What's in the Moneyness? Moneyness Spread and Future Stock Returns

Zhan Li*

Abstract

There exists a significant and positive cross-sectional relation between moneyness spread and future stock returns. Stocks with high moneyness spread outperform stocks with low moneyness spread, measured by raw and risk-adjusted returns. This predictability can last for at least 15 days, and the predictability of open interest-weighted moneyness spread is more persistent than that of dollar-volume weighted moneyness spread. The long-short portfolio, which buys stocks in the top decile and shorts stocks in the bottom decile, outperforms the market. After accounting for transaction costs, this outperformance continues to hold except the daily-rebalanced portfolio based on dollar volume-weighted moneyness spread.

*Address for correspondence: Zhan Li, Faculty of Business and Economics, University of Winnipeg, Email: z.li@uwinnipeg.ca.

1 Introduction

Options have embedded leverage, that is, increased exposure to the underlying stock per unit of invested capital. Black (1975) and Easley et al. (1998) argue that leverage makes an informed trader prefer trading options to stocks. We posit that if the informed trader has stronger conviction on a stock, she will prefer an option with higher leverage to an option with lower leverage. Other things equal, an option's leverage is higher when it is deeper out of money, thus, the information content of an option is tied to its moneyness: A deeper out of money call contains more favorable information on a stock, and a deeper out of money put contains more unfavorable information. If the stock market slowly incorporates the information from the option market to stock prices, option moneyness will predict future stock returns.

To test the above hypothesis, we construct moneyness spread. Moneyness spread is the weighted average difference in moneyness between calls and puts, where an option's moneyness is defined as the ratio of its strike price to its underlying stock's price, and an option's weight is calculated from its dollar trading volume or open interest.

To examine the predictive power of moneyness spread, we first sort stocks into quintile portfolios based on moneyness spread. We find a significant and positive cross-sectional relation between moneyness spread and future stock returns from 2005 to 2020. The raw and risk-adjusted returns increase monotonically with quintiles. A long-short portfolio that buys stocks of high moneyness spread and shorts stocks of low moneyness spread generates economically and statistically significant raw and risk-adjusted returns (alphas). To test the incremental predictability of moneyness spread, we include a number of stock-based and option-based control variables in the Fama and MacBeth (1973) regression. The coefficient on moneyness spread is 0.029 with a t-statistic of 8.318 for dollar volume-weighted moneyness spread and 0.028 with a t-statistic of 3.905 for open interest-weighted moneyness spread.

To understand the nature of information in moneyness spread and the efficiency of the stock market, we examine how persistent the predictability of moneyness spread is. The returns and alphas of the long-short portfolio remains significant up to 15 days for the dollar volume-weighted moneyness spread and over 15 days for the open interest-weighted moneyness spread. The long persistence implies it is likely that moneyness spread contains private information from informed option traders and the stock market only incorporates this information gradually. Autocorrelation of dollar volume-weighted moneyness spread is much smaller and declines much faster than that of open interest-weighted moneyness spread. This implies moneyness spread is more persistent when weighted by open interest.

Finally, we examine the investment performance of the long-short portfolio which buys stocks in the top decile and shorts stocks in the bottom decile, sorted by moneyness spread. Without accounting for transaction costs, daily and quarterly-rebalanced long-short portfolios generate higher returns than the SPDR S&P 500 trust (SPY), while providing much better downside protection. For example, the daily-rebalanced portfolio based on dollar volume-weighted moneyness spread has a Sharpe ratio of 1.65 from 2005 to 2020, while SPY has a Sharpe ratio of 0.56 over the same sample period.

After accounting for transaction costs, the daily-rebalanced portfolio based on dollar volume-weighted moneyness spread has an annualized return of -16.88%, while the portfolio based on open interest-weighted moneyness spread still outperforms SPY by a large margin. Such divergence in performance is caused by differences in portfolio turnovers: The portfolio based on dollar volume-weighted moneyness spread has an average turnover of 0.778, about 15 times higher than that of the portfolio based on open interest-weighted moneyness spread. High turnover leads to high transaction costs, which completely dominate the return of the portfolio based on dollar volume-weighted moneyness spread. Transaction costs have a smaller impact on performance for portfolios rebalanced at lower frequencies. For quarterly-rebalanced portfolios, the outperformance over SPY continues to hold and performance measures are similar with or without transaction costs. These results imply that for a trading strategy with high turnover, rebalancing at a lower frequency is more likely to preserve its performance.

This paper contributes to the literature in two ways. First, it provides the novel empirical evidence that there exists a positive relation between moneyness spread and future stock returns, and the information content in moneyness spread is incremental to existing option-based signals such as IV spread, IV skew, and volatility risk premium (Bali and Hovakimian, 2009; Xing et al., 2010; Cremers and Weinbaum, 2010). There is some existing research on option leverage and future stock returns. Frazzini and Pedersen (2020) examine how embedded leverage in financial assets is related to required returns by alleviating investors' leverage constraint. Wang (2017) demonstrates that weighted average of option elasticity predicts both future earnings and stock returns. Neither of these studies examines moneyness spread.

Second, our paper is related to the literature on information discovery in the option market, specifically, whether the option market leads the stock market. While Manaster and Rendleman Jr (1982) and Kumar et al. (1992) find evidence that the option market leads the stock market, other studies (Chan et al., 2002, 1993; Stephan and Whaley, 1990; Muravyev et al., 2013) find that the option market plays no or very limited role in the price discovery of the stock market. More recent studies show that variables constructed from options can predict stock returns. These variables are based on option volume(Ge et al., 2016; Johnson and So, 2012; Pan and Poteshman, 2006; Roll et al., 2010; Cao et al., 2005)), implied volatility (An et al., 2014; Bali and Hovakimian, 2009; Xing et al., 2010; Yan, 2011; Cremers and Weinbaum, 2010; Chan et al., 2015; Fu et al., 2016; Schlag et al., 2021; Han and Li, 2021; Holowczak et al., 2014), or risk-neutral skewness (Bali et al., 2019; Conrad et al., 2013; Rehman and Vilkov, 2012; Stilger et al., 2017; Chordia et al., 2021; Ratcliff, 2013). Complementary to these studies, this paper shows that moneyness spread predicts future stock returns. Our results provide empirical evidence that the option market leads the stock market.

2 Data

We obtain option data from OptionMetrics and stock data from the Center for Research in Security Prices (CRSP). The sample period is from January 2005 to December 2020. We merge option data with stock data at the daily frequency and restrict the sample to ordinary common shares (CRSP share code 10 or 11). Our final sample contains 6.76 million observations, 4028 trading days, and

5193 stocks.

Moneyness spread is defined as the weighted average differences in moneyness between calls and puts, with moneyness measured by the ratio of the option strike price to the stock price. Mathematically, moneyness spread for stock i on day t, $MS_{i,t}$ is defined as

$$MS_{i,t} = \Sigma_j^{N_i} (-1)^{1_{put(j)}} w_{i,j,t} \frac{K_j}{S_i} \tag{1}$$

where N_i is the total number of options for stock i, and j is the jth option for stock i, $\frac{K_j}{S_i}$ is the ratio of the jth option's strike price K_j to stock i's price S_i, $w_{i,j,t}$ is the weight, which is calculated from option j's dollar trading volume or open interest on day t. $1_{put(j)}$ is an indicator function:

$$1_{put(j)} = \begin{cases} 1 & if\ j = put \\ 0 & if\ j = call \end{cases}$$

Clearly, $(-1)^{1_{put(j)}} w_{i,j,t}$ is negative for puts and positive for calls, thus, calls have positive weights and puts have negative weights when constructing moneyness spread.

Panel A of Table 1 reports the average, standard deviation, and quantiles of dollar volume-weighted moneyness spread for the full sample period and three subsample periods: 2005-2009, 2010-2015, and 2016-2020. For the full sample period, the average is 0.25, the standard deviation is 1.56, and the median is 0.40. The distribution is right-skewed. Across three subsample periods, moneyness spread kept increasing: Its average increased from 0.21 during 2005-2009 to 0.24 during 2010-2015 and 0.30 during 2016-2020. The same pattern holds for all quantiles with the exception of the 95% quantile.

Panel B reports summary statistics on moneyness spread weighted by open interest. Compared with dollar volume-weighted moneyness spread, open interest-weighted moneyness spread has higher mean and lower standard deviation in both the full sample and subsamples. The time-series trend is also slightly different: Moneyness spread weighted by open interest decreased from 0.43 during 2005-2009 to 0.31 during 2010-2015 before bouncing back to 0.40 during 2016-2020, while

Table 1: Summary Statistics

This table reports summary statistics on moneyness spread and a set of stock characteristics. Panel A reports summary statistics on dollar volume-weighted moneyness spread, Panel B reports summary statistics on open interest-weighted moneyness spread, and Panel C reports summary statistics on size, B/M ratio, turnover, and illiquidity. Moneyness spread is the weighted average differences in moneyness between calls and puts. Size is measured by market capitalization in billions of dollars, B/M ratio is the book-to-market ratio, turnover is the ratio of the stock's daily trading volume to the total number of shares outstanding, illiquidity is the average ratio of absolute daily returns to daily dollar trading volumes for the last 21 trading days. The full sample period is from January 2005 to December 2020. For moneyness spread, we report summary statistics for three subsample periods: January 2005 to December 2009, January 2010 to December 2015, and January 2016 to December 2020.

Panel A: Dollar Volume-weighted Moneyness Spread

	Full Sample	2005-2009	2010-2015	2016-2020
Mean	0.25	0.21	0.24	0.30
Standard Deviation	1.56	2.02	0.80	1.69
5% Quantile	-1.00	-1.03	-1.00	-0.99
25% Quantile	-0.25	-0.29	-0.26	-0.20
50% Quantile	0.40	0.35	0.38	0.46
75% Quantile	0.85	0.83	0.84	0.88
95% Quantile	1.11	1.11	1.09	1.15

Panel B: Open Interest-weighted Moneyness Spread

	Full Sample	2005-2009	2010-2015	2016-2020
Mean	0.38	0.43	0.31	0.40
Standard Deviation	1.18	1.67	0.66	1.15
5% Quantile	-0.38	-0.28	-0.41	-0.43
25% Quantile	0.06	0.10	0.04	0.05
50% Quantile	0.30	0.32	0.27	0.32
75% Quantile	0.60	0.58	0.55	0.66
95% Quantile	1.12	1.14	1.01	1.24

Panel C: Stock Characteristics

	Mean	Standard Deviation	5%	25%	50%	75%	95%
Size	8.3419	33.4506	0.1059	0.4877	1.4356	4.5064	32.2221
B/M Ratio	0.5213	2.2794	0.0240	0.2165	0.4104	0.6965	1.4052
Turnover	0.0113	0.0449	0.0016	0.0041	0.0070	0.0124	0.0309
Illiquidity	0.0776	16.9604	0.0000	0.0003	0.0013	0.0058	0.0682

dollar volume-weighted moneyness spread kept increasing in all our subsample periods.

Panel C reports stock-level characteristics. Size is measured by market capitalization, calculated as the product of closing stock price and the number of shares outstanding. The units are in billions of dollars. B/M is the book-to-market ratio, calculated as the ratio of the most recent quarter-end book value of common equity to the firm's market value at the end of each trading day.[1] Turnover is the ratio of the stock's daily trading volume to the total number of shares outstanding. Following Amihud (2002), the illiquidity measure for stock i on day t, is defined as

$$Illiquidity_{i,t} = \frac{1}{21}\Sigma_{j=0}^{-20}\frac{|r_{i,j,t}|}{vold_{i,j,t}} * 10^6$$

which is the average ratio of the absolute daily return to the daily dollar trading volume for the past 21 trading days.[2]

Panel C shows that average market capitalization is 8.34 billion, and average B/M ratio is 0.52. The full CRSP sample has an average market capitalization of 5.04 billion and B/M ratio of 0.66 from 2005 to 2020. Firms in our sample are thus larger with lower B/M ratios. Average illiquidity is 0.078. Firms in the full CRSP sample have an average illiquidity of 5.785, thus, firms in our sample are more liquid. With means larger than medians, distributions of all four stock characteristics are right-skewed. The right skewness is more evident for the illiquidity measure as its mean is 60 times larger than its median.

[1] To make sure the book value of equity has become public information when calculating the B/M ratio, we set the the availability date of book value of common equity as the latest date among these three Compustat variables: fdateq(final reporting date), pdateq(preliminary reporting date), and rdq(report date of quarterly earnings).

[2] Unlike Amihud (2002), who calculates illiquidity as an annual average, we use monthly average because the shorter look-back window enables our measure to incorporate more recent information.

Table 2: Quintile Portfolios Sorted on Moneyness Spread

Panel A and B report raw returns and alphas on equal-weighted quintile portfolios sorted on dollar volume-weighted and open interest-weighted moneyness spread, respectively. FF5 alpha and q-factor alpha are risk-adjusted returns estimated by the Fama and French (2015) 5-factor model and Hou et al. (2015) q-factor model. Both models are augmented by the Carhart (1997) momentum factor. Daily returns and alphas are reported in percentages. t-statistics are reported in parentheses.

Panel A: Dollar Volume-weighted Moneyness Spread

	L	2	3	4	H	H-L
Return	0.037	0.046	0.065	0.064	0.083	0.046
	(1.410)	(1.907)	(2.721)	(2.738)	(3.364)	(7.086)
FF5 Alpha	-0.006	0.002	0.020	0.021	0.041	0.047
	(-1.073)	(0.529)	(5.291)	(5.722)	(9.324)	(7.792)
q-factor Alpha	-0.003	0.007	0.024	0.025	0.045	0.048
	(-0.504)	(1.720)	(6.584)	(6.836)	(9.928)	(7.776)

Panel B: Open Interest-weighted Moneyness Spread

	L	2	3	4	H	H-L
Return	0.041	0.046	0.054	0.060	0.091	0.050
	(1.769)	(2.044)	(2.309)	(2.417)	(3.220)	(5.460)
FF5 Alpha	0.001	0.004	0.011	0.016	0.050	0.049
	(0.272)	(1.596)	(3.860)	(4.584)	(6.126)	(5.694)
q-factor Alpha	0.003	0.006	0.015	0.020	0.053	0.050
	(0.769)	(2.503)	(5.217)	(5.759)	(6.495)	(5.726)

3 Moneyness Spread and Stock Return Predictability

3.1 Portfolio Sorts

To examine the predictability of moneyness spread on subsequent stock returns, we sort stocks into quintile portfolios based on moneyness spread and calculate the equal-weighted portfolio's return on the next trading day. Table 2 presents the raw returns and risk-adjusted returns (alphas) for quintile portfolios and the long-short portfolio which is long the top quintile portfolio and short the bottom quintile portfolio.

Panel A presents the raw returns and alphas for quintile portfolios sorted on dollar volume-weighted moneyness spread. FF5 and q-factor alphas are estimated by Fama and French (2015) 5-factor model and Hou et al. (2015) q-factor model, augmented by Carhart (1997) momentum factor. Panel A shows that both raw returns and alphas increase monotonically with all quintiles. The bottom quintile portfolio has a raw return of 3.7 bps and FF5 alpha of -0.6 bps, and the top quintile portfolio has a raw return of 8.3 bps and FF5 alpha of 4.1 bps. The long-short portfolio has a return of 4.6 bps, a FF5 alpha of 4.7 bps, and a q-factor alpha of 4.8 bps, with t-statistics all above 7. Panel B presents the raw returns and alphas for portfolios sorted on open interest-weighted moneyness spread, and the results are qualitatively similar with slightly higher returns and lower statistical significance.

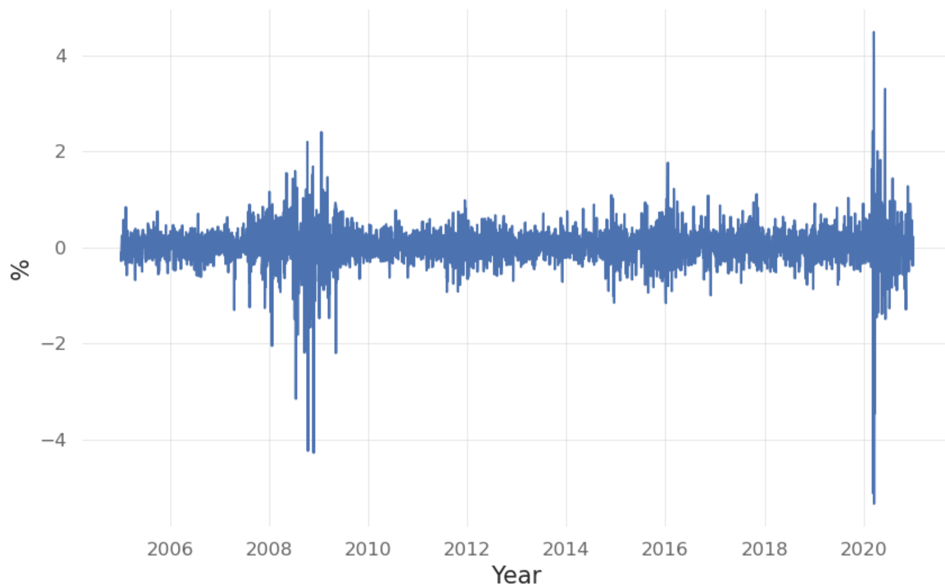
Figure 1 plots the long-short portfolios' daily returns from 2005 to 2020. There exist notable time variations in the portfolios' returns, with the extremest returns occurring during the 2008 financial crisis and 2020 Covid pandemic. Positive extreme returns are more frequent than negative extreme returns in both Figure 1a and Figure 1b; negative returns are larger in magnitude than positive extreme returns for the portfolio based on dollar volume-weighted moneyness spread, while the opposite is true for the portfolio based on open interest-weighted moneyness spread. Importantly, positive returns are generally larger than negative returns over the full sample period. This implies the predictability of moneyness spread is not driven by a particular sample period.

3.2 Fama–MacBeth Regression

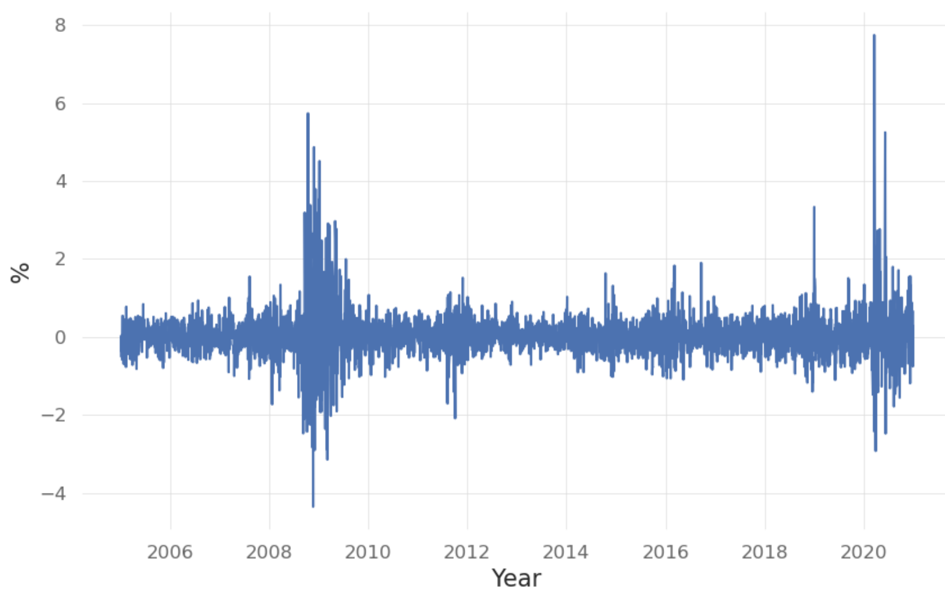
The above univariate portfolio sorts have shown that stocks with high moneyness spread outperform stocks with low moneyness spread. However, the empirical asset pricing literature has documented a number of variables predictive of future stock returns. To understand the incremental predictability of moneyness spread, we include a set of control variables in Fama–MacBeth (FM) regressions (Fama and French, 1993). Specifically, we estimate:

$$r_{i,t+1} = \alpha_t + \beta_t MS_{i,t} + \gamma^T X_{i,t} + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is stock i's return on day $t+1$, $MS_{i,t}$ is stock i's moneyness spread on day t, and $X_{i,t}$ are control variables for stock i on day t.



(a) Portfolio Returns, Dollar Volume-weighted Moneyness Spread



(b) Portfolio Returns, Open Interest-weighted Moneyness Spread

Figure 1: **Time-series Plot of Long-short Portfolios' Daily Returns.** The long-short portfolios take a long portion in the top quintile portfolio and a short position in the bottom quintile portfolio. Portfolios are sorted on dollar volume-weighted moneyness spread in Figure a. and open interest-weighted moneyness spread in Figure b. The sample period is from January 2005 to December 2020. The sample includes all CRSP common stocks (share code 10 and 11) with options.

The control variables include size, B/M, turnover, and illiquidity, defined in Section 2. Other control variables are: σ_r, the volatility of stock returns over the last 21 trading days; r_1, the cumulative return over the last 21 trading days, which is a proxy for short-term return reversals (Lehmann, 1990; Jegadeesh, 1990); r_{12-2}, the cumulative return over the last 12 to 2 month, which is a proxy for the momentum effect (Jegadeesh and Titman, 1993); IV skew, the difference between the implied volatilities of OTM puts and ATM calls (Xing et al., 2010); IV spread, the differences in implied volatilities between calls and puts (Cremers and Weinbaum, 2010); RV-IV spread, the difference between realized volatility and implied volatility, which is a measure of volatility risk premium (Bali and Hovakimian, 2009).

Table 3 reports coefficients estimated from FM regressions with t-statistics computed using Newey-West standard errors. Panel A and B report results on moneyness spread weighted by dollar volume and open interest. Model (1) uses only moneyness spread as the independent variable.[3] With a coefficient of 0.022 and t-statistic of 5.891, there exists a statistically significant positive relationship between dollar volume-weighted moneyness spread and future stock returns. The average moneyness spread is -0.903 for the bottom quintile portfolio and 1.122 for the top quintile portfolio, thus, the difference in moneyness spread between the highest and lowest quintile is 2.025. This implies the difference in return between the highest and lowest quintile is 0.045 (2.025*0.022) percent, which is similar to the result obtained by portfolio sorts.[4] Compared with Panel A, the coefficient reported in Panel B is similar but with lower statistical significance.

Model (2) controls stock-based variables. Compared with Model (1), the coefficient on moneyness spread has the same value but a higher t-statistic of 7.477 in Panel A; the coefficient is slightly larger but again with a higher t-statistic in Panel B. Model (3) controls both stock-based and option-based variables. Compared with Model (1) and (2), the coefficients on both moneyness spreads are larger and continue to be statistically significant. Thus, moneyness spread has incremental explanatory power in the presence of common asset pricing factors.

[3] All models also include an intercept, which is unreported in Table 3.

[4] Panel A of Table 2 reports a return of 0.046% for the long-short portfolio based on dollar volume-weighted moneyness spread.

Table 3: Fama–MacBeth Regressions

This table reports the Fama-MacBeth regression results of daily stock returns on lagged moneyness spread and a set of control variables from 2005 to 2020. Model 1 only includes moneyness spread. Model 2 controls turnover, illiquidity, size, past-month return volatility σ_r, past-month return r_1, past 12 to 2 month return r_{12-2}, and book-to-market ratio B/M. Model 3 additionally controls option-based measures: IV skew is the difference between implied volatilities of OTM puts and ATM calls; IV spread is the difference in implied volatilities between calls and puts; RV-IV spread is the difference between the realized and implied volatilities. The dependent variable, daily stock returns, are in percentages. t-statistics are computed using Newey-West standard errors with 5 lags.

Panel A: FM Regression on Dollar Volume-weighted Moneyness Spread

	(1)		(2)		(3)	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Moneyness Spread	0.022	5.891	0.022	7.477	0.029	8.318
Turnover			0.175	0.797	-0.342	-1.682
Illiquidity			0.046	0.391	-0.662	-1.067
Size			-0.000	-1.461	-0.000	-0.795
σ_r			-0.345	-0.993	-0.411	-1.266
r_1			-0.118	-3.046	-0.063	-1.634
r_{12-2}			-0.010	-0.813	-0.004	-0.355
B/M			0.004	0.739	0.007	0.978
IV Skew					-0.228	-7.132
IV Spread					0.168	8.464
RV-IV Spread					-0.114	-3.955

Panel B: FM Regression on Open Interest-weighted Moneyness Spread

	(1)		(2)		(3)	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
mMoneyness Spread	0.023	3.753	0.026	5.029	0.028	3.905
Turnover			0.488	2.138	-0.390	-1.919
Illiquidity			-0.047	-1.076	-0.765	-1.237
Size			-0.000	-1.152	-0.000	-0.794
σ_r			-0.506	-1.535	-0.528	-1.638
r_1			-0.125	-3.335	-0.028	-0.723
r_{12-2}			-0.007	-0.515	0.000	0.040
B/M			0.003	0.578	0.006	0.844
IV Skew					-0.227	-7.156
IV Spread					0.167	8.449
RV-IV Spread					-0.107	-3.768

3.3 Predictability among Different Subgroups of Stocks

The results in the last sections are based on the full sample, including 5193 stocks with options in the CRSP database. To understand whether the predictive power of moneyness spread is driven by a particular type of stocks, we sort all stocks in our sample into tercile groups based on different firm characteristics and run Fama-Macbeth regression within each group.[5]

Panel A reports FM coefficients on dollar volume-weighted moneyness spread. For the size group, the predictability of moneyness spread is larger and more significant in small firms: The coefficient among small firms is 0.056 with a t-statistic of 5.902, and the coefficient among large firms is 0.01 with a t-statistic of 3.209. Examining the magnitude of FM coefficients for all other groups shows that the predictability is stronger among stocks of low price, high illiquidity, high B/M ratio, low past one month return, and low past 12-2 month return. The predictability is not completely independent of size, liquidity, value, price reversal, and momentum effects. However, FM coefficients on moneyness spread are statistically significant among all groups. The predictive power of dollar volume-weighted moneyness spread is not driven by a particular type of stocks.

Panel B reports FM coefficients on open interest-weighted moneyness spread. Coefficients are larger for stocks of medium size, low price, medium illiquidity, high B/M ratio, low past one-month return, and medium past 12-2 month return. Compared with dollar volume-weighted moneyness spread, coefficients are smaller with lower statistical significance: Only 10 out of 18 t-statistics are larger than 2. The predictive power of open interest-weighted moneyness is likely driven by firm characteristics.

3.4 How Persistent is the Predictability of Moneyness Spread?

We examine the persistence of the predictability of moneyness spread in this section. This question is related to the nature of information content in moneyness spread and the efficiency of the stock market. If the predictability persists over a longer horizon, then it is likely driven by informed trading and the market is slow in price discovery; if the predictability is short-lived, then either

[5] Fama-Macbeth regression includes all stock and option-based control variables defined in Section 3.2.

Table 4: Predictability among Different Subgroups of Stocks

This table reports the predictability of moneyness spread in different subgroups of stocks. We sort stocks into tercile groups based on size, price, illiquidity, B/M ratio, past month return, and past 12 to 2 month return. The sample period is from 2005 to 2020, and the sample includes all optionable common stocks from CRSP (share code 10 and 11). The dependent variable is the next-day stock return, which is in percentages. t-statistics are corrected using Newey-West standard errors with 5 lags.

Panel A: Dollar Volume-weighted Moneyness Spread

Size	Coeff	t-statistic	Price	Coeff	t-statistic
Small	0.056	5.902	Low	0.050	6.192
Medium	0.035	7.328	Medium	0.024	5.148
Large	0.010	3.209	High	0.017	4.842
Illiquidity	Coeff	t-statistic	B/M	Coeff	t-statistic
Low	0.011	3.354	Low	0.025	5.022
Medium	0.039	8.227	Medium	0.025	5.546
High	0.047	4.508	High	0.034	5.898
r_1	Coeff	t-statistic	r_{12-2}	Coeff	t-statistic
Low	0.035	6.535	Low	0.036	6.076
Medium	0.032	7.459	Medium	0.025	6.058
High	0.021	4.070	High	0.021	4.378

Panel B: Open Interest-weighted Moneyness Spread

Size	Coeff	t-statistic	Price	Coeff	t-statistic
Small	0.035	2.351	Low	0.039	2.990
Medium	0.039	4.074	Medium	0.010	1.072
Large	0.012	1.635	High	0.018	2.296
Illiquidity	Coeff	t-statistic	B/M	Coeff	t-statistic
Low	0.011	1.357	Low	0.018	1.779
Medium	0.039	4.139	Medium	0.013	1.389
High	0.027	1.618	High	0.036	3.490
r_1	Coeff	t-statistic	r_{12-2}	Coeff	t-statistic
Low	0.031	3.099	Low	0.020	1.852
Medium	0.014	1.517	Medium	0.029	3.210
High	0.021	2.022	High	0.026	2.715

the market is efficiently incorporating the information in moneyness spread into stock prices or the information content in moneyness spread is transitory; if the predictability reverses over a longer horizon, then the predictability is likely driven by investors' behavior biases.

We sort stocks into quintile portfolios based on moneyness spread and examine n-day ahead raw returns and risk-adjusted returns of the long-short portfolio, where n = 1, 2, 3, 4, 5, 10, 15. Note that we examine the portfolio's daily return on the nth day instead of its cumulative n-day return.

Table 5 reports equal-weighted returns and alphas for day 1, 2, 3, 4, 5, 10 and 15. Panel A reports the results on dollar volume-weighted moneyness spread. When the predictive horizon extends from 1 day to 15 days, the long-short portfolio's return decreases from 0.047% to 0.015%, and t-statistic drops from 7.390 to 2.528. The biggest drop occurs on day 2 with the return dropping from 0.047 to 0.025. However, the return remains statistically significant for up to 15 days. Thus, the predictability of moneyness spread is persistent. We observe the same pattern in alphas: The magnitude and significance of alphas drop as the predictive horizon extends to 15 days, however, alphas are still marginally significant on day 15. It is likely the predictability of moneyness spread is driven by private information from informed option traders and the stock market incorporates this information slowly.

Panel B reports raw returns and alphas for the long-short portfolio based on open interest-weighted moneyness spread. As the predictive horizon extends to 15 days, the magnitude and significance of the raw returns and alphas decrease. For example, the raw return decreases from 0.049 to 0.035 and t-statistic decreases from 5.438 to 4.129 from day 1 to day 15. However, the speed of decrease is much slower when compared with dollar volume-weighted moneyness spread. Thus, the predictability of moneyness spread is much more persistent when it is weighted by open interest.

Panel C reports autocorrelation of moneyness spread. Autocorrelation of open interest-weighted moneyness spread is much larger than that of dollar volume-weighted moneyness spread: The average first-order autocorrelation is 0.209 for the dollar volume-weighted moneyness spread but 0.953

Table 5: How Long Can the Predictability of Moneyness Spread Last?

The sample period is January 2005 to December 2020 and we include all CRSP common stocks (share code 10 and 11) with options. Panel A and Panel B report the n-day ahead daily return and alpha for the long-short portfolio sorted on the moneyness spread, with n = 1, 2, 3, 4, 5, 10, and 15. The long-short portfolio takes a long position in the top quintile portfolio and a short position in the bottom quintile portfolio. Panel C reports the average (across firms) autocorrelation in moneyness spread. All returns and alphas are in percentages. t-statistic are reported in parenthesis.

Panel A: N-day Ahead Return, Dollar Volume-weighted Moneyness Spread

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 10	Day 15
r_{Q5-Q1}	0.047	0.025	0.017	0.022	0.018	0.020	0.015
	(7.390)	(4.013)	(2.706)	(3.515)	(3.015)	(3.485)	(2.528)
α_{FF5}	0.044	0.021	0.013	0.017	0.013	0.016	0.010
	(7.212)	(3.482)	(2.203)	(2.785)	(2.318)	(2.855)	(1.815)
$\alpha_{QFactor}$	0.044	0.022	0.013	0.018	0.014	0.016	0.010
	(7.208)	(3.606)	(2.273)	(2.828)	(2.356)	(2.885)	(1.889)

Panel B: N-day Ahead Return, Open Interest-weighted Moneyness Spread

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 10	Day 15
r_{Q5-Q1}	0.049	0.043	0.041	0.039	0.039	0.035	0.035
	(5.438)	(4.841)	(4.591)	(4.484)	(4.441)	(4.142)	(4.129)
α_{FF5}	0.044	0.038	0.035	0.034	0.033	0.030	0.029
	(5.144)	(4.480)	(4.178)	(4.032)	(4.049)	(3.752)	(3.717)
$\alpha_{QFactor}$	0.045	0.040	0.037	0.036	0.035	0.031	0.031
	(5.203)	(4.533)	(4.225	(4.113	(4.119	(3.805	(3.788)

Panel C: Autocorrelation of Moneyness Spread

	Dollar Volume-Weighted	Open Interest-Weighted
Autocorrelation(1)	0.209	0.953
Autocorrelation(2)	0.162	0.920
Autocorrelation(3)	0.141	0.890
Autocorrelation(4)	0.125	0.863
Autocorrelation(5)	0.115	0.841
Autocorrelation(10)	0.084	0.736
Autocorrelation(15)	0.069	0.652

for open interest-weighted moneyness spread. Autocorrelation of dollar volume-weighted moneyness spread also decreases much faster than that of open interest-weighted moneyness spread: Autocorrelation of dollar volume-weighted moneyness spread decreases from 0.209 for the 1st order to 0.069 for the 15th order, while autocorrelation of open interest-weighted moneyness spread decreases from 0.953 for the 1st order to 0.652 for the 15th order. Consistent with results from Panel A and B, Panel C shows that the information contained in open interest-weighted moneyness spread is more persistent.

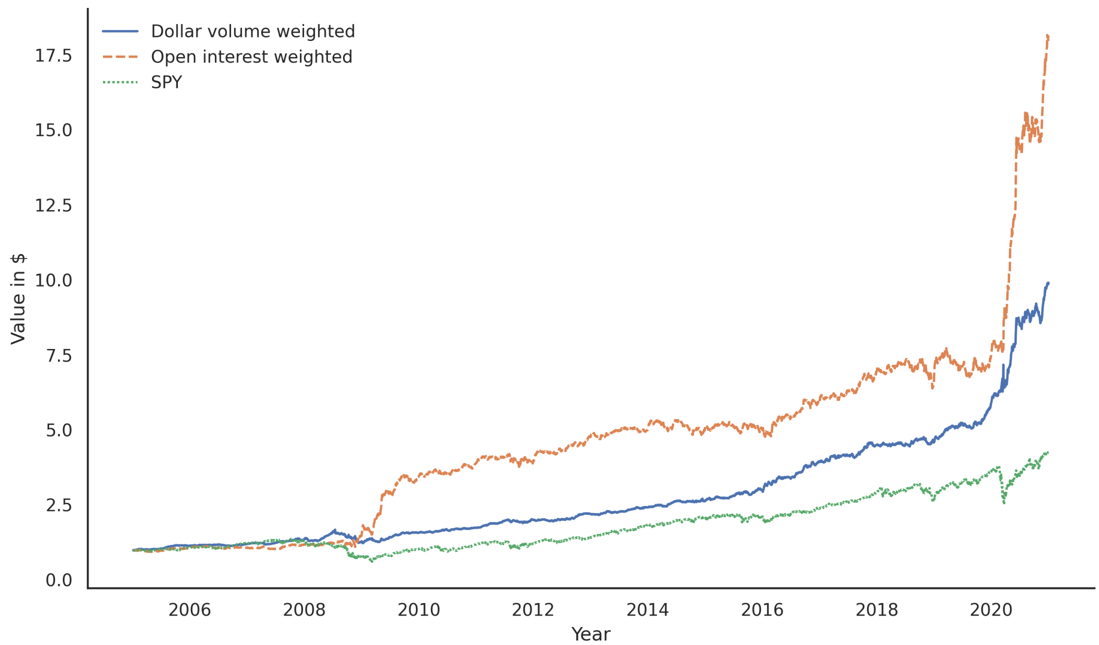
In summary, the predictive power of moneyness spread is persistent, and its persistence is much stronger when weighted by open interest. Intuitively, open interest accounts for cumulative outstanding option contracts, thus, the information content in open interest is cumulative and slow-moving. The slower-moving information contained in open interest leads to stronger persistence in predictability for open interest-weighted moneyness spread. This implies that a trading strategy based on open interest-weighted moneyness spread is likely to have lower turnover, and be more robust to trading costs.

4 Investment Performance

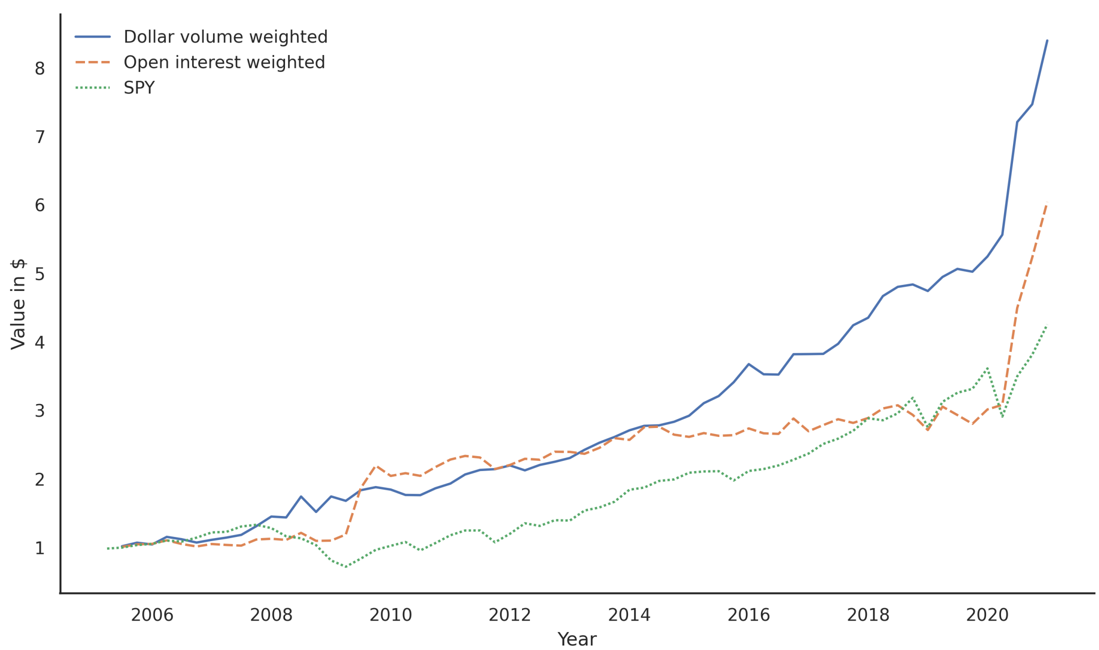
4.1 Performance without Transaction Costs

To examine the investment performance of moneyness spread, we construct four long-short portfolios which buy stocks in the top decile and short stocks in the bottom decile, sorted by moneyness spread. These four portfolios are based on dollar volume-weighted or open interest-weighted moneyness spread and rebalanced daily or quarterly. We first examine these portfolios' performance without transaction costs and consider the effect of transaction costs on investment performance in Section 4.2. For comparison, we also examine the performance of the SPDR S&P 500 trust (SPY) over the same sample period.

Figure 2 plots terminal values of long-short portfolios and SPY with $1 initial investment. Figure 2a and Figure 2b plot the performance of portfolios rebalanced at the end of each day and



(a) Rebalance Daily



(b) Rebalance Quarterly

Figure 2: **Portfolio Values under Different Rebalance Schedules**. The above figures plot the terminal values of investing $1 starting from 2005 to 2020 by taking a long position in the top decile portfolio and a short position in the bottom decile portfolio, sorted on dollar volume-weighted and open interest-weighted moneyness spread respectively. The long-short portfolio is equal-weighted. Figure a. plots the performance of daily-rebalanced portfolios and the SPDR S&P 500 trust (SPY). Figure b. plots the performance of quarterly-rebalanced portfolios and SPY.

quarter respectively.[6] All four long-short portfolios in Figure 2 have higher returns than SPY, with significant outperformance during the 2020 Covid pandemic. The portfolio based on open interest-weighted moneyness spread outperforms the portfolio based on dollar volume-weighted moneyness spread when rebalanced daily, while the opposite happens when the portfolio is rebalanced quarterly. Daily-rebalanced portfolios have much higher returns than quarterly-rebalanced portfolios. Intuitively, trading signals suffer a smaller decay at a higher rebalancing frequency and thus have better performance. However, depending on portfolio turnover, rebalancing daily will likely incur large transaction costs, and the real-world performance of daily-balanced portfolios is likely to be worse.

Panel A of Table 6 reports return, risk, and performance measures. The annualized returns are 15.41% and 19.89% for daily-rebalanced portfolios and 14.23% and 11.90% for quarterly-rebalanced portfolios, while SPY has an annualized return of 9.49%. Risks are measured by volatility, downside deviation, and maximum drawdown, where downside deviation is the standard deviation of negative returns and maximum drawdown is the maximum loss from a portfolio's peak to its trough. All portfolios have smaller volatility than SPY except the quarterly-rebalanced portfolio sorted on open interest-weighted moneyness spread. All portfolios have better downside protection: The largest downside deviation among all portfolios is 7.43% while SPY has a downside deviation of 16.50%; the largest maximum drawdown is 26.78% while SPY has a maximum drawdown of 55.19%. Finally, we measure investment performance by Sharpe Ratio, Sortino Ratio, and Calmar ratio, which are the ratio of average return to volatility, downside deviation, and maximum drawdown, respectively. The lowest Sharpe ratio among all portfolios is 0.64, while SPY has a Sharpe ratio of 0.56; the lowest Sortino ratio and Calmar ratio among all portfolios are 2.03 and 0.55, while SPY has a Sortino ratio of 0.67 and Calmar ratio of 0.20. Clearly, all portfolios outperform SPY, and this outperformance is more evident when measured by Sortino and Calmar ratio.

Panel B examines how the long-short portfolios would perform when the market was under

[6] For the quarterly-rebalanced portfolio, moneyness spread is calculated as the average of daily moneyness spread for the current quarter.

Table 6: Investment Performance

This table reports long-short portfolios' investment performance for daily and quarterly rebalance schedules. Panel A reports return, risk, and performance ratios. Panel B reports returns under market stress. The long-short portfolios take a long position in the top decile portfolio and short position in the bottom decile portfolio. MS_{vol} is the dollar volume-weighted moneyness spread, and MS_{oi} is the open interest-weighted moneyness spread. Downside deviation is the standard deviation of all negative returns, maximum drawdown is the loss from the portfolio's peak to its trough. Sharpe ratio, Sortino ratio, and Calmar ratio are ratios of average return to volatility, downside deviation, and maximum drawdown, respectively. Volatility and downside deviation in Panel A are annualized. All numbers except Sharpe, Sortino, and Calmar ratio, are in percentages. SPY refers to the SPDR S&P 500 trust.

Panel A: Performance Statistics

		Daily Rebalance		Quarterly Rebalance	
	SPY	MS_{vol}	MS_{oi}	MS_{vol}	MS_{oi}
Annualized Return	9.49	15.41	19.89	14.23	11.90
Volatility	19.62	8.94	12.33	12.21	20.85
Downside Deviation	16.50	7.26	7.43	6.35	5.31
Maximum Drawdown	55.19	26.78	17.15	12.89	11.73
Sharpe Ratio	0.56	1.65	1.53	1.18	0.64
Sortino Ratio	0.67	2.03	2.54	2.27	2.51
Calmar Ratio	0.20	0.55	1.10	1.12	1.14

Panel B: Portfolio Returns Under Market Stress

Daily Rebalance				Quarterly Rebalance			
Date	SPY	MS_{vol}	MS_{oi}	Quarter End	SPY	MS_{vol}	MS_{oi}
2020-03-16	-10.94	3.71	0.63	2008-12-31	-21.57	14.86	0.35
2008-10-15	-9.84	0.50	-2.14	2020-03-31	-19.45	6.05	2.23
2020-03-12	-9.57	1.69	-0.56	2011-09-30	-13.82	0.56	-7.28
2008-12-01	-8.86	0.50	-2.29	2018-12-31	-13.53	-1.97	-7.50
2008-09-29	-7.84	1.26	-1.44	2010-06-30	-11.36	-0.15	-1.87
2020-03-09	-7.81	2.36	-1.69	2009-03-31	-11.25	-3.67	8.09
2008-11-20	-7.42	-0.09	-4.26	2008-03-31	-9.29	-0.88	-1.51
2008-10-09	-6.98	3.50	-0.55	2008-09-30	-8.84	-12.89	-9.64
2011-08-08	-6.51	0.26	-2.43	2015-09-30	-6.42	6.29	0.36
2008-11-19	-6.41	1.26	-2.07	2007-12-31	-3.67	10.72	1.01

Table 7: Summary Statistics on Portfolio Turnover

This table reports summary statistics on long-short portfolios' turnovers. Long-short portfolios take a long position in the top decile portfolio and a short position in the bottom decile portfolio. Decile portfolios are sorted on dollar volume-weighted moneyness spread (MS_{vol}) and open interest-weighted moneyness spread (MS_{oi}) respectively.

	Daily Rebalance		Quarterly Rebalance	
	MS_{vol}	MS_{oi}	MS_{vol}	MS_{oi}
Mean	0.778	0.049	0.611	0.461
Standard Deviation	0.039	0.038	0.040	0.037
5% Quantile	0.704	0.026	0.531	0.402
25% Quantile	0.761	0.034	0.589	0.436
50% Quantile	0.783	0.041	0.613	0.463
75% Quantile	0.803	0.048	0.638	0.485
95% Quantile	0.830	0.118	0.664	0.529

extreme stress. We examine portfolio returns during periods when SPY performed the worst. Most of these periods occurred during the 2008 financial crisis and 2020 covid pandemic. These long-short portfolios have much higher returns than SPY during all these periods except the 3rd quarter of 2008. The portfolios based on moneyness spread provide effective downside protection even during the most stressful times.

4.2 Performance with Transaction Costs

In this section, we examine how transaction costs affect the investment performance of our moneyness spread-based portfolios. Specifically, we are interested in whether the superior performance presented in the last section can survive transaction costs. To understand this, we first estimate portfolio turnover.

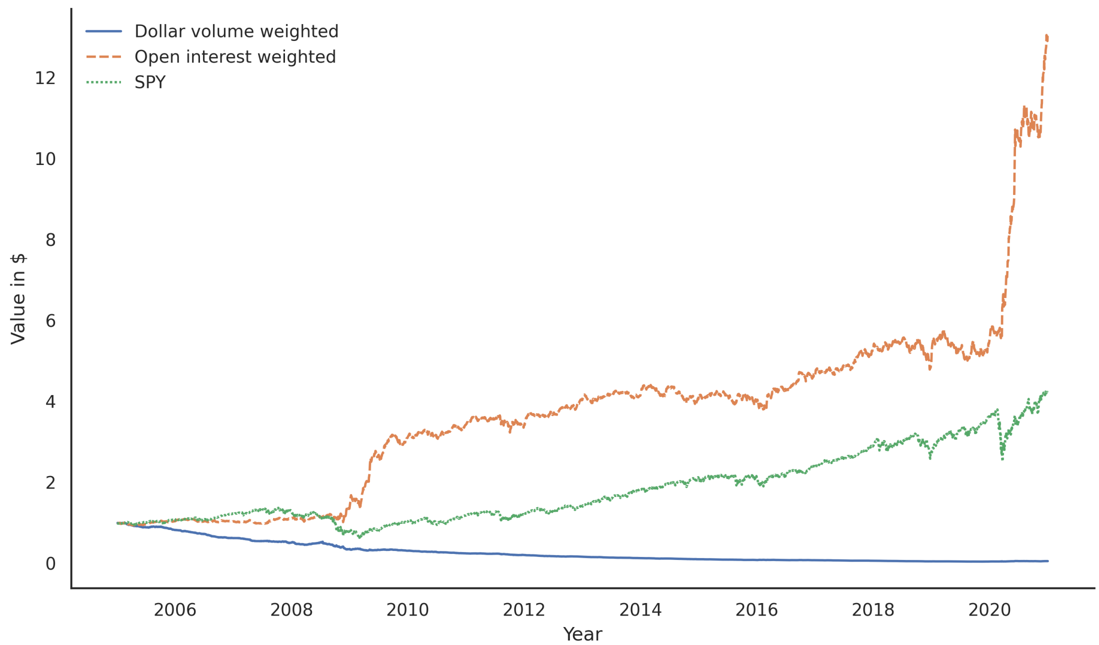
Table 7 reports summary statistics on portfolio turnover. The portfolio based on dollar volume-weighted moneyness spread has much higher turnover than the one based on open interest-weighted moneyness spread: The former has an average turnover of 0.778 while the latter has an average turnover of 0.049. This is consistent with Table 5, which shows that the predictability of open interest-weighted moneyness spread is much more persistent. Unlike daily-rebalanced portfolios, quarterly-rebalanced portfolios have more similar turnovers: The turnover is 0.611 for dollar volume-weighted moneyness spread and 0.461 for open interest-weighted moneyness spread.

Frazzini et al. (2018) estimate the one-way trading cost of long-short portfolios, measured by market impact, is 8.37 basis points from January 2006 to June 2016. Since turnover measures the fraction of position changes at each rebalance, the round-trip transaction cost is $2*8.37*turnover$ basis points. Compared with Section 4.1, portfolio returns in this section are reduced by the amount equal to the round-trip transaction cost at each rebalance.

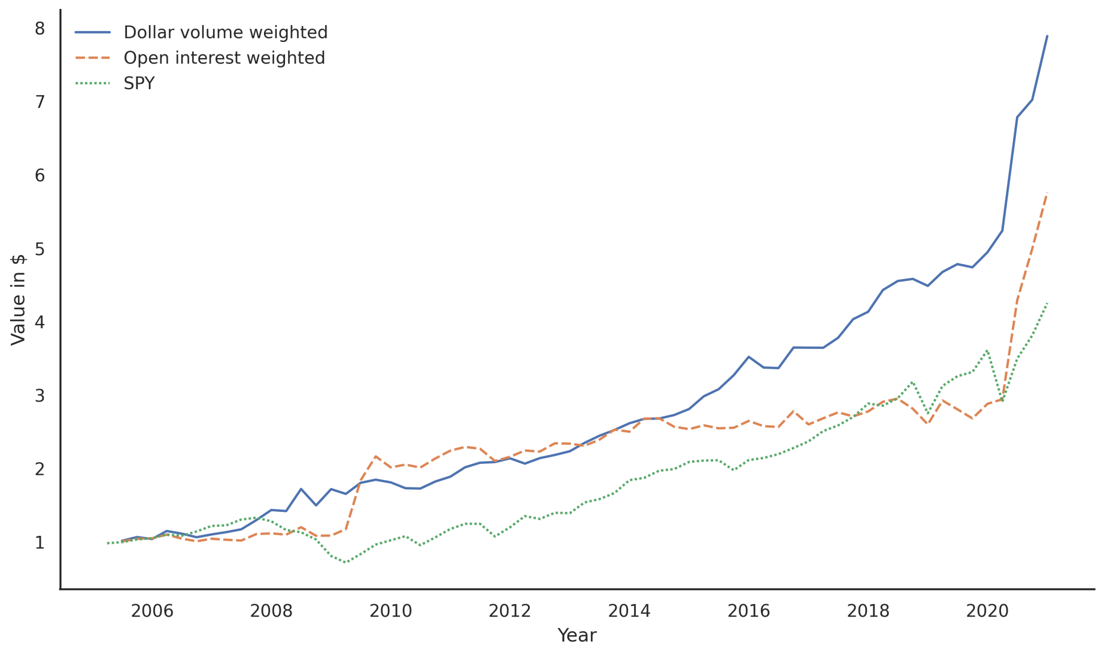
Figure 3 plots long-short portfolios and SPY's terminal values with \$1 initial investment, after accounting for transaction costs. At the daily rebalance frequency, the portfolio based on open interest-weighted moneyness spread has a terminal value of almost \$14, about \$10 higher than the terminal value of SPY. However, the portfolio based on dollar volume-weighted moneyness spread is overwhelmed by transaction costs: Its terminal value is smaller than the \$1 initial investment. This drastic divergence in performance between two daily-rebalanced portfolios is a result of large differences in portfolio turnover: As reported in Table 7, the turnover of the portfolio based on dollar volume weighted moneyness spread is almost 15 times higher than the turnover of the portfolio based on open interest-weighted moneyness spread.

Comparing Figure 2b and Figure 3b, quarterly-rebalanced portfolios' terminal values are almost the same with or without transaction costs. This is expected: At lower frequencies, cumulative returns between two rebalance windows are much larger than transaction costs, which thus have a smaller impact on investment performance. Trading strategies at lower frequencies are more likely to survive transaction costs.

Table 8 reports performance statistics. For daily-rebalanced portfolios, the portfolio based on dollar volume-weighted moneyness spread has a -16.88% annualized return and 96% maximum drawdown, while the portfolio based on open interest-weighted moneyness spread has a 17.43% annualized return and 17.40% maximum drawdown. Compared with performance statistics reported in Table 6, both quarterly-rebalanced portfolios have only slightly lower annualized return and performance ratios. For example, the portfolio based on dollar volume-weighted moneyness



(a) Rebalance Daily



(b) Rebalance Quarterly

Figure 3: **Portfolio Values with Transaction Costs under Different Rebalance Schedules.** The above figures plot the terminal values of investing $1 from 2005 to 2020 with portfolios rebalanced daily and quarterly. Portfolios are equally-weighted, and take a long position in the top decile portfolio and a short position in the bottom decile portfolio. Each figure plots returns of three different portfolios: The portfolio based on dollar value-weighted moneyness spread, the portfolio based on open interest-weighted moneyness spread, and the SPDR S&P 500 trust (SPY).

Table 8: Performance Statistics with Transaction Costs

This table reports long-short portfolios' investment performance with transaction costs. Long-short portfolios take a long position in the top decile portfolio and short position in the bottom decile portfolio. MS_{vol} is dollar volume-weighted moneyness spread, and MS_{oi} is open interest-weighted moneyness spread. Downside deviation is the standard deviation of all negative returns, maximum drawdown is the loss from the portfolio's peak to its trough. Sharpe ratio, Sortino ratio, and Calmar ratio are ratios of average return to volatility, downside deviation, and maximum drawdown, respectively. Volatility and downside deviation are annualized. All numbers except Sharpe, Sortino, and Calmar ratios, are in percentages. SPY refers to the SPDR S&P 500 trust.

		Daily Rebalance		Quarterly Rebalance	
	SPY	MS_{vol}	MS_{oi}	MS_{vol}	MS_{oi}
Annualized Geometric Return	9.49	-16.88	17.43	13.78	11.57
Volatility	19.62	8.95	12.32	12.22	20.85
Downside Deviation	16.5	6.92	7.42	6.29	5.30
Maximum Drawdown	55.19	96.09	17.40	12.98	11.87
Sharpe Ratio	0.56	-2.02	1.37	1.15	0.62
Sortino Ratio	0.67	-2.61	2.27	2.23	2.46
Calmar Ratio	0.20	-0.19	0.97	1.08	1.10

spread has an annualized return of 13.78% and a Sharpe ratio of 1.15, while it has a return of 14.23% and a Sharpe ratio of 1.18 without transaction costs. Performance statistics reported in Table 8 are consistent with Figure 3.

The results in this section have two important lessons on trading strategies based on pricing anomalies. First, it is important to understand the persistence of the signal. A trading strategy based on a persistent signal is likely to have low portfolio turnover and survive transaction costs at even higher rebalancing frequencies. Second, if the signal is transitory and the portfolio has high turnover, it is worthwhile to examine the signal's performance at lower rebalancing frequencies.

5 Conclusion

In this paper, we show that moneyness spread, the weighted average difference of moneyness between calls and puts, can predict future stock returns. Stocks with high moneyness spread outperform stocks with low moneyness spread, measured by both raw and risk-adjusted returns from 2005 to 2020. The incremental predictability of moneyness spread is statistically significant after including a set of stock-based and option-based variables known to predict stock returns. The predictability decreases over time but remains statistically significant for at least 15 days, suggesting that the stock market incorporates the information from the option market slowly.

We then examine the investment performance of a trading strategy which buys stocks in the top decile and shorts stocks in the bottom decile, sorted by moneyness spread. Without transaction costs, long-short portfolios based on moneyness spread outperform the SPDR S&P 500 trust at both daily and quarterly rebalancing frequencies.

After accounting for transaction costs, portfolios based on open-interest weighted moneyness spread continue to outperform, while portfolios based on dollar volume-weighted moneyness spread have dramatically different performances depending on how often they are rebalanced: The daily-rebalanced portfolio has an annualized return of -16.88%, and the quarterly-rebalanced portfolio has an annualized return of 13.78%. Such divergence is caused by high portfolio turnover: With an average turnover of 0.778, the portfolio cannot survive transaction costs when rebalanced daily. These results imply that for a trading strategy with high turnover, rebalancing at a lower frequency is more likely to preserve its performance.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

An, B.-J., Ang, A., Bali, T. G., Cakici, N., 2014. The joint cross section of stocks and options. The Journal of Finance 69, 2279–2337.

Bali, T. G., Hovakimian, A., 2009. Volatility spreads and expected stock returns. Management Science 55, 1797–1812.

Bali, T. G., Hu, J., Murray, S., 2019. Option implied volatility, skewness, and kurtosis and the cross-section of expected stock returns. Working Paper, Georgetown University, Singapore Management University, Georgia State University .

Black, F., 1975. Fact and fantasy in the use of options. Financial Analysts Journal 31, 36–41.

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

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance 52, 57–82.

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

Chan, K., Chung, Y. P., Johnson, H., 1993. Why option prices lag stock prices: A trading-based explanation. The Journal of Finance 48, 1957–1967.

Chan, K., Ge, L., Lin, T.-C., 2015. Informational content of options trading on acquirer announcement return. Journal of Financial and Quantitative Analysis 50, 1057–1082.

Chordia, T., Lin, T.-C., Xiang, V., 2021. Risk-neutral skewness, informed trading, and the cross section of stock returns. Journal of Financial and Quantitative Analysis 56, 1713–1737.

Conrad, J., Dittmar, R. F., Ghysels, E., 2013. Ex ante skewness and expected stock returns. The Journal of Finance 68, 85–124.

Cremers, M., Weinbaum, D., 2010. Deviations from put-call parity and stock return predictability. Journal of Financial and Quantitative Analysis 45, 335–367.

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

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Frazzini, A., Israel, R., Moskowitz, T. J., 2018. Trading costs. Working paper, AQR Capital Management. .

Frazzini, A., Pedersen, L. H., 2020. Embedded leverage. Working Paper, AQR Capital Management .

Fu, X., Arisoy, Y. E., Shackleton, M. B., Umutlu, M., 2016. Option-implied volatility measures and stock return predictability. The Journal of Derivatives 24, 58–78.

Ge, L., Lin, T.-C., Pearson, N. D., 2016. Why does the option to stock volume ratio predict stock returns? Journal of Financial Economics 120, 601–622.

Han, B., Li, G., 2021. Information content of aggregate implied volatility spread. Management Science 67, 1249–1269.

Holowczak, R., Hu, J., Wu, L., 2014. Aggregating information in option transactions. The Journal of Derivatives 21, 9–23.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. The Review of Financial Studies 28, 650–705.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of Finance 45, 881–898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48, 65–91.

Johnson, T. L., So, E. C., 2012. The option to stock volume ratio and future returns. Journal of Financial Economics 106, 262–286.

Kumar, R., Sarin, A., Shastri, K., 1992. The behavior of option price around large block transactions in the underlying security. The Journal of Finance 47, 879–889.

Lehmann, B. N., 1990. Fads, martingales, and market efficiency. The Quarterly Journal of Economics 105, 1–28.

Manaster, S., Rendleman Jr, R. J., 1982. Option prices as predictors of equilibrium stock prices. The Journal of Finance 37, 1043–1057.

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

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

Ratcliff, R., 2013. Relative option prices and risk-neutral skew as predictors of index returns. The Journal of Derivatives 21, 89–105.

Rehman, Z., Vilkov, G., 2012. Risk-neutral skewness: Return predictability and its sources. Working Paper, BlackRock and Frankfurt School of Finance and Management .

Roll, R., Schwartz, E., Subrahmanyam, A., 2010. O/s: The relative trading activity in options and stock. Journal of Financial Economics 96, 1–17.

Schlag, C., Thimme, J., Weber, R., 2021. Implied volatility duration: A measure for the timing of uncertainty resolution. Journal of Financial Economics 140, 127–144.

Stephan, J. A., Whaley, R. E., 1990. Intraday price change and trading volume relations in the stock and stock option markets. The Journal of Finance 45, 191–220.

Stilger, P. S., Kostakis, A., Poon, S.-H., 2017. What does risk-neutral skewness tell us about future stock returns? Management Science 63, 1814–1834.

Wang, Z., 2017. Option trading leverage and stock returns. Working Paper, State of Wisconsin Investment Board .

Xing, Y., Zhang, X., Zhao, R., 2010. What does the individual option volatility smirk tell us about future equity returns? Journal of Financial and Quantitative Analysis 45, 641–662.

Yan, S., 2011. Jump risk, stock returns, and slope of implied volatility smile. Journal of Financial Economics 99, 216–233.