This paper investigates the response of the option market to mispricing in the underlying stock around the stock price extremes. The motivation for this paper comes from the literature studying the informational value of derivatives and informed trading in the options market. The traditional option pricing theory conjectures that the intrinsic value of an option is derived from the price of the underlying asset (Black and Scholes (1973)). This suggests that the stock price contains information regarding the value of its underlying stock option. However, Diamond and Verrecchia (1987) argue that the ability to engage in short positions in the option market makes the options market more informative than the underlying stock market. In fact, Black (1975) argues that relative to the stock market, the option market provides traders with higher leverage in exploiting their private signals regarding the underlying stock price. Recent studies by Atilgan (2014), Bali and Murray (2013), Cremers and Weinbaum (2010), Bali and Hovakimian (2009), Chang, Hsieh and Lai (2009), Pan and Poteshman (2006), Chen, Lung and Tay (2005) and Chakravarty, Gulen and Mayhew (2004) offer supporting evidence that the option market leads the underlying stock market in price discovery mechanism by incorporating new information before the stock market. Furthermore, Hayunga, Holowczak, Lung and Nishikawa (2012) and Chen, Diltz, Huang and Lung (2011) find that the option market investors have the ability to recognize the degree of price inefficiency in the stock market and correct for the mispricing.

This paper builds on previous research which finds that deviations from put-call parity can predict stock returns because of informed trading in the options market (Cremers and Weinbaum (2010) and Atilgan (2014)). Put-call parity represents a no arbitrage relationship between a European put and a European call option with matching strike price and maturity date (Black and Scholes (1973)). In practice, individual stocks have only American options, where put-call parity is characterized by an inequality sign because of the early exercise premium for American put options. While put-call parity deviations may present arbitrage opportunities, market frictions such as transaction costs and restrictions on short selling make it daunting to engage in arbitrage trading. The implied volatility (IV) spread, representing the difference between the IV of a put and that of a call option with the same strike price and expiration date, has been extensively used in empirical studies to measure divergences from put-call parity.[1] Although there are numerous triggers of put-call parity deviations, the trading activities of informed investors have played a significant role in explaining the deviations. Specifically, informed investors who believe that the stock is mispriced will be inclined to use the option market to buy more call (put) options when they expect the stock price to increase (decrease). This will intensify the IV of the call (put) options relative to the IV of the corresponding put (call) options, thereby decreasing (increasing) the IV spread. When positive (negative) private information materializes, the stocks with relatively more expensive call (put) options will most likely generate positive (negative) stock returns. Garleanu, Pedersen and Poteshman (2009) and Bollen and Whaley (2004) present an option pricing model where the demand for the option has an effect on its price and the expensiveness of the option can be measured by its IV. Therefore, IV spreads are just mechanisms symbolizing relative price pressures in the underlying options market.

As mentioned earlier, previous research has shown that stocks are mispriced around stock price extremes and option market investors can identify and correct the mispricing in the underlying stock since they tend to be more informed than stock market investors. If the trading activity of informed investors is an important driver of the IV spreads (measure of put-call parity deviations), then IV spreads will predict stock returns around the stock price extreme. Specifically, the main hypothesis of this paper is that around the stocks' 52-week highs and lows, stocks with comparatively more expensive call options (lower IV spread) will have higher stock returns than stocks with comparatively more expensive put options (higher IV spread).

This paper uses stock and options data from January 1996 to June 2013 to investigate whether IV spreads predict stock returns around the 52-week highs and lows. The IV spreads are calculated as the implied volatility of the put option minus the implied volatility of the call option. On average the IV spreads are positive, which means that on average, the put options are more valuable than call options perhaps due to the short sale constraints (Ofek, Richardson and Whitelaw, 2004) or the

[1] The mere existence of a non-zero IV spread does not mean that the American option put-call parity inequality has been violated. In this paper, the implied volatility spread helps us examine the relative position of put and call options within the put-call parity range for American options. Essentially, the put-call implied volatility spread captures the deviations from the option pricing model values. The implied volatility spread do not indicate the existence of arbitrage opportunities, but it helps us identify the price pressures in put and call options.

inherent assumptions in Black-Scholes (1973) modeling framework in deriving the IV spreads. There is a significant change in the IV spread when the stock hits its 52-week high or low. The IV spread increases on 52-week highs, which means that on average put options are relatively more expensive than call options when the stock hits a 52-week high, and IV spread decreases on 52-week lows, suggesting that call options are relatively more expensive than put options when the stock hits a 52-week low. The IV spreads revert back to their average values after the 52-high or low event has passed. This shows that the option market investors are following a contrarian strategy and they have private information that they expect to see reversals after the stock price extremes. This is consistent with the results of Mizrach and Weerts (2009) where they find strong reversals after the stock price extremes. A significant change in the IV spread when the stock hits its 52-week high or low indicates a divergence in the stock price and the implied stock price from the options market. If the option market investors are informed investors, then the level and change in IV spread should predict stock returns.

In order to investigate the main hypothesis of the paper, the stocks are sorted into quintiles based on the level of the IV spreads on the day of the 52-week high or low, and the returns on the quintiles are calculated over a two-day window following the stock price extreme event. For both the 52-week high and low sample, stocks with lower IV spread (relatively expensive call options) have higher returns than stocks with higher IV spread (relatively expensive put options). The return difference between the extreme quintiles was 54 basis points for the 52-week high sample and 146 basis points for the 52-week low sample. This is consistent with the hypothesis that IV spread predicts stock returns. Further quintile and regression analysis are done to argue that the return predictability reflects informed trading in the options market. We find that stock return predictability is stronger for stocks with higher probability of informed trading (PIN) and for stocks with low stock market liquidity.

By studying the singular trading patterns in the options market around the stocks' 52-week high and low, this paper extends the recent strand of literature which supports the view that price discovery occurs in options as opposed to the underlying stock market. In spite of the attention given to the stock 52-week highs and lows, only one paper has examined the the option market around stock price extremes (Driessen, Lin and Van Hemert (2013)). They focus only on the behavior of call option-implied volatilities when stock prices approach or breach their 52-week high or low thresholds and the effects of highs and lows on a stock's beta and return volatility. They find that IVs and stock betas decrease when stocks approach high or low while volatilities spike following the violations of the highs and lows. However, this paper shows that when studying the options market around the stock price extremes it is important to examine both the call and the put option implied volatilities since hitting the 52-week high or low has a significant impact on the IV spread. The call and put option implied volatilities deviate more around the stock price extremes. This paper also suggests that the stock price extremes can have a significant influence on the pricing of stock options in the existence of market inefficiencies. It sheds more light on whether informed investors trade in the options market or stock market and how investors sort out information around the stock price extremes. Furthermore, the results show that the implied volatility spread which is a measure of put-call parity deviations, can be used to predict future stock price movements when the stock hits its 52-week high or low.

The rest of the paper is organized as follows: Section 2 discusses the methodology. Section 3 presents the data and descriptive statistics. Section 4 details the empirical results and Section 5 concludes the paper.

2. Methodology

This section discusses how the 52-week highs and 52-week lows are defined and how the implied volatility spread is measured. The 52-week period is chosen based on its importance in the business press and the extensive research that has been done in examining the behavior of the stock market around this period. On any given trading day, the stock is considered to have a 52-week high (low) if the closing stock price is higher (lower) than the closing stock price in the past 52-weeks. We rule out the 52-week highs and lows that surpass those set in the recent past, since they may not signify a reference point, or attract the attention of traders. Specifically, we require that the previous 52-week high or low was set at least 30 days ago. We also exclude the 52-week high and low days that had a stock split or dividend payout event (includes cash dividend and stock dividend) in the past 52 weeks. Huddart *et al*. (2009) and Driessen *et al*. (2013) use a similar methodology to define the 52-week high and low. The implied volatility spread is used in order to understand the behavior of the options market around the 52-week highs and lows. The implied volatility of each American put and call option is solved using the the Cox-Ross-Rubinstein binomial tree option pricing model.[2] The implied volatility spread for each option pair (matched in terms of strike price and expiration dates) is calculated as put option implied volatility minus call option implied volatility. It is possible that multiple pairs of matched put and call options may be present on any given day. This presents hurdles in construction of the IV spread of a specific stock. To circumvent such hurdles, this study derives a single IV spread for each stock on each trading day using the weighted average of the multiple IV spreads.[3] The average open interest of each put and call option pair is used as weights, therefore only the options which have positive open-interest are included in the analysis. The weighted average IV spread for stock "i" on day "t" is derived as follows:

$$IVspread_{it} = \sum_{k=1}^{N_{it}} w_k[IVput_k - IVcall_k] \tag{1}$$

[2] We obtain the implied volatility data from OptionMetrics. The Cox-Ross-Rubinstein binomial tree model used by OptionMetrics incorporates either discrete dividend payments or a continuous dividend yield. Therefore, the reported implied volatility spreads account for the dividend payments before the option expiration.

[3] Consistent with past studies (Atilgan (2014) and Cremers and Weinbaum (2010)), we include option pairs with all available expiration days.

where "k" denotes the option pair for stock "i" on day "t", N_{it} is the number of option pairs for stock "i" on day "t" that are used to calculate the IV spread, $IVput_k$ and $IVcall_k$ refer to the implied volatility of the put and the call option and w_k refers to the weight of each option pair.

3. Data and Descriptive Statistics

The data sample consists of all stocks listed in both the Center for Research in Security Prices (CRSP) and OptionMetrics databases from January 1996 to June 2013. The OptionMetrics database has the closing option prices, volume, open-interest and implied volatility data on both call and put options on individual stocks traded on the U.S. stock exchange. OptionMetrics calculates the implied volatility data for each call and put option.[4] For each option pair with the same maturity and exercise price, both the put and call option implied volatilities are required to calculate the IV spread, therefore put and call options that do not have a matching call or put implied volatility data are eliminated from the sample.

Table 1: Descriptive statistics for the implied volatility spread

Panel A: 52-Week High	**Full Sample**		**1996 - 2002**		**2003 - 2008**		**2009 - 2013**	
Number of Observations	19,392		5,427		7,381		6,584	
Number of Firms	3,267		1,646		1,722		1,653	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Day of 52-week high	2.653	7.154	2.422	8.057	2.056	4.853	3.514	8.347
20th trading day before the 52-week high	1.088	6.977	1.197	7.021	1.107	5.635	0.981	8.154
20th trading day after the 52-week high	1.132	7.125	1.181	7.688	1.136	4.584	1.086	8.787
Panel B: 52-Week Low	**Full Sample**		**1996 - 2002**		**2003 - 2008**		**2009 - 2013**	
Number of Observations	16,133		6,862		6,014		3,257	
Number of Firms	3,393		2,127		1,725		1,300	
Day of 52-week low	-0.995	11.268	-0.909	11.392	-0.638	9.524	-1.835	13.678
20th trading day before the 52-week low	1.444	9.953	0.670	9.686	1.451	8.215	1.542	12.871
20th trading day after the 52-week low	1.265	10.673	0.396	10.783	1.404	8.606	1.795	13.318
Panel C: All Days	**Full Sample**		**1996 - 2002**		**2003 - 2008**		**2009 - 2013**	
Number of Observations	11,214,698		3,795,383		3,827,971		3,591,344	
Number of Firms	7,988		2,984		2,085		2,919	
All available trading days	1.293	8.023	1.028	7.994	1.333	6.658	1.529	9.278

[4] Option Metrics does not calculate implied volatilities on certain options if the average bid-ask price of the option is below its intrinsic value, the option has a special settlement, the option has a Vega less than 0.5, the implied volatility calculation does not converge, or the underlying stock price is not available.

The CRSP database provides the stock prices, stock split and dividend payout data which are used to calculate the stocks' 52-week highs and lows and stock returns. Only non-financial firms and firms with CRSP share codes 10 and 11 are included in this paper. Additional data like the book value of equity is obtained from COMPUSTAT, data on the probability of informed trading (PIN) is obtained from Stephen Brown's website and data on the Amihud (2002) illiquidity ratio is obtained from Joel Hasbrouck's website.[5]

Table 1 shows the descriptive statistics for the implied volatility (IV) spread on and around the 52-week highs (Panel A), the 52-week lows (Panel B) and on all available trading days (Panel C). The descriptive statistics are provided for the full sample and three sub periods (1996 to 2002, 2003 to 2008 and 2009 to 2013). The full sample consists of 19,392 firm days of 52-week highs and 16,133 firm days of 52-week lows. There are 3,267 unique firms in the sample of 52-week highs and 3,393 firms in the sample of 52-week lows. Panel A shows that the average IV spread on the day of the 52-week high is 2.653% and Panel B shows that the average IV spread on the day of the 52-week low is -0.995%. This indicates that when the stock reaches its 52-week high the put options are on average more expensive than call options. When the stock reaches its 52-week low the call options are on average more expensive than put options. This result becomes more pronounced in the third (2009 – 2013) sub period where the average IV spread is 3.514% on the day of the 52-week high and -1.835% on the day of the 52-week low.

Table 1 also shows the average IV spread on the 20th trading day before and after the stock reaches its 52-week highs and lows. The average IV spread before the 52-week high is 1.088% and the average IV spread after the 52-week high is 1.132%. The results are similar for the 52-week low where the average IV spread before the 52-week low is 1.444% and the average IV spread after the 52-week low is 1.265%. This indicates that put options are on average more expensive than call options when the stock prices are not at their extreme values. These results hold for the sub period analysis as well.[6] It is important to note that the IV spread increases significantly when the stock reaches its 52-week high and decreases significantly when the stock reaches its 52-week low. If we consider the IV spread to be a deviation in put-call parity, then we can conclude that the deviations in put-call parity increase when the stock reaches its prices extremes.

4. Empirical Results

4.1. Returns on Implied Volatility Spread quintiles

This section provides a summary of the returns on the stock portfolios formed

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[5] We would like to thank Dr. Stephen Brown from University of Maryland for sharing his PIN dataset. We would also like to thank Dr. Joel Hasbrouck from New York University for sharing his liquidity estimates dataset.

[6] The results are robust to other trading day selections before and after the 52-week highs and lows (such as 15th trading day, 30th trading day and 45th trading day).

based on the implied volatility spread on the day of the 52-week high or 52-week low. The day of the 52-week high or 52-week low is defined as day 0. The stocks are first sorted in three different ways according to their IV spreads (level), changes in IV spread (change) and a combination of level and changes in IV spreads (level/change). Then, five quintiles of stock portfolios are formed based on each sorting criterion and portfolio returns are then derived. Here the change in IV spread is measured from the end of day -6 to the end of day 0. It must be noted that when stocks are sorted based on the level of IV spread, quintile 1 (quintile 5) contains stocks with the lowest (highest) IV spread and when stocks are sorted based on the change in the spread, quintile 1 (quintile 5) contains stocks whose IV spread has decreased (increased) the most over the six-day trading period before the 52-week high/low.

In the third sorting criterion, stocks are double-sorted based on both the level and change in IV spread (level/change). Specifically, twenty-five (25) groups of equities are constructed as follows: All the stocks are first sorted into five portfolios/groups based on the level of their IV spreads on day 0. Five additional groups are formed based on changes in their IV spreads on day 0. A matrix of five by five quintiles is formed, resulting in twenty-five portfolios. The post-formation portfolio returns are calculated for the diagonal equity portfolios [Quintiles 1,1 through quintile (5,5)]. Quintile (1,1) contains stocks with the steepest decline in IV spread and relatively expensive call options, compared to quintile (5,5) which contains stocks with the highest increase in IV spread and relatively expensive put options.

The three sorting criteria as well as portfolio formations and computation of portfolio returns are carried on the days of the 52-week highs and 52-week lows. The portfolio returns for each quintile are equal to the 2-day returns, spanning the opening of day 1 and the closing of day 2. The overnight returns from closing of day 0 are disregarded due to potential non-synchronicity between the options and the stock markets.[7]

Panel A and panel B in Table 2 provide the results for the 52-week high sample and for the 52-week low sample, respectively. Results from panel A show that the portfolio returns for quintile 1 (quintile 5), which consists of stocks with relatively expensive call (put) options, earn an average 2-day return of 61.99 (7.93), 69.93 (17.58) and 84.52 (14.46) basis points for portfolios sorted based on level, changes and level/changes, respectively after attaining the 52-week high. The differences between the portfolio returns of quintile 1 and quintile 5 are 54.06, 52.35 and 70.06 basis points for the three sorting criteria, respectively. The differences in portfolio returns are economically and statistically material at 1% significance level (according to the t-statistics of 3.63, 3.57 and 3.32). Panel B of table 2 summarizes the portfolio returns of five quintiles for the 52-week low threshold. Quintile 1(quintile 5) portfolio earns an average return of 25.73 (-120.54), 10.25 (-90.04) and 51.02 (-119.33) basis points for level, changes and level/changes based portfolios, respectively. The differences in

[7] The Chicago Board of Option Exchange closed at 4:10 PM EST until June 22nd, 1997 and at 4:02 PM EST after that date. In contrast, stock exchanges close at 4:00 PM.

portfolio returns, which are economically and statistically significant, between these two extreme quintiles are 146.28, 100.29 and 170.35 basis points for the three sorting criteria, respectively. These results clearly show that stocks with relatively expensive call options (lower IV spread) have higher returns than stocks with relatively expensive put options (higher IV spread) around both stock 52-week highs and lows.

Table 2: Returns on quintiles created based on the level and change in the implied volatility spread

Panel A: 52-Week High

	Quintiles of stock portfolio returns					(1-5)	
Sorting criterion	1	2	3	4	5	Return diff	t-stat
Level	61.99	21.08	16.01	18.89	7.93	54.06***	3.63
Change	69.93	4.52	24.32	11.19	17.58	52.35***	3.57
Level/Change	84.52	4.61	18.40	17.71	14.46	70.06***	3.32

Panel B: 52-Week Low

	Quintiles of stock portfolio returns					(1-5)	
Sorting criterion	1	2	3	4	5	Return diff	t-stat
Level	25.73	2.36	-20.05	-47.16	-120.54	146.28***	5.91
Change	10.25	-2.74	-12.91	-71.56	-90.04	100.29***	4.02
Level/Change	51.02	-3.33	-11.58	-55.06	-119.33	170.35***	5.19

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Other studies have documented statistically significant differences in portfolio returns of extreme quintiles using different sorting benchmarks. For example: Cremers and Weinbaum (2010) examine the predictability of the IV spreads without focusing on a particular day or event. They perform similar analysis by forming portfolios each week based on the level of implied volatility spread and examining the one-week portfolio returns. They find a weekly return difference of 21 basis points. In our paper we find a two-day return difference of 54.06 (146.28) basis points for the 52-week high (low) sample. Cremers and Weinbaum (2010) also sort the IV spread based on the level and change in IV and they find a weekly return difference of 50 basis points. When we perform a similar sorting, we find a two-day return difference of 70.06 (170.35) basis points for the 52-week high (low) sample. This shows that there is a lot more return predictability at a 52-week low. A similar analysis by Atilgan (2014) but around earnings announcements finds a two-day return difference of 92.84 basis points between the two extreme quintiles of volatility spread portfolios. The present study focuses on the predictability of IV spread around the stock price extremes.

It is apparent from panel A and B that the average returns largely decrease monotonically from quintile 1 through quintile 5 for both the 52-week high and 52-week low sample. Consistent with the hypothesis, the results offer supporting evidence that the level of as well as changes in IV spreads contain predictive information on the stock returns around the stock price extremes. In the case of both the 52-week high and 52-week low sample the return predictability is strongest when the stocks are double-sorted based on both the level and change in IV spread (level/change). Results from table 2 also reveal that predictability is stronger when the stock price attains its 52-week low than when it reaches its 52-week high. The return differences for the sample of 52-week low are economically and statistically higher than return differences of the 52-week high sample. This is consistent with the frictions in short selling on the underlying stock. Specifically, in a bear market pigeonholed by declining stock prices, it is more difficult for the investors to short sell the stocks compared to rising stock prices. Therefore, informed investors utilize put options as trading vehicles, making the put options more valuable than the call options. This will cause a significant increase in IV spreads. When negative private information materializes, the stocks with higher IV spreads (relatively more expensive put options) will most likely generate negative stock returns.

The 52-high sample on average have a 2-day positive return and a high IV spread where the put options are, on average, overvalued relative to call options. However, within this sample, firms with low IV spread (call option is overvalued relative to puts) predict higher returns than firms with high IV spread. The same holds for the 52-week low sample. This conflicting result could arise due to the high demand for put options when the stock price is high. As the stock prices increase the put options become out of the money and investors can easily buy these options as insurance to protect themselves from sudden fall in prices. This increases the demand for put options and their price and hence increases their implied volatility as suggested by Bollen and Whaley (2004). If we also have informed investors trading in the options market, then, the level of volatility spreads can predict the stock returns.

Past studies have documented irrational trading behaviors by stock market investors whenever the stock price hits its 52-high or 52-week low. Informed investors and investors with positive (negative) information about the stock trade in the option markets, anticipate the behavioral biases and mispricing around the stock price extremes. To this end, these investors are likely to bid up the prices of call (put) options relative to the prices of put (call) options. These actions will potentially amplify the put-call parity deviations and result in significant variations in the IV spreads. In presence of limits to arbitrage, (which, according Ng, Rusticus and Verdi (2008) and Brav, Heaton and Li (2010) is caused by transaction costs, margin requirements, taxes and short sale constraints), there will be a delay in correcting the mispricing. Arbitrageurs will observe the put-call parity violations and subsequently take advantage of the mispricing. Their trading activities gradually trigger adjustments in the misaligned prices; resulting in eventual convergence of prices (put-call parity) after all the private information is fully assimilated in the underlying stock price. It is therefore apparent that the IV spreads around 52-week highs and 52-week lows can predict stock returns. The results also suggest that behavioral biases and mispricing around the stock price extremes may trigger singular pattern in IV spreads.

4.2. *The Importance of Private Information*

The seminal study by Easley, O'Hara and Srinivas (1998) shows that informed investors are more likely to use the options market as the trading platform when they have private information associated with an underlying stock. This implies that the greater the amount of private information regarding the underlying stock, the higher the degree of return predictability around the stock price extremes. We test this conjecture using the well-established probability of informed trading (PIN) of Easley, Hvidkjaer and O'Hara (2002) which measures the extent of informed trading arising from private information. Essentially, PIN measures the proportion of stock trades arising from informed traders. Therefore, PIN is a reliable proxy of the magnitude of private information associated with a stock. The higher the PIN, the more the private information available for informed trading of a stock. To this end, the attainment of the 52-week high or 52-week low price enables investors in the option market to better ascertain the mispricing and the behavioral biases inherent in the stock market at the price extremes. If investors have private information, then they are more likely to use that information to trade first in the options market compared to the stock market. This will result in the option market leading in the price discovery process.

Table 3: Returns on quintiles created based on PIN and the level of the implied volatility spread

Panel A: 52-Week High

	Quintiles of stock portfolio returns					(1-5)	
	1	2	3	4	5	Return diff	t-stat
PIN (low)	24.189	8.271	13.07	13.042	20.664	3.53	0.105
PIN (2)	60.148	30.272	8.704	36.862	8.477	51.67	1.636
PIN (high)	108.301	22.04	22.546	-3.43	-6.904	115.21***	4.558

Panel B: 52-Week Low

	Quintiles of stock portfolio returns					(1-5)	
	1	2	3	4	5	Return diff	t-stat
PIN (low)	-12.02	9.05	16.22	-33.72	-80.18	68.16	1.475
PIN (2)	-14.97	13.90	-37.16	-78.95	-77.36	62.39	1.257
PIN (high)	63.69	8.49	-17.22	-76.08	-160.75	224.44***	4.461

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

The stocks are first sorted into three groups (33%) on the basis of PIN values (Low PIN, median PIN and high PIN) for each of the price extreme (52-week high and 52-week low). Five portfolio quintiles are formed within each PIN group and the portfolio returns are computed. The hypothesis that the degree of return predictability is increasing in PIN values is investigated. The summary results are presented in Table 3. For each of the three PIN value-based groups of stocks, the stocks are further sorted into five groups/quintiles based on their IV spread levels.

For the 52-week high sample, the portfolio return difference between the high and low IV spreads quintiles for the low PIN, median PIN and high PIN group is 3.53, 51.67 and 115.21 basis points respectively (with t-statistics of 0.105, 1.636 and 4.558, respectively). However, the 52-week low sample, registers differences in the portfolio returns difference between the high and low IV spreads quintiles for the low PIN, median PIN and high PIN group as 68.16, 62.39 and 224.44 basis points respectively (with t-statistics of 1.475, 1.257 and 4.461, respectively). These results suggest that private information, as proxied by PIN, plays a significant role in the predictability of returns by IV spreads around the stock price extremes.

4.3. *The Importance of Stock Liquidity*

The sequential trading model of Easley *et al*. (1998) suggests that informed investors bear higher proclivity to trade in the options market whenever the the underlying stock has lower liquidity. We investigate this supposition by testing the predictive power of IV spreads on stock returns at varying degrees of liquidity (illiquidity) of the underlying stocks. Specifically, we test whether the predictive power of IV spreads strengthens (weakens) as liquidity decreases (increases). We proceed as follows: Using the Amihud (2002) illiquidity ratio as a proxy for the liquidity of each stock, we sort all the stocks into three portfolios based on low illiquidity (high liquidity), moderate illiquidity and high illiquidity (low liquidity). We employ the double sorting procedure where we then sort each of the three illiquidity-based portfolios into five groups or quintiles based on their level of IV spreads. We perform this procedure for the 52-week high and 52-week low samples of stocks. We then compute the portfolio returns of each quintile. The summary results are presented in Table 4.

Focusing on the 52-week high price extreme, we find that the difference between quintile 1 and quintile 5 portfolio returns is 8.13, 46.56 and 111.61 basis points for the high liquidity, moderate liquidity and low liquidity, respectively. Only the low liquidity return difference of 111.61 is statistically significant at 5% (t-statistic of 2.08). The evidence on the 52-week low price extreme reveals that the difference between quintile 1 and quintile 5 portfolio returns is 85.29, 109.28 and 228.10 basis points for the high liquidity, moderate liquidity and low liquidity, respectively. Only the moderate liquidity and low liquidity return differences are statistically material significant at 5% and 1% significance levels, respectively (t-statistic of 2.05 and 3.75 respectively). These results indicate that informed investors prefer trading in the options market when the stocks have low liquidity.

Table 4: Returns on quintiles created based on stock liquidity and the level of the implied volatility spread

Panel A: 52-Week High								
		Quintiles of stock portfolio returns					(1-5)	
		1	2	3	4	5	Return diff	t-stat
Illiquidity (low)	-->	-29.67	10.03	27.15	23.50	-37.80	8.13	0.23

Liquidity (high)								
Illiquidity (2)		97.68	17.57	28.89	17.83	51.12	46.56	1.20
Illiquidity (high) Liquidity (low)	-->	107.42	101.68	8.82	19.89	-4.19	111.61**	2.08

Panel B: 52-Week Low

		Quintiles of stock portfolio returns					(1-5)	
		1	2	3	4	5	Return diff	t-stat
Illiquidity (low) Liquidity (high)	-->	-3.64	-58.15	-3.12	-128.47	-88.93	85.29	1.34
Illiquidity (2)		120.00	-10.72	37.73	-39.09	10.71	109.28**	2.05
Illiquidity (high) Liquidity (low)	-->	75.12	17.46	-30.19	-103.91	-152.98	228.10***	3.75

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

4.4. *Regression Results for Robustness checks*

Our analysis in section 4.2 confirmed and offered supporting evidence that IV spreads contain important and predictive information on stock returns around the 52-week high and low. The predictive power is stronger the more the investors are informed (high PIN) and the more they are likely to exploit their private information to execute their trades in the option markets. This section extends quintile-based results presented in Table 2, 3 and 4 by providing additional robustness checks using pooled panel regressions. The regressions offer additional insights on the predictive ability of the IV spreads around 52-week high and 52-week low events.

For all the regression models presented in panel A and panel B in Table 5, the dependent variable is the individual 2-day stock returns based on the opening values on day 1 and the closing value on day 2. To ensure that the results of the pooled panel regressions are not driven by firm-specific characteristics, a number of commonly used control variables are included. These control variables are (i) The market beta (calculated from daily returns over the past twelve months) to control for the market risk premium postulated in the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965); (ii) The firm size proxied by the market value of equity to capture the size effect (see Banz (1981)). The size effect is premised on the notion that small, higher-risk and illiquid firms earn a premia over their large, lower-risk and more liquid counterparts; (iii) The book-to-market (BM) ratio (see Fama and French (1992)) which captures the premia commonly associated with value stocks over the growth stocks and (iv) Momentum effect of Jegadeesh and Titman (1993) which suggests that past winners continue to outperform past losers over the intermediate horizon. Momentum effect is measured by the one-month prior to the stock price extreme. The values below the coefficient estimates are the t-statistics based on robust standard errors clustered by the firms.

The results from six different regression models are presented in Table 5. Each model consistently includes all the control variables but proscribes some of the first six explanatory variables. For example: The regression model 1 (for panel A and panel B) includes only the IV spread in levels and restrict the coefficients of the variables 2 through 6 to zero. The results of model 1 in panel A and panel B (52-week high and 52-week low price extremes respectively) show that the coefficients of the IV spread in levels are negative and significantly material. However, the results are statistically and economically stronger for the 52-week low sample in panel B (-0.0523 and t-statistic of -8.59 compared to -0.0189 and t-statistic of -3.23). Similar qualitative results are documented in regression model 2 which utilizes changes in IV spreads as opposed to levels IV spreads. These results are largely consistent with the evidence from quintile analysis in Table 2 and confirm that changes in and levels of IV spreads contain predictive information.

The quintile results from Table 3 and table 4 confirmed that the IV spreads provide stronger predictability of stock returns when (i) PIN is high and (ii) the stocks have low liquidity. Regression models 3, 4, 5 and 6 test these hypotheses by interacting the level of IV spreads and change in IV spreads with PIN dummies and liquidity dummies. The regression models 3 and 4 investigate the impact of the degree of informed trading on the predictive ability of the IV spreads for the stock returns. Specifically, for each of the 52-week high and 52-week low sample, the stocks are grouped into three portfolios based on their PIN levels. A ''PIN low dummy'' is created and it is equal to one if stocks fall in the lowest PIN group and zero otherwise. Likewise, a ''PIN high dummy'' is created and it is equal to one if stocks fall in the highest PIN group and zero otherwise.

In the regression model 3 (model 4), each of the "PIN low dummy" and "PIN high dummy" is interacted with the levels of (changes in) the IV spreads. For the 52-week high and 52-week low samples (panel A and panel B), the level of and the changes in IV spreads have negative coefficients. However, a noteworthy result is that the coefficient associated with PIN high dummy (PIN low dummy) interaction is significantly (insignificantly) negative suggesting stronger stock return predictability in presence of higher PIN around the stock price extremes but limited difference between low and intermediate levels of PIN.

A procedure similar to the one used to create the "PIN low dummy" and "PIN high dummy" is followed to create the "Liquidity low dummy" and "Liquidity high dummy" variables. In regression model 5 (model 6), both liquidity dummies are interacted with IV spread levels (changes in IV spreads). For 52-week high and 52-week low stock samples, the level of and the change in IV spreads have negative coefficients. However, the coefficients of the liquidity low dummy (liquidity high dummy) interactions in panels A and panel B are larger (smaller) and significantly (insignificantly) negative suggesting stronger and significant predictability of returns for low liquidity stocks. These results ratify the importance of stock illiquidity for the predictability of stock returns around the stock price extremes.

Table 5: Panel A
Regressions: Information asymmetry and stock liquidity
Dependent Variable: 2-day Stock Returns around 52-week Highs and Lows

Panel A: Regression results for 52-week high						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.0409***	0.0401***	-0.0197*	0.0453***	0.0553***	0.0557***
Implied Volatility Spread	-0.0189***		-0.0426***		-0.0344***	
Change of Volatility Spread		-0.0159***		-0.0175**		-0.0278***
PIN High dummy interaction			-0.0332***	-0.0285**		
PIN Low dummy interaction			-0.0085	0.0021		
Liquidity Low dummy interaction					-0.0466***	-0.0344***
Liquidity High dummy interaction					-0.0087	-0.0094
Return [-20, -1]	-0.0150***	-0.0125***	-0.0030***	-0.0155***	-0.0221***	-0.0183***
Firm Size	-0.0026***	-0.0026***	-0.0006	-0.0029***	-0.0035***	-0.0036***
Beta	0.0002	0.0002	-0.0007	-0.0005	-0.0005	0.0000
Book-to-Market	-0.0011	-0.0004	0.0080**	0.0002	-0.0023	-0.0001
Adjusted R squared (%)	3.9300	3.5800	3.7600	3.8800	4.5300	4.2400

Table 5: Panel B
Regressions: Information asymmetry and stock liquidity
Dependent Variable: 2-day Stock Returns around 52-week Highs and Lows

Panel B: Regression results for 52-week Low						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	-0.0269***	-0.0265***	-0.0214***	-0.0216***	-0.0086	-0.0073
Implied Volatility Spread	-0.0523***		-0.0482***		-0.0872***	
Change of Volatility Spread		-0.0280***		-0.0331***		-0.0356**
PIN High dummy interaction			-0.0876***	-0.0510***		
PIN Low dummy interaction			-0.0195	-0.0177		
Liquidity Low dummy interaction					-0.0671***	-0.0326**
Liquidity High dummy interaction					0.0148	-0.0104
Return [-20, -1]	-0.0395***	-0.0373***	-0.0440***	-0.0449***	-0.0482***	-0.0481***
Firm Size	0.0014**	0.0013**	0.0010	0.0010	0.0002	0.0001
Beta	-0.0007	-0.0007	-0.0008	-0.0008	-0.0022	-0.0024*
Book-to-Market	0.0017**	0.0020***	0.0007	0.0009	0.0000	0.0003
Adjusted R squared (%)	7.3100	4.4700	6.1000	5.9000	6.6000	3.9000

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

5. Conclusion

News about 52-week high and low stock prices is extensively covered by the media and followed by investors. Previous evidence shows that investors use this form of technical information and make unfounded trading decisions. This has resulted in mispricing in the stock market around the stock price extremes. The options market, on the other hand, consists of informed investors who may not be subject to the same trading biases as stock market investors. This kind of market segmentation can lead to significant increase in put-call parity deviations which is measured using the implied volatility spread. The IV spread is expressed as the difference between the implied volatility of the put option and call option matched based on exercise price and maturity. This paper infers that if the option market is more informed than the stock market then the implied volatility spread can predict the stock returns around the stock price extremes.

Using the most comprehensive sample of data, this is the first paper to examine the predictability of implied volatility spread around the stock price extremes. This paper widens the research on informed trading in the options market. The results show that there is a significant change in the level of the IV spread when the stock hits its 52-week high or low and both the level and change in implied volatility spreads predict the stock returns. The two-day returns on a portfolio of stocks with comparatively expensive call options is significantly higher than the return on a portfolio of stocks with comparatively expensive put options around the stock price extreme. The results are more pronounced for the 52-week low sample. When portfolios of stocks are created based on the level and change in the relative expensiveness of the options, the two-day return difference is 170.35 basis points for the 52-week low sample and 70.06 for the 52-week high sample (Table 2)

In conclusion, the results confirm that the predictability is driven by informed traders in the options market since the predictability is stronger for stocks with a high probability of informed trading and illiquidity. This paper shows how the information around the stock price extreme is spread in the option and stock markets and the evidence suggests the requirement for option pricing theories that integrate put-call parity deviations, specifically around the stock price extremes. Furthermore, the findings indicate potentially lucrative trading strategies that use the deviations in put-call parity around the 52-week highs and lows.

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